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Matched, Somewhat-Matched or Mismatched? Predictors of Degree-Job Match among STEM Graduates

Taghreed Ahmed Alhaddab
taghreed.alhaddab@student.shu.edu

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Predictors of Degree-Job Match among STEM Graduates

By

Taghreed Ahmed Alhaddab

Dissertation Committee

Eunyoung Kim, Ph.D., Committee Chair
Rong Chen, Ph.D., Committee Member
Joseph Stetar, Ph.D., Committee Member

Dissertation

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APPROVAL FOR SUCCESSFUL DEFENSE

Doctoral Candidate, **Taghreed A. Alhaddab,** has successfully defended and made the required modifications to the text of the doctoral dissertation for the **Ph.D.** during this **Fall Semester 2015**.

DISSERTATION COMMITTEE
(please sign and date beside your name)

Mentor:
Dr. Eunyoung Kim 11/23/2015

Committee Member:
Dr. Rong Chen 11/23/2015

Committee Member:
Dr. Joseph Stetar 11/23/15

The mentor and any other committee members who wish to review revisions will sign and date this document only when revisions have been completed. Please return this form to the Office of Graduate Studies, where it will be placed in the candidate's file and submit a copy with your final dissertation to be bound as page number two.

Abstract

The current third-generation globalization caused structural, organizational and functional changes in the STEM workforce along with changes in human capital flow. The new globalization shift produced new world order causing the STEM workforce to adopt new frameworks, new skills, and new policy approaches to maintain economic strength and achieve growth and prosperity. Available data indicate that the U.S. secondary and postsecondary education system prepares and produce more than an adequate number of STEM graduates. The perceived crisis in the number of U.S. STEM graduates was not confirmed by any data or policy report. Thus, attention should not be caught simply by the quantity of graduates, but rather on the quality and level of competitiveness. The federal government, along with private organizations, allocates substantial fiscal aid and resources to the STEM education system. However, concerns over the quality and competence of STEM graduates, and the U.S. position in the global market continue to grow as STEM graduates increasingly work in non-STEM occupations (degree-job mismatch).

Degree-job match in this study refers to the match between degree field, or degree knowledge and skills, to the job. The impact of mismatching degree, or degree knowledge and skills, to jobs, is substantial resulting in lower wages, low job satisfaction and productivity, loss of unused skills, higher turnover, feelings of loss in educational return on investments, loss of return on human capital investment, and an inadequate labor force for workforce' expansion and growth. The current research in the area focused substantially on the consequences of the mismatch with little to no attention to the causes of the mismatch. Using a sample of 1864 participants taken from the National Center for Education Statistics (NCES): the Education Longitudinal Study of 2002 (ELS: 2002), this study looked at predictors to degree-job match among recent bachelor degree STEM graduates. The study used the Social Cognitive Career Theory (SCCT) as a foundation for its Degree-Job Match Model. Results show that cognitive abilities and career-related experiences during college are by far the most influential predictors of the match between degree and job. The adequacy of the degree-job match was found as well to be influenced by discriminatory factors; race and socioeconomic status. This study also documented that mismatched workers suffer from nearly 33% wage penalty as compared to their adequately matched peers. This study contributes substantially to the existing line of literature concerned about career choice and college major choice.

To my husband, Suleman for his unconditional support
To my parents, Ahmed and Badria for their continued encouragement
To my siblings, Maram, Abdulaziz, Yasser, and Saad
And, to my children Farrah and Abdullah

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Chapter I

INTRODUCTION

Background

Numerous reports on the lack of sufficient numbers of Science, Technology, Engineering, and Mathematics (STEM) graduates have recently dominated discussions raising concerns about the overall health of U.S. economy and its global position as innovation preeminence (Butz, Kelly, Adamson, Bloom, Fossum, & Gross, 2004; Charette, 2013; Freeman, 2006; Freeman & Goroff, 2009; Lowell & Salzman, 2007; Lowell, Salzman, Bernstein, & Henderson, 2009; Lynn & Salzman, 2006; Salzman, 2007; Salzman & Lynn, 2010; Salzman, Kuehn & Lowell, 2013; Teitelbaum, 2014). Policymakers are concerned with the quality and competence levels of STEM graduates, the quality of K-12 math and science education, and the overall declining interest in STEM-related fields and STEM careers among students (Lowell & Salzman, 2007; Lowell et al., 2009; Teitelbaum, 2014). On the contrary, many reports claim the opposite; data show that the supply of STEM-qualified graduates is adequate enough, the retention rate of undergraduates in STEM-related fields has grown, K-12 math and science education shows steady improvement; test scores are better than two decades ago, and high school students' interest in STEM majors or occupations is higher than ever by historical standards (American College Testing, 2013; Butz et al., 2004; Freeman, 2006; Lowell & Salzman, 2007; NSF, 2012; Salzman et al., 2013). In fact, some reports even claim that recently more students graduate from STEM disciplines than the United States workforce can absorb; causing wages to stagnate, or even fall, and even the unemployment rate to rise (Butz et al., 2004; Charette, 2013; Lowell & Salzman, 2007; Lowell et al., 2009; Teitelbaum, 2014; Zeigler & Camarota, 2014). Lowell and Salzman (2007) reported in their study that the number of students who graduate with a four-year degree in Science and Engineering (S&E) fields "...are three times as many as S&E job openings" (Lowell & Salzman, 2007, p. 1), pointing out that the demand side is unable to more STEM graduates into the STEM workforce. According to the National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT), nearly half of S&E degree holders are working in non-S&E occupations (see Table1).

Table 1.

Employed Scientists and Engineers by Occupation Type in 2013

Total Employed	S&E Occupations	S&E-Related Occupations	Non-S&E Occupations
21,903,000	5,398,000	6,957,000	9,549,000

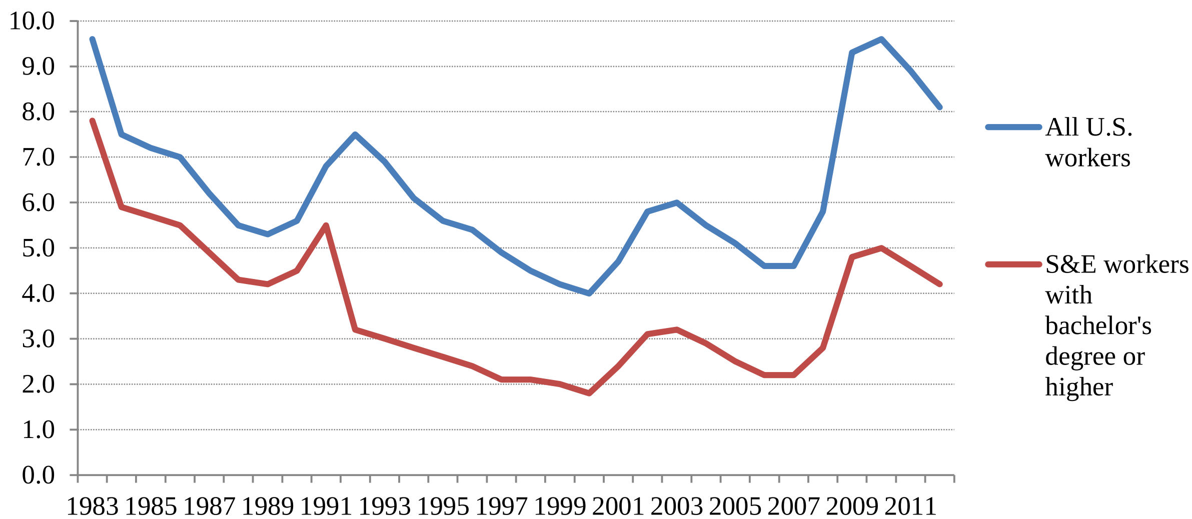
SOURCE: National Science Foundation, National Center for Science and Engineering Statistics, Scientists and Engineers Statistical Data System (SESTAT), 2013.

Economic indicators such as unemployment rate and earning patterns are often used as the best measurements of STEM workers' shortage/surplus. If the demand side is unable to absorb the supply of workers, wages will fall while unemployment rate increases. In examining earnings and employment patterns of STEM workers, Butz et al. (2004) concluded that shortage patterns do not exist. In fact "underemployment patterns" were relatively high for STEM workers compared to the non-STEM workers, indicating that a large number of STEM workers are involuntarily working out of their fields (Butz et al., 2004), which is an indicative of surpluses, rather than shortages.

Unemployment in STEM Occupations

For the period from 1983 to 2010, The Bureau of Labor Statistics' Current Population Survey data shows that unemployment rate for S&E occupations ranged from 1.3% to 4.3%, where the rate is slightly higher for technicians and computer programmers that ranged from 2.1% to 7.4% (Bureau of Labor Statistics, 2013). The 4.3% unemployment rate for S&E

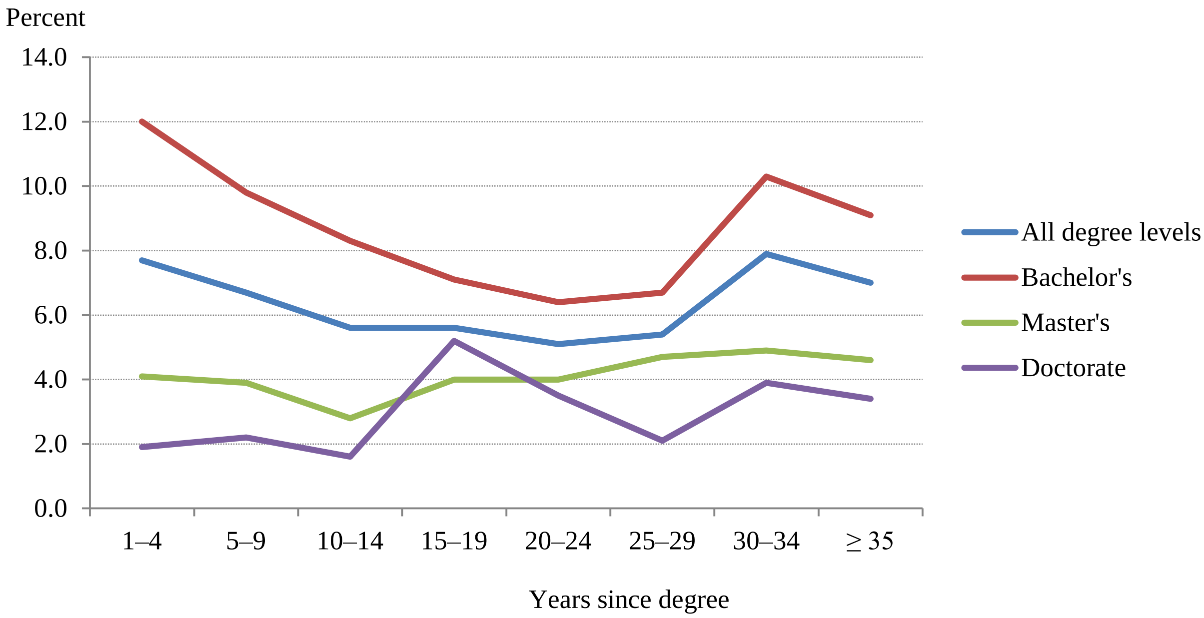
workers, although lower compared to other fields, is the highest in the last twenty-five years (Bureau of Labor Statistics, 2013). In the period from 1984 to 2010, STEM unemployment rates were lower than the national average (The Bureau of Labor Statistics, 2010), but are in line with the unemployment rate for other occupations. Figure 1 shows the trend in STEM workers' unemployment rate compared to all U.S. workers. If there is a shortage of STEM workers, then the STEM unemployment pattern should at least show a different/better trend than the national average trend. Mirroring the national average could be taken as an indication that the STEM problem is not associated with the supply adequacy, but rather with the overall health of the U.S. economy.



SOURCE: SEI 2012: Unemployment in the S&E Labor Force, Chapter 3.
Science and Engineering Indicators Digest, 2012.

Figure 1. Unemployment rates for all workers compared to workers in S&E occupations: 1984–2011

Further, involuntarily out-of-field rate (IOF) which is an indication of underemployment; working involuntarily outside the field of the worker's highest degree because a job in that field is not available, increased since 1999 to reach 12% in 2010 for newly-graduated (within five years since receiving the degree) STEM bachelor's degree holders (NSF, 2014). The IOF rate varied by STEM-degree type and field, in 2010; for example newly-graduated STEM master's degree holders had an IOF rate of 4.1% whereas newly-graduated STEM doctorate holders had an IOF rate of 1.9% (see Figure 2, NSF, 2014).

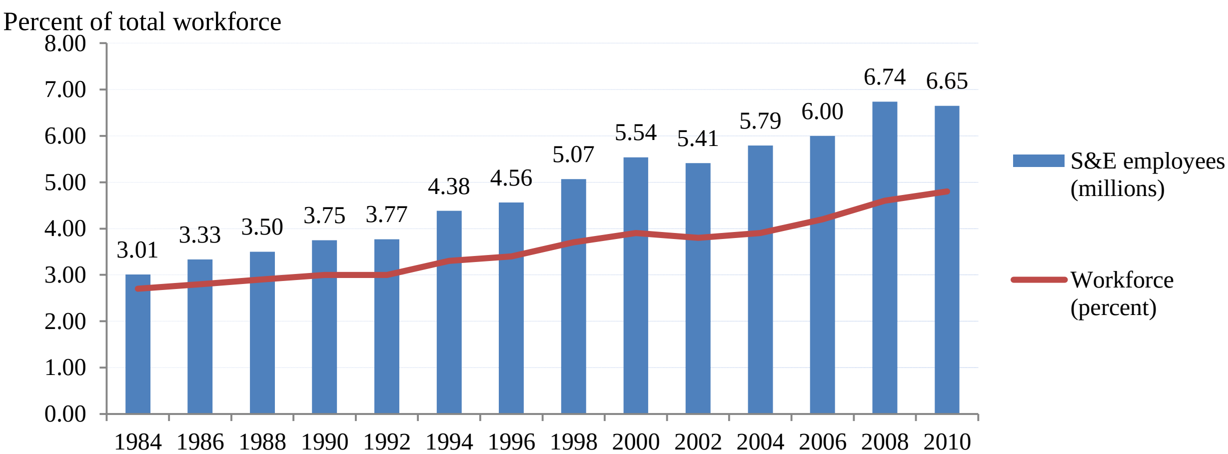


SOURCE: National Science Foundation, National Center for Science and Engineering Statistics, Scientists and Engineers Statistical Data System (SESTAT) (2010), http://sestat.nsf.gov.

Figure 2. Scientists and engineers who are working involuntarily out of field, by level of and years since highest degree: 2010

Figure 2 also shows that the IOF rate, for nearly all STEM-degree types, slowly decline through career stages. However, when it reaches mid-to-late career years (25-34), it starts to increase. It is also clear that among STEM-degree holders, master’s degree has an IOF rate that remains slightly stable across career stages. The IOF rate shows significant differences among STEM fields as well; computer and mathematical sciences, and engineering show a lower IOF rate (5.1 and 4.9 respectively) compared to life, or social sciences; 10.1% and 11.3% respectively (NSF, 2014).

To further challenge the shortage claim, Figure 3 shows the percentage of STEM workforce in the U.S. workforce for the period from 1983 to 2010. During that period, STEM workforce has grown faster compared to the overall U.S. workforce growth; the average annual growth rate of the S&E workforce is 3.3% compared to 1.5% of the U.S. workforce (NSF, 2012). In fact, the Department for Professional Employees (DPE) notes that the STEM workforce has more than doubled in size since 1960 (1.6%), and it represented nearly 5.2% of the total workforce nationwide in 2011 (DPE, 2014).



SOURCE: National Science Foundation, SEI 2012: Size of the S&E Workforce, Chapter 3. *Science and Engineering Indicators 2012*

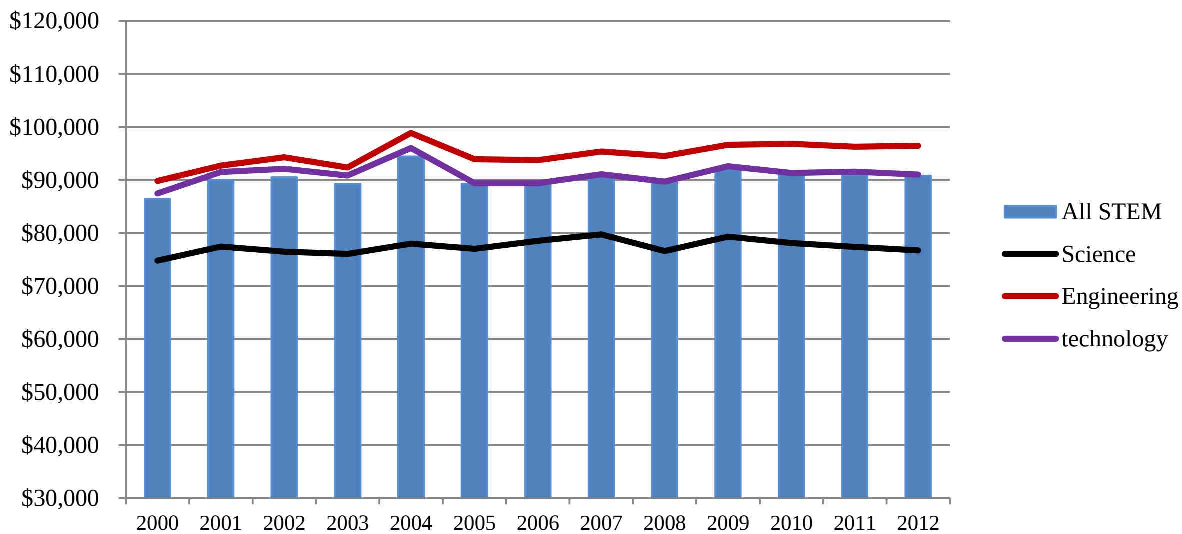
Figure 3. Individuals in S&E occupations and as a percentage of the U.S. workforce: 1983–2010

The "total" U.S. STEM workforce differs by geographic location; California has over 13% of the U.S. STEM workforce accounting for over one million jobs (DPF, 2014). In Washington, D.C. the STEM market represents 10.1% of the total "regional" workforce while it only represents 2.8% in Mississippi (DPE, 2014).

The increasing growth trend of the STEM job market might support the shortage claim if accompanied by a declining trend of STEM unemployment rate. There is an unstable correlation between STEM market growth (demand-side) and STEM unemployment rate (supply-side). For instance, the unemployment rate of STEM-degree holders increased 0.6% between 2007 and 2008 where, during the same period, the STEM workforce hired 440,000 more individuals (2007 to 2009 represent a recession period). It is clear that the demand side is economically healthy as reflected in the overall growth. What might explain the increasing STEM unemployment pattern is that there are more STEM-degree holders than STEM job openings which contradict with the shortage claim. It is also possible that the demand side is looking to fill its jobs by employing either non-STEM degree holders or non-citizen STEM-degree holders or for other reasons that are not yet explored, such as outsourcing and off-shoring.

Earning Patterns

In general, individuals in STEM occupations have a median annual earning that is higher (in some cases double) than other occupations in the U.S. workforce (NSF, 2014). The Occupational Employment Statistics (OES) survey notes that in 2012 individuals in STEM occupations had median annual earnings of $75,840 (regardless of education level or field) compared with $34,750 of all U.S. workers (Bureau of Labor Statistics, 2012). However, employment trends in STEM occupations have been unstable over the years. Lazonick (2009) examined the employment and wages trends in different U.S. industries including the S&E job market. The analysis revealed a steep increase in employment and wages for STEM occupations (particularly the Information Technology labor market) during the dot-com period (the 1990s), followed by a collapse in 2001. A slow improvement in hiring followed, along with stagnation in wages- excluding some regions and occupation-specific (Lazonick, 2009). The same trend was documented by other researchers as well; low unemployment rate accompanied by high wages reflecting the strong demand during the 1990s. After the bursting of the dot-com bubble in 2001, the unemployment rate went up along with a tapering off of wages growth (Costa 2012; Matloff 2013; Salzman et al., 2013). As shown in Figure 4, though a slight improvement started around 2004 reflected in salary increase, wage rates never recovered and are stagnated for the past decade. Unmet demands accompanied by a rise in wage rates are usually an indication of a labor shortage. Having stagnant wages for the past ten years does not support the shortage claims (Salzman et al., 2013).



SOURCE: Public-use files of the 2000-2012 American Community Survey. Analysis confined to STEM workers with at least a bachelor's degree age 64 and under, working 35 hours or more per week and at least 50 weeks a year.

Figure 4. Average annual wages for STEM workers with a Bachelor's degree or higher (in 2012 dollars)

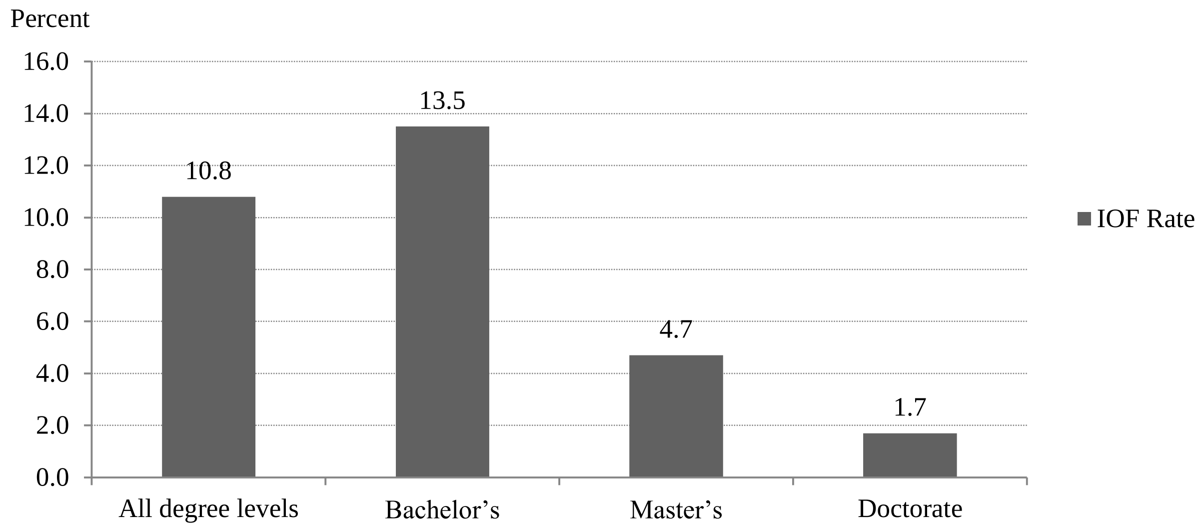
The low annual wage growth rates (all STEM 0.4%, Science 0.2%, Engineering 0.6%, and Technology 0.3%) over the past decade indicate no shortage or high demand for labor; in contrast, it shows that the supply is adequate to meet the demand. It is important to note that earnings vary by degree levels; in 2010, doctorate STEM-degree holders earned an average of $85,000 while bachelor's and master's STEM-degree holders earned $57,000 and $68,000, respectively (NSF, 2014). Further, individuals with S&E-degree working in an S&E or S&E-related fields earn more ($78,000 and $65,000 respectively) than those with S&E degree ($50,000) but are working in a non-S&E occupation (NSF, 2014). In fact, S&E degree holders working in a non-S&E field earn less ($50,000) than non-S&E degree holders who are working in S&E or S&E-related fields; $70,000 and $53,000 respectively (NSF, 2014).

Statement of the Problem

The supply of STEM workers seems to be larger than what might at first appear based on economic indicators: unemployment rates and earning patterns. The supply of qualified STEM workers appears to be adequate; to the point where a shortage of STEM workers did not exist nor will it in the near future (Butz et al., 2004). The fact that new STEM graduates (1 to 5 years since receiving the degree) are struggling with worker surpluses might result from the mismatch between supply and demand. Such mismatch varies by STEM degree type and field, degree holders' demographic characteristics, geographic locations and many other factors (NSF, 2014; Salzman, 2014; U.S. Census Bureau, 2014).

Differences by STEM Degree Type

In 2010, recent STEM graduates had an unemployment rate of 6.6%; higher than the average unemployment rate (4.3%) of all STEM workers (NSF, 2014). In the same year, young scientists with bachelor's degree who recently graduated had an even higher unemployment rate (7.7%) than master's and doctoral recent STEM graduates; 4% and 1.6% respectively (NSF, 2014). It also seems that the number of recent STEM bachelor's degree holders involuntarily working out of their field (IOF rate) is significantly higher compared to other degree types within the same field. As shown in Figure 5, nearly 11% of S&E recent graduates reported working out of their field because a job in their field was not available, compared with 6.4% of the overall S&E population (NSF, 2014). The percentage is more than double for bachelor's degree holders (13.5%) compared with 6.4% of the national average of all S&E workers working involuntarily out of their fields (NSF, 2014).



SOURCE: National Science Foundation, National Center for Science and Engineering Statistics, Scientists and Engineers Statistical Data System (SESTAT) (2010), http://sestat.nsf.gov.
Science and Engineering Indicators 2014

Figure 5. Involuntarily out-of-field (IOF) rate for recent S&E degree recipients up to 5 years after receiving degree, by level of highest degree: 2010

Concerning the relationship between their degree and current job, nearly 36% of recent bachelor's S&E degree holders work in non-S&E fields stated it is "not related" (NSF, 2014). Table 2 further notes the significant difference in job relation to the field of study among different S&E degree holders working in non-S&E occupations. When asked about the reasons for working out of their field, 29% reported a lack of a suitable job in their degree field as a reason; 20% cited wages and promotion opportunities as a factor while 13% reported a change in career or professional interests (NSF, 2014). Over 80% of S&E master's degree holders and 84% of doctoral degree holders working in a non-S&E occupations reported that their job is either "closely related" or "somehow related" to their field of study, compared with 64% of bachelors' degree holders.

Table 2.

Relationship of highest degree to job among S&E highest degree holders not in S&E occupations, by degree level: 2010

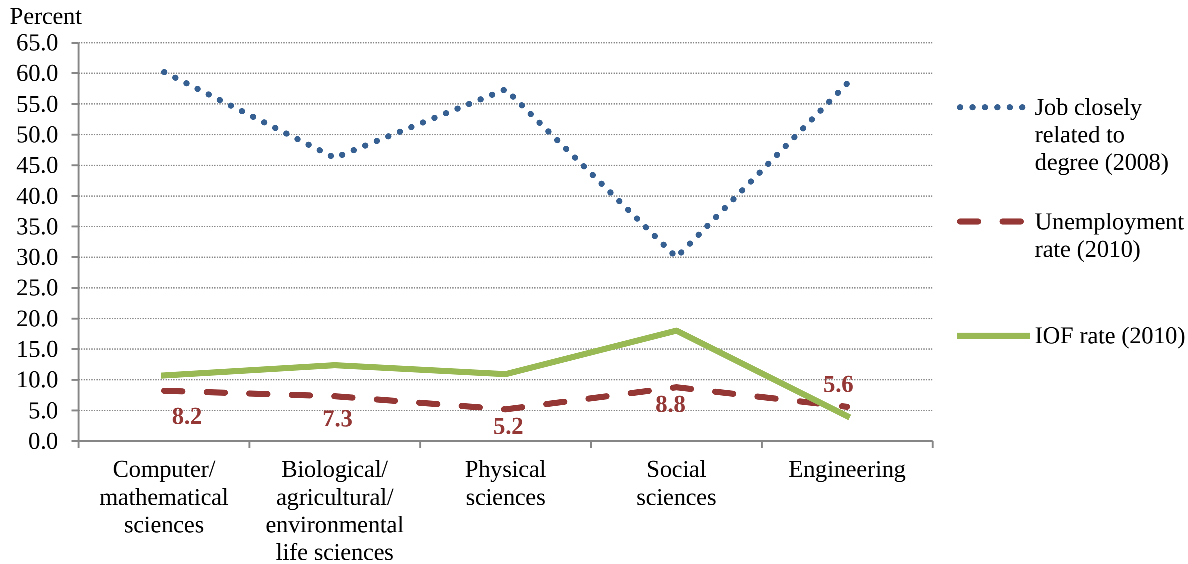
		Degree related to job (%)		
Highest degree	Workers (*n*)	Closely	Somewhat	Not
All degree levels [a]	7,386,000	35.2	32.4	32.4
Bachelor's	5,902,000	31.1	33.1	35.8
Master's	1,242,000	51.8	28.7	19.5
Doctorate	236,000	49.6	34.3	16.1

[a] Includes professional degrees not broken out separately.

SOURCE: National Science Foundation, National Center for Science and Engineering Statistics, Scientists and Engineers Statistical Data System (SESTAT) (2010), http://sestat.nsf.gov.
Science and Engineering Indicators 2014

Differences by STEM Degree Field

The significant differences among recent graduates are not only shown in degree type, but it is obvious as well in degree fields. As stated earlier, recent graduates holding a bachelor's degree in STEM are of particular interest to this study considering their significant differences in unemployment rates, wages, and IOF rates compared to STEM master or doctoral degree holders. Among newly-graduated S&E bachelor's degree holders, individuals with an engineering, or computer/mathematical sciences degrees are struggling less than other S&E majors (NSF, 2014). Notable in Figure 6 below, among S&E recent bachelor's degree recipients, individuals with computer/mathematical sciences degrees work in jobs closely related to their degree in higher rates than other S&E degree types, especially compared to the social science field. Unemployment rate ranged from 5.6% for those with engineering degrees, to 8.8% for individuals with social science degrees. As for the IOF rate, again the social science field shows higher rate (18%) than other majors.

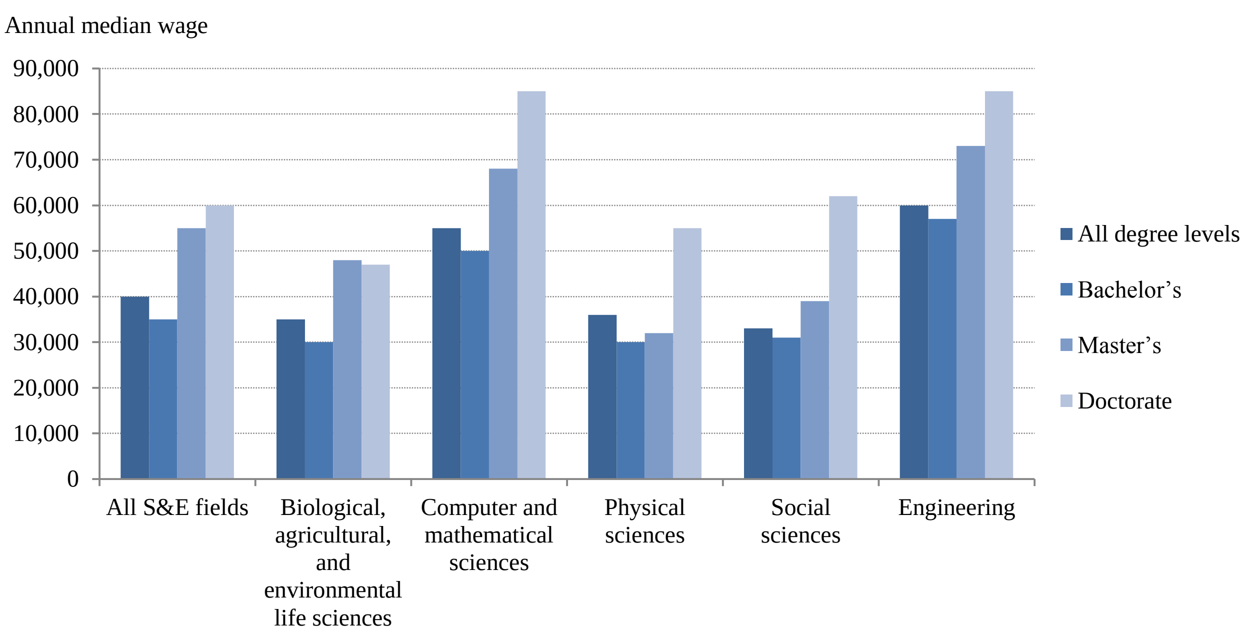


SOURCE: National Science Foundation, National Center for Science and Engineering Statistics, Scientists and Engineers Statistical Data System (SESTAT) (2008), http://sestat.nsf.gov.
Science and Engineering Indicators 2014

Figure 6. Labor market indicators for recent S&E bachelor's degree recipients up to 5 years after receiving degree, by field of degree: 2008/2010

It is worth noting that this pattern of field's significant differences is generally at either a bachelor's or master's degree level. At the doctoral level, such field differences shrink substantially where doctoral degree recipients work in occupations related to their doctoral field (NSF, 2014). For instance, nearly 70% of individuals with a doctoral degree in social science are working in S&E occupations, compared to 13% for individuals with bachelor's degree in the same field, and compared to 75% for those with a doctoral degree in engineering (NSF, 2014). Furthermore, the relationship between occupation and degree type is robust across career stages for doctoral degree holders compared to bachelor's and master's although such relationship becomes weaker over time possibly due to changes in career interests or promotion to managerial positions (NSF, 2014).

Economic variation among STEM degree fields for recent graduates (5 years after receiving a degree) is notable as well in annual wages. As shown in Figure 7, the engineering field followed by the computer/mathematical sciences are the two fields with higher annual income; 60K and 55K respectively for all degree levels. The latter applies across different S&E degree types reflecting how lucrative it is to hold a degree in these two fields.



SOURCE: National Science Foundation, National Center for Science and Engineering Statistics, Scientists and Engineers Statistical Data System (SESTAT) (2008), http://sestat.nsf.gov.
Science and Engineering Indicators 2014

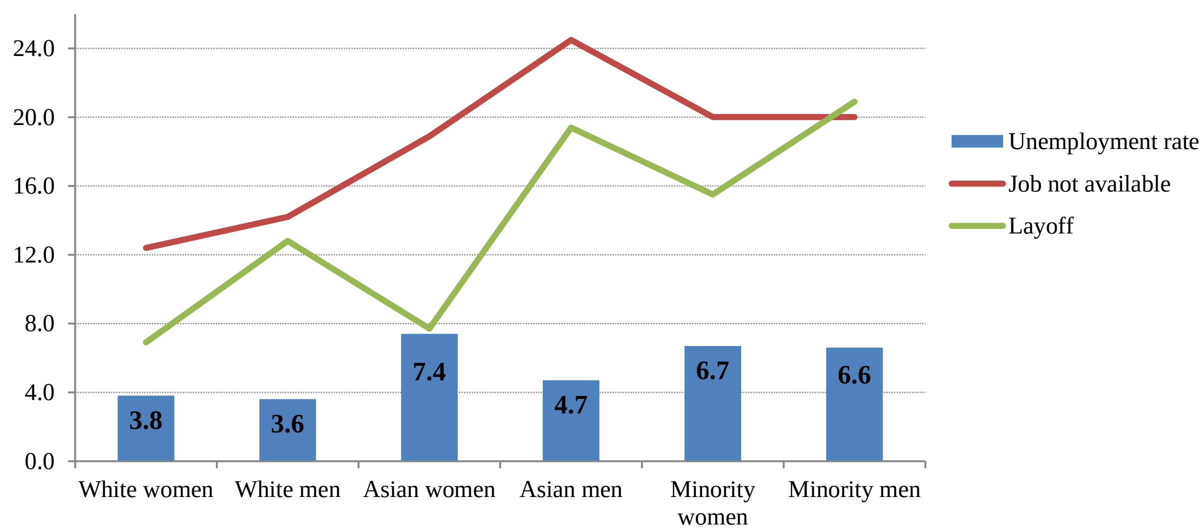
Figure 7. Annual income for recent S&E degree recipients up to 5 years after receiving degree, by level and field of highest degree: 2010

Differences by Demographic Attributes

In general, the S&E workforce is largely dominated by white male individuals representing more than half of the STEM job market (NSF, 2013). Women, of all races and ethnicities, and minorities working in STEM fields are underrepresented and underpaid (DPE, 2014; Hill, Corbett, St. Rose, 2010; Ong, 2005). Previous research noted several reasons related to the underrepresentation of minorities and women in the STEM pipeline. These include lack of role models, inadequate social integration into the field, feelings of academic or social isolation and marginalization due to one's race/ethnicity, gender, or a combination of both (American Institutes for Research, 2012; Stout, Dasgupta, Hunsinger, & McManus, 2011). The underrepresentation of women and minorities differs considerably by the STEM field. In 2013, for example, women made up 46% of professional science workers (with even larger representation in fields like dietitians and therapists), but only had a small representation in math/computer and engineering professionals; 26% and 14%, respectively (DPE, 2014). Further, in 2013, male practitioners in the STEM workforce and related occupations earned on average 27% more than women (Bureau of Labor Statistics, 2013). As for minorities, African Americans comprised 9.3% of the professional workforce, while Hispanic professionals represented only 8.2%; similar representation to Asians (DPE, 2014). The underrepresentation of minority professionals is even larger in some STEM fields. In occupations like architecture and engineering African Americans were just 5.5% of the workforce (Bureau of Labor Statistics, 2013). Overall, African Americans and Hispanic professional workers were more proportionally represented in lower-paying support positions such as computer support personnel or technicians (DPE, 2014). As for wages, Asian and White workers had higher than average earnings, while

Hispanic and African American professionals reported lower than average wages in 2012 (DPE, 2014).

Unemployment status did not show a significant gender gap. However, a deeper look into unemployment rate by race/ethnicity shows significant gender/race differences, especially for female Asian scientists and engineers. As shown in Figure 8, Asian female scientists and engineers had the higher unemployment rate (7.4%) compared to other races in 2010. When asked for reasons why not employed, 45% of Asian female scientists and engineers cited "family responsibilities" as a reason (NSF, 2013). Both males and females and different race/ethnicity professionals cited “not able to find a job in the field” as a frequent reason for unemployment (see Figure 8).



SOURCE: National Science Foundation, National Center for Science and Engineering Statistics, Scientists and Engineers Statistical Data System (SESTAT), 2010.

Figure 8. Unemployment rate of scientists and engineers by race and reasons for unemployment: 2010

Limitations of Previous Research

Although recent graduates' degree type and field along with their demographic characteristics can greatly affect their retention in the field after graduation (Bureau of Labor Statistics, 2013; DPE, 2014; Hill, Corbett, St. Rose, 2010; NSF, 2014; Ong, 2005), their unemployment rate, IOF rate, annual income, and the current attrition problem at the end of the STEM pipeline cannot be simply explained by graduates’ attributes. The crisis of recent STEM graduates is a result of a combination of problems where individuals (students), the supply (K-16 education), and the demand (workforce) are all involved. Such combination can be grouped into two major categories (besides the previously explained students' attributes): the supply-side competency, and the demand-side deficiencies, where the latter is constantly changing as a result of globalization and internationalization forces (Salzman, Kuehn, Lowell, 2013). These two categories are explained in greater depth in Chapter 2.

So far empirical evidence shows that recent STEM graduates especially bachelor's degree holders, if not unemployed, are working in large proportions in fields that unrelated to their degrees. Data shows that economic indicators such as unemployment rate, IOF rate, and wages trends, point to a surplus in the supply of young scientists. Finding a job in the STEM field or STEM-related fields immediately after graduation (even few years after) is becoming an inevitable challenge for STEM recent graduates. Some graduates struggle more than others due to factors related to their degree type/field, geographic location, and some demographic characteristics (Bureau of Labor Statistics, 2013; DPE, 2014; Hill, Corbett, St. Rose, 2010; NSF, 2014; Ong, 2005). It is, therefore, important to investigate why some recent STEM graduates are successful in securing a job in their field or related fields upon graduation while others struggle even to find a job years after they earned their degrees.

Unlike the supply side, the demand side has received some scholarly attention (e.g., Lynn & Salzman, 2006; Manning, Massini & Lewin, 2008; Salzman, 2007; Salzman, Kuehn & Lowell, 2013; Salzman & Lynn, 2010; Sargent Jr., 2010). Little focus has been given to the supply side which requires immediate attention, especially on the student level, since the current issue is a result of both the supply and the demand. Some researchers examined the concept of shortage, comparing the number of STEM graduates to job openings in their fields (e.g., Salzman, 2007) without providing further analysis. Others went deeper to follow students through the STEM pipeline's main pathways (e.g., Lowell, Salzman, Bernstien, & Henderson, 2009) analyzing several longitudinal datasets. However, their conclusions focused mainly on trends in the rates of retention and attrition along the STEM pipeline. Some research has focused on one field of STEM, engineering, with no consideration to other STEM fields (e.g., Lowell & Salzman, 2007; Shuman, Delaney, Wolfe, Scalise, & Besterfield-Sacre, 1999).

Although research exists to investigate education and job match, studies conducted in that area looked at all majors with no particular attention to STEM and mainly focused on the match between years of schooling and the educational attainment required for the job (e.g., Cohn & Kahn, 1995; Groot & Van Den Brink, 2000; Hartog, 2000). As Sloane (2003) states, educational attainment is one way to measure the match between degree and career (Sloane, 2003). A worker may spend years on schooling and thus have the appropriate educational attainment, but not in a highly demanded field; noting that the college major may relate to educational mismatch (Sloane, 2003). To date, limited research has looked into degree-job matching by the degree field which contributes to the research literature on college major choice (e.g., Robst, 2006). Although such studies contribute significantly to the current literature on college major choice, their conclusions are not robust enough to draw evidence on explaining the current worker-job mismatch phenomenon. For instance, such studies conclude that the mismatch is more likely to occur among workers with degrees in English and foreign languages, social sciences, and liberal arts, and less likely to occur among workers with degrees in engineering, architecture, and business management (Robst, 2006). However, these conclusions lack empirical evidence on how individuals with similar degrees vary in their likelihood to be matched with their careers, or how broader factors, beyond degree fields, can influence the mismatch. Finally, the majority of research on educational career matching had largely focused on wage differences between the matched and mismatched workers' return on investment in their education (e.g., Cohn & Kahn, 1995; Hartog, 2000; Robst, 2006).

There is a surprising lack of any empirical analysis in the literature about how the mismatch between job and degree can be influenced by educational outcomes, demographic attributes, institutional characteristics, or even broader personality and cultural influences. Studies done in this line of research seem to be sufficient to draw attention to particular causes of shortage/surplus rather than clearly defined or well-understood factors of the actual issue.

Furthermore, focusing on the supply side (STEM graduates) is crucial for several reasons: first, graduates of the STEM field play a fundamental role in innovation and technological advancement; an area that witness a global competition. As a result, a healthy supply of scientists can greatly impact technological progress and the United States' position as innovation preeminence. Second, policymakers concerned with the STEM market productivity and advancement need to understand how the mismatch between degree and occupation influences job satisfaction, and thus market productivity. Third, federal agencies and private organizations allocate substantial fiscal aid and resources to the STEM field and its students. However, concerns over the quality and competence of STEM graduates, and the U.S. position in the global market continue to grow as STEM graduates increasingly work in non-STEM occupations (Preston, 2004). Furthermore, the consequences of the mismatch not only affect individuals, but also exceed to reach institutions and, in the longer run, the entire workforce. One might perceive that it is cheaper for workers to remain mismatched as alternatives (searching for a new job or a new applicant) may cost money and time for both the employer and the employee (Bender & Heywood, 2009). However, remaining mismatched is costly; it results in significantly diminished earnings, lower job performance, loss in human capital investments, high quit rate, and lower levels of job satisfaction and productivity; setbacks that could affect the entire STEM field (Allen & Van der Velden, 2001; Belman & Heywood 1997; Bender & Heywood, 2009; Borghans, Bruinshoofd & de Grip, 2000; Clark & Oswald 1996; Freeman 1978; McGoldrick & Robst 1996; Sattinger, 1993, 2012; Sloane, Battu & Seaman 1996; Solomon, Kent, Ochsner & Hurwicz, 1981; Tsang 1987). For those reasons, focusing on the supply side (STEM graduates in this study) is the first step towards better understanding the origin of the problem and addressing the current STEM crisis.

In the age of accountability, universities and policyholders should be aware of what could contribute to a successful transition into the STEM workforce. Universities need to be held accountable for their graduates; it should not stop at awarding degrees. Knowing what could help a graduate to find a job in his/her field is crucial not only to the graduate's overall economic health but the U.S economy as well and its position as an innovation leader. Keeping a healthy STEM supply that is responsive to the STEM market's needs will ensure prosperity in all phases and transition pathways of the STEM pipeline. Universities need to connect their students' education plan to their career plan by preparing them for the market's needs. Most universities include in their mission a goal to make their students lifelong learners. If their graduates cannot find a job or a job placement related to their academic majors, then universities will fail in their mission since career life is a learning stage as well. It is critical at this point to investigate what increases the odds of finding a job in the field. Factors like training during degree thus gaining hands-on experiences may contribute to the chances of successful transition into the workforce. It could be as well factors that relate to students' soft skills; such as self-efficacy, social intelligence, or other non-technical skills are highly needed in the current third-generation globalization era, and, fortunately, can be acquired during college years as well. If job opportunities for recent STEM graduates relate to degree field or type, then universities should predict the market needs through collaboration with the demand side, and thus offer programs that match the future demand. Postsecondary institutions should obtain a more in-depth understanding of how individuals are matched with their careers. As a result, universities can modify courses or even an entire program based on attributes to degree-job matching. By doing so, individuals, and the society as a whole can maximize returns to educational investments. Only when job opportunities are correlated with demographic attributes, which are unalterable factors, can the policymakers enforce policies that ensure equal opportunity for all graduates regardless of their race/ethnicity or gender.

Purpose of Study & Research Questions

The purpose of this study is to examine whether career self-efficacy and expectancy are related to the degree-job matching among recent STEM college graduates. Degree-job matching in this study refers to the match between degree field, or degree knowledge and skills, to jobs. The impact of mismatching degree, or degree knowledge and skills, to jobs is substantial to the point where it not only affects individuals but also exceeds, in the long run, to reach the entire STEM field. The mismatch, as documented by previous research on STEM and other fields, can result in multiple adverse outcomes. These include lower wages, job dissatisfaction, low productivity, loss of unused skills, higher turnover, feelings of loss in returns in educational investments, loss of returns to human capital investments, and inadequate labor force for workforce' expansion and growth (Belman & Heywood 1997; Bender & Heywood, 2009; McGoldrick & Robst 1996; Sattinger, 1993, 2012; Sloane, Battu, & Seaman 1996; Tsang 1987). In an attempt to fulfill the purpose of this study, the following research questions that guide the study are derived from Lent, Brown and Hackett's (1987) Social Cognitive Career Theory (SCCT) which focuses on the relationship between self, learning experiences, and surrounding factors, and how the interrelated relationships among these factors affect self-efficacy and outcome expectations, thereby influencing an individual's career choices. The SCCT theory is explained fully in the next chapter.

(Demographic Characteristics)

1) How do demographic characteristics of recent STEM graduates influence the match between their degree and their current job?

(Institutional Characteristics)

2) Controlling for demographic characteristics, how do institutional characteristics (i.e., selectivity and control) influence recent STEM graduates' current degree-job match?

(College Attributes)

3) While controlling for both demographic and institutional characteristics:

- How do a graduate's major and academic cognitive abilities relate to the match between degree and current job?

- Does participating in hands-on learning opportunities (e.g., internship and onsite training) during college years increase the odds of match between STEM graduates' degree and current job?

(*Career Self-efficacy and Outcome Expectations*)

4) Controlling for demographic characteristics, institutional characteristics, and college attributes, to what extent do individuals' career self-efficacy and expectancy predict the odds of match between degree and job for recent STEM graduates?

Research Model

The aim of this study is to examine whether career self-efficacy and expectancy are related to the degree-job matching among recent STEM college graduates. The conceptual model of this study is based on the Social Cognitive Career Theory (SCCT) and includes four major constructs:

- Demographic characteristics, including gender, race/ethnicity, social backgrounds (e.g., socioeconomic status).
- Institutional characteristics, including postsecondary institution's level (four-year vs. two-year), sector (public vs. private), and selectivity level.
- College attributes, including participation in hands-on learning opportunities during college years (e.g., internship and onsite training), personal abilities (e.g., cognitive and non-cognitive skills), and college major.
- Career self-efficacy and outcome expectations, including participants' perceived confidence in their career abilities and their abilities to meet their career plans.

Figure 9, below, explains how individual's demographic characteristics and institutional characteristics could affect career-related learning experiences that reflect on career self-efficacy and career outcome expectations leading to career decision-making.

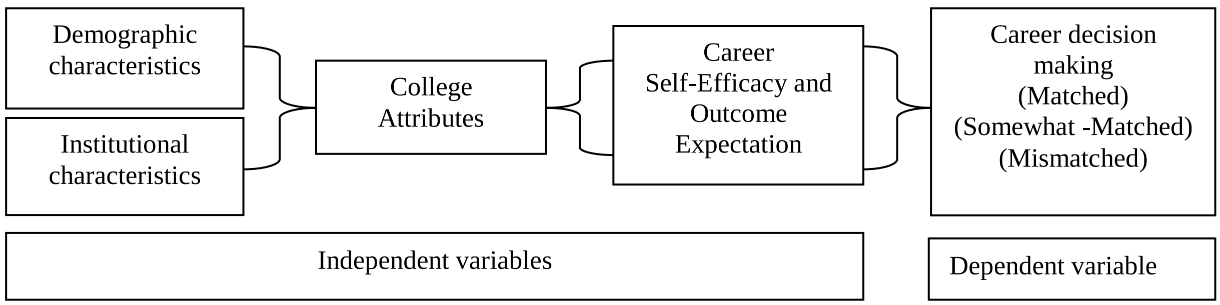


Figure 9. Research Model for Predictors of Degree-Job Match among Recent STEM Graduates

Significance of the Study

This study will contribute to the current field by highlighting factors associated with the mismatch between supply and demand in the STEM pipeline. A large portion of the existing research has focused on either the first phase of the STEM pipeline; primary and secondary education and the transition to postsecondary education or the second phase; persistence through college years to graduation. However, little attention has been paid to the third and final phase (transition to the STEM workforce). This study will look at factors that relate to graduates' successful transition into the STEM workforce, and thus retaining them in the field.

The demand side has gone under tremendous changes in the past decade or so due to the globalization and internationalization of the field along with many other factors making the transition into the STEM workforce a challenging task for recent graduates. Offshoring and outsourcing jobs along with the increasing number of foreign-born individuals on temporally visa working in the STEM workforce are all factors in influencing the attrition rate of the STEM pipeline. Increasing the supply of STEM workers through immigration can considerably impact the field's economic indicators. For example, increasing the supply of immigrant workers by only 10 percent can lower wages in a given STEM field by 3 to 4 percent (Borjas, 2009). Retirement age of STEM workers increased in the past years adding difficulties to recent graduates who seek a job in their field. Between 1993 and 2008 the median age of S&E workers in the STEM workforce increased from 37 to 41, where individuals in their 50s who reported they were still in the labor force rose from 18 percent in 1998 to 27 percent in 2008 (NSF, 2012). All of these factors can play a significant role in affecting the recent STEM graduates' attrition problem. Given that a large number of recent graduates work in occupations related to their fields despite the obstacle of high labor productivity and low labor market stability, identifying factors that ease the transition into the workforce, especially in the current globalization era, will help recent STEM graduates' to retain in the field. Working in jobs related to the individuals' field of study results in higher job satisfaction and higher productivity where individuals feel rewarded for their investments in education.

Although many researchers have attempted to validate the current concern over the STEM pipeline (Butz, Kelly, Adamson, Bloom, Fossum, & Gross, 2004; Lowell & Salzman, 2007; Salzman, Kuehn, Lowell, 2013; Salzman & Lynn, 2010; Sargent Jr, 2013; Zeigler & Camarota, 2014), little research exists to empirically investigate the STEM attrition at the end of the pipeline. The STEM pipeline received a massive research contribution over the years, but as stated earlier the pipeline has many pathways where most research focused on the first and second transition phases with little-to-no attention paid to the third and final transition phase; transition to the STEM workforce. Some researchers like Lowell et al. (2009) performed a rigorous analysis of six longitudinal datasets to validate the STEM shortage, and their study concluded that STEM students are sufficient both in numbers and preparation levels. What is missing from Lowell et al. (2009) findings and many other studies is the focus on STEM students' characteristics and attributes. Research work done in this field concluded no shortage in STEM graduates, yet attrition rate at the end of the STEM pipeline keeps raising with no clear evidence of who stays and who leaves. STEM supply differs by demographic attributes, and it varies as well by type and level of degrees. STEM demand also different by industry, occupation, and geographic locations.

These variations both in supply and demand, impact the STEM pipeline and to better understand the current mismatch a critical analysis supported by data is warranted. Studies that have attempted to examine career choices by different demographic attributes along with what could predict a STEM student’s choice of STEM career are very limited. Many U.S. employers have concern with the lack of cross-cultural skills "social cognitive skills" in such globalized market, but to what extent such skills impact the chances of a STEM graduate to hold a STEM job? Do low levels of social cognitive skills lead to employment in non-STEM occupations? How do students with similar levels of social cognitive skills, but different demographic features, gender/race, differ in their probability of holding a STEM job after graduation? The following section examines the problem of soft skill. The current gap in the literature, the shortage of evidence, and the forthcoming burst of the STEM bubble requires an immediate policy intervention based on empirical findings.

Organization of the Dissertation

Chapter one includes an introduction to current concerns over the STEM pipeline. The chapter then, supported with statistical figures, moves to highlighting the issue of the mismatch between supply (graduates' fields) and demand (careers), and why the mismatch should be considered as a serious problem. Further, chapter one also includes the statement of the problem, purpose of research, significance of the study, and research questions. The study moves then to chapter two, where both the review of the literature and the theoretical frameworks are presented. The literature review in chapter two provides a comprehensive review of the current STEM concern; starting with a brief history of the issue, moving to highlight the concept of the third-generation globalization, and ending with both a micro and a macro analysis of the STEM pipeline. Chapter two then, concludes with theoretical frameworks guiding the current research. The third chapter in this study presents the proposed methodological procedures that will be applied in this research; proposed dataset, list of variables, and proposed statistical analysis methods.

CHAPTER II

Literature Review and Theoretical Framework

To understand the nature of the ongoing STEM crisis debate a fine-grained analysis is critical, and thus the following sections will address three main points. First, it is important to take a brief look at the history of U.S. research and technological development (R&D) and the recent move to the "Third-Generation Globalization" era to understand better the root of STEM concerns and the increasing emphasis on the importance of maintaining the world's leader position. Second, to identify the deficiencies or the leak in the STEM pipeline, it is necessary to follow the flow of students through the pipeline or the pathways; from high school to college, and until they reach the workforce. The third section will address the concept of STEM "shortage" by looking at the nature of STEM workforce and the recent structural changes in the field.

Historical Development

Brief Look

In 1957, the Soviet Union launched the Sputnik satellite breaking the United States' R&D monopoly and creating fear and concerns among American citizens about their national security (Dickson, 2001; Michael, 1960; Nisbet, M. C., & Scheufele, 2009; Swinehart & McLeod, 1960). Concerns were not only about national security status but also the possibility that Soviet youth may have a much better education in science and technology than American students, which eventually may lead the U.S. to lose its global domination (Lynn & Salzman, 2006). A few years after that, America was shocked by another global advancement from Japan and Korea. Their success in steelmaking and auto production industries raised the bar even higher for the United States. While countries like Japan enrolled their students in S&E fields, U.S. students majored in law and finance, enabling Japan to take over some key technological fields. The economic threat from the Soviet Union and East Asia led U.S. policymakers to question their ability to maintain America's global dominance and high standard of living, such threat quickly diminished; the Soviet Union with its Communist system slipped into tough times (Lynn & Salzman, 2006; Nye, 1990).

In the 1980s several firms started what became known as the "multinational" move; offshoring jobs and production to low-cost locations outside the United States. At the same time, Japan and Korea increased their production into the global market taking over a fair amount of market share (Lynn & Salzman, 2006). Such race to dominance in the industrial field along with the offshore trend led the U.S. to lose hundreds of thousands of jobs, and it was painful for both workers and small domestic companies. With all that challenge, the U.S. managed to recover and grow its economy, keeping up with the overall growth in world trade market and switching its workforce into high-end technological development (Lynn & Salzman, 2006). The U.S. ability to overcome these challenges was attributable to several reasons: the ongoing improvement of the education system, the increasing production of qualified scientists and engineers, the fertile environment that attracted highly-talented foreigners to its universities and businesses, and the flexible system that fosters innovation and encourages new business ventures. To ensure its dominance, by the end of the 20th century the United States spent more than Japan and double what France, Germany, and the United Kingdom combined spent on R&D (Lynn & Salzman, 2006).

Third-Generation Globalization

During the era between the 1950s and early 1960s, U.S. companies outsourced simple and easy task technological jobs to boost profit and cut costs. At that time, U.S. firms enjoyed trade privileges provided to them by world trade regulations. Further, the U.S. was filled with talented workers and superior technology where there wasn't much foreign competition. In short, that period of globalization was marked by U.S. firms' dominance (Lynn & Salzman, 2006). The era after that was clearly different; in the late 1960s the world moved into the second generation of post-war globalization where companies from East Asia started taking over the automobile industries, electronics production, and steelmaking. The U.S. companies responded to the emergence of their new non-Western rivals with a cold shoulder doubting their abilities to compete and considering their products as lower-grade and unsophisticated merchandise (Lynn & Salzman, 2006). Soon as the technology became more mobile, East Asian firms slowly dominated the innovation and global market. As a response, U.S. firms used their strong technological lobby and access to capital to ask for market protection to maintain its competitiveness; yet many U.S. firms failed (Lynn & Salzman, 2006).

The twenty-first century marks a turning point in a new era of globalization known as Third-Generation Globalization. It started at the end of the 1990s when the trade environment shifted tremendously due to new communication channels and work-sharing technologies that significantly reduced geographical barriers making the world an open society and enabling human capital, technological services, production, and capital to flow free and fast around the globe (Lynn & Salzman, 2006). U.S. firms, at this globalization stage, faced challenges to stay dominant since the newly emerging economies are much more solid and stronger than those that emerged two decades ago (Freeman, 2006). Further, multinational strategies that U.S. firms exercised before soon became a threat to U.S. economy. Such strategies jeopardized U.S. national identities by making these firms citizens of the countries in which they do business with (Lynn & Salzman, 2006). Also, multinational strategies caused U.S. firms to be loosely tied to their country, making the effort to maintain U.S. global hegemony an overwhelming challenge; if it is even feasible at all. What marked this period (the 1990s) as well is the declining number of S&E immigrants who the United States heavily depend on as its science, engineering, and technology human capital. For immigrants, the emerging economy of their home countries presented greater opportunities than the U.S., leading them to move back to their countries and causing the U.S. the loss of a vital source of technology entrepreneurship and innovation (Lynn & Salzman, 2006). During this time as well, U.S. students enrolling in STEM fields or pursuing STEM careers declined, raising concerns over the availability of adequate human resources to maintain global leadership (Freeman, 2006; Lowell et al., 2009).

Policies were created to encourage more students to major in STEM fields to address the perceived U.S. technology challenge. The problem is, however, as Lynn and Salzman (2006) point out in their interviews with engineering managers, that inducing more STEM graduates into the market will not solve the issue, it will, in fact, worsen it. None of the engineering managers interviewed complained about a shortage of new STEM graduates, thus increasing the supply of STEM graduates will increase the unemployment rate, stagnate wages, and discourage future students from pursuing either a STEM degree or a STEM career (Lynn & Salzman, 2006). What engineering managers highlighted as an issue when hiring new S&E graduates is not the lack of technical knowledge and skills (talent) but the lack of soft-skills. In today's world, cross-cultural skills (social cognitive skills) are critical to function in the current third-generation globalization. Firms are looking for individuals who can successfully communicate their ideas in a market setting more diverse than ever, and individuals who understand cross-cultural differences and appreciate them. For the U.S., to assure, or even gain back in some areas, its global leadership, STEM education system must be refined. U.S. universities need to reconstruct their STEM curricula to meet the needs of the new global market, by increasing understanding of cross-cultural differences, encouraging collaborative competencies, and teaching how to manage global teams. In the current third-globalization generation era, it is critical for STEM graduates to know how to work "across disciplinary, organizational, cultural, and time/distance boundaries" (Lynn & Salzman, 2006, p 81). Universities can achieve this by introducing cross-cultural management courses, providing exchange programs and internships, and fostering communication across disciplinary boundaries (Lynn & Salzman, 2006).

The current third-generation globalization caused structural, organizational and functional changes in the STEM working environment along with changes in human capital flow. The new globalization shift produced a new world order causing the STEM workforce to adopt new frameworks and policy approaches to maintain economic strength and achieve growth and prosperity. The collaborative advantage is the new approach most firms adapted, based on building strength through collaboration with other nations by participating in the global supply of human capital. Available data indicate that the U.S. secondary and postsecondary education system prepares and produces more than an adequate number of qualified STEM graduates. No data or policy report confirms the perceived crisis in the number of U.S. STEM graduates. Thus, the ongoing quest to increase the supply will only result in a STEM bubble that may burst in the not-too-distant future if the current trend persists. The new globalization patterns produced a new collaborative STEM market environment that requires a broad education that incorporates teaching technical skills along with non-technical skills to meet the needs of the new global STEM market. The mismatch between what the supply offers and what the demand needs could be what causes the current STEM crisis. Lynn and Salzman (2006) pointed out the new requirements of the STEM field and further provided recommendations to strengthen education pedagogy, but what their analysis is missing is a critical look at students' perspective and student-level factors that may influence their STEM degree and career choices. For an understanding of student-level factors, it is important to follow the flow of students through the STEM pipeline from high school, to college, and lastly to career choice and the workforce.

The STEM Pipeline: A Micro Analysis

The Development of Transition Pathways

There are three transition pathways along the STEM pipeline; the transition from high school to college, completion of a STEM college degree, and transition into the STEM workforce (see Figure 10). Before looking into the flow of each of the transition phases, an understanding of the development of each transition phase is important to understand the flow of phases in the STEM pipeline. Lowell et al. (2009) highlighted three perspectives identifying why students decide to pursue STEM as a course of study. First, students who receive early exposure to math and science, and thus attain high proficiency, tend to choose STEM pathways. From this perspective, due to their math and science qualifications, such students end up choosing STEM as a career (Lowell et al., 2009). This perspective deals with the quality of K-12 education where early exposure and high-quality preparation lead to the continued pursuit of STEM education, along with the ability to later compete in the STEM workforce. In the second perspective, Lowell et al. (2009) consider career choices as simply "idiosyncratic" where students try to match their interests with future occupations, and thus qualifications alone are not sufficient to predict career outcomes. Drawn from the career counseling theories, Lowell et al. (2009) second perspective; matching interest with career choice is a result of individuals' developmental outcomes. In this sense, better matches are affected by students' personality traits (which are a developmental process) and career characteristics (Adelman, 1998; Lowell et al., 2009).

Lowell et al. (2009) third perspective on the reasons why students decide to pursue STEM deals with market mechanism and demand-related factors, where market incentives attract students to career paths. Supply and demand are the driving wheels behind labor prices and in this sense STEM shortage may not be caused by a shortage in the number of qualified STEM graduates, but caused by the workforce "demand" deficiencies. Demand deficiencies may mean that STEM employers are unable to attract highly qualified STEM college graduates, or that STEM graduates are choosing non-STEM related careers because of the STEM market's low wage incentives, less professional stability, high susceptible to offshoring, and more competitive job-environments from emerging economies (Freeman, 2009; Lowell et al., 2009). Another deficiency in the market mechanisms could be the so-called Freeman's (1976) "cobweb" model that deals with the supply and demand cyclical patterns. In the cobweb model, when market wages increase, an increase of job-seekers follows, as a result, but in turn wages stagnate/depress as a consequence of the overdose in supply numbers. What follows after wages decline is a decline in students' interest in the field, followed by a decline in enrollment. For example, the decline in mathematics enrollments in 1996 was attributed to the cobweb cycle (Davis, 1997). Understanding the main factors contributing to the development of STEM pathways may help in spotting the leakage in the STEM pipeline. The next section follows the flow of each of the transition phases in the STEM pipeline to detect the leakage while keeping in mind Lowell's et al. (2009) three perspectives, and the turning point of S&E workforce — the beginning of the third-generation globalization era. Moving from one phase to another, e.g. from high school to college, marks a "transitions" phase along the STEM pipeline, at the same time the pipeline can have many exits and entries, and reentries along the way.

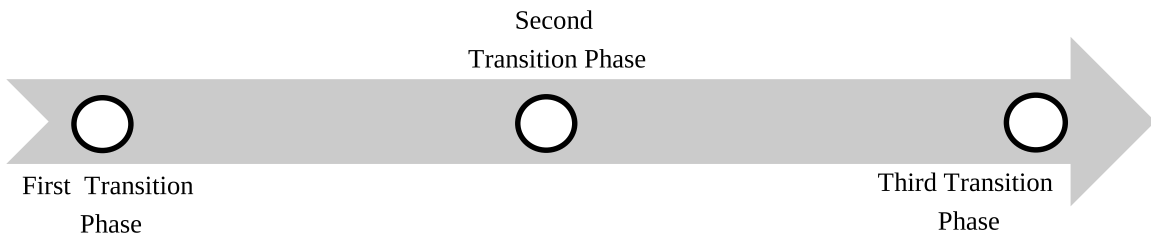
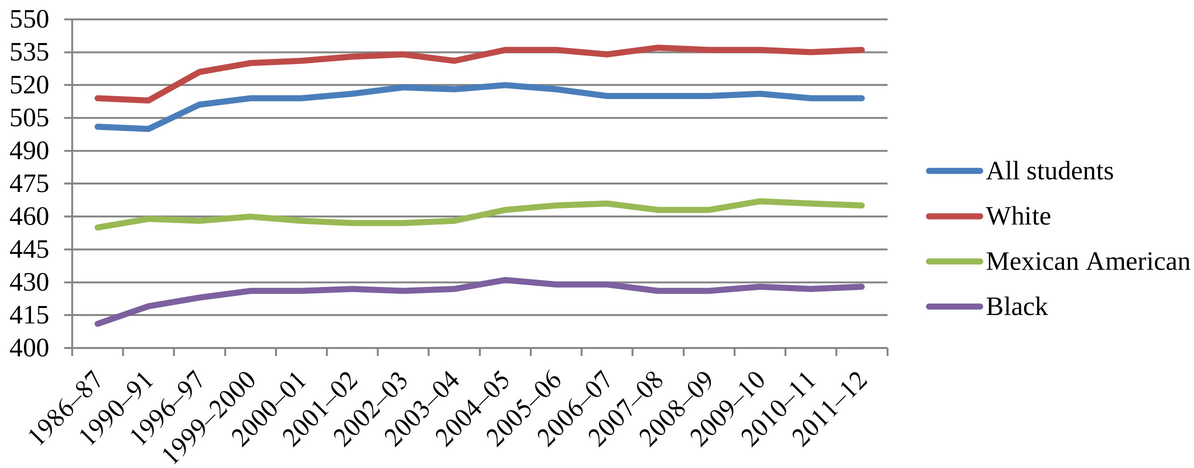


Figure 10. STEM pipeline transition pathways.

First Transition Phase: From High School to College

In general, the National Center for Educational Statistics (NCES) shows that the percentage of students who finish high school has increased in the past thirty years from 83 percent in 1972 to 93 percent in 2012 (NCES, 2014). Further, demographic groups showed steady improvement in their high school completion rate, and more students are staying in schools and are on track (NCES, 2013). For instance, the period between 1994 and 2003 witnessed a six percentage point increase to 75 percent for students aged 12- to 17-years old and who were considered to be academically on track (Dye & Johnson, 2007; Lowell & Salzman, 2007). Further, a significant increase in science and math course-taking occurred for students from all racial/ethnic groups, and both for male and female students (Lowell & Salzman, 2007). Also, the National Assessment of Educational Progress (NAEP) shows a steady progress in math test scores for both 13-year-old and 17-year-old cohorts. The Scholastic Aptitude Tests (SAT) and the American College Testing (ACT) both show as well an increase in test scores over that past thirty years (College Board, 2013; Lowell & Salzman, 2007; NCES, 2012). Figure 11 below shows an overall steady increase of SAT mean test scores for the period between 1986/87 and 2011/12 across different race/ethnicity groups.



SOURCE: U.S. Department of Education, National Center for Education Statistics. (2013). Digest of Education Statistics, 2012 (NCES 2014-015), Chapter 2.

Figure 11. SAT-Math mean scores of college-bound seniors by race/ethnicity

The TIMSS (Trends in International Mathematics and Science Study), is an international test administered to third and eighth graders in forty-six different countries around the globe. It shows no decline but, in fact, a slight improvement in U.S. students' test scores across all race, gender, and socioeconomic groups (Gonzales, Guzmán, Partelow, Pahlke, Jocelyn, Kastberg, & Williams, 2004). The Program for International Student Assessment (PISA) is an international assessment measuring 15-year-old’s achievement in reading, mathematics, and science literacy. On the other hand, PISA results show that U.S. students' math and science performance do not compare favorably with results for students in leading industrialized nations (OECD, 2010). Furthermore, over the years elementary science instructional time declined to reach an average of 2.3 hours per week, the lowest since 1988 (Blank, 2012). The decline came as a result of the

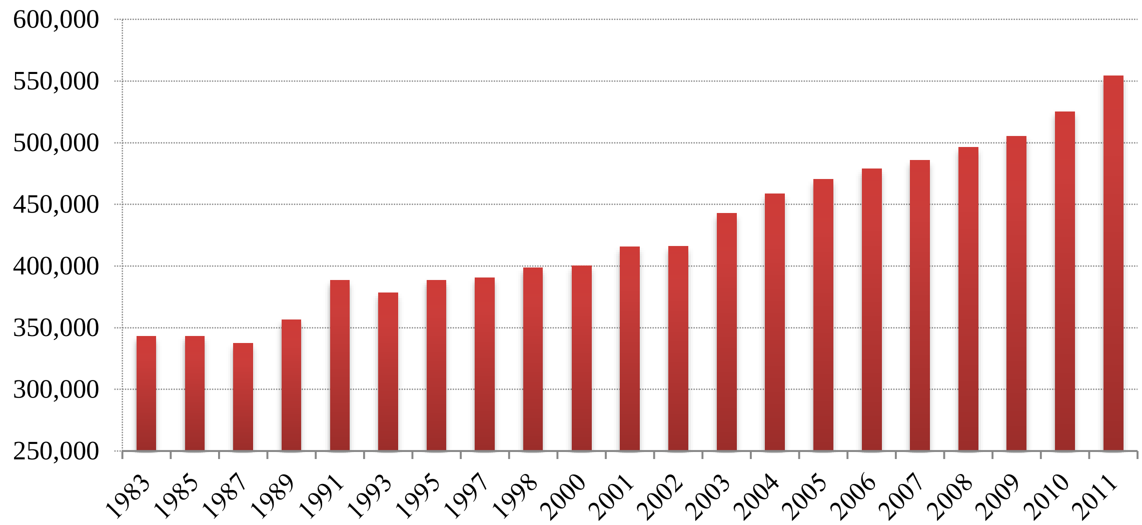
2001 No Child Left Behind (NCLB) law currently known as the Education and Secondary Education Act (ESEA) (Blank, 2012). The ESEA test measures schools' performance (as a way to measure accountability) by students' math and English language arts scores, since then instructional time for science, dropped whereas math increased steadily and English language arts substantially increased (Blank, 2012). All different measurements presented so far evidence that there is no decline, but rather an improvement, of U.S. domestic trends relating to high school students' educational outcomes. There might be a slight shift in focus on K-12 science education resulting from policy shift that favors other subjects (e.g. math and English language arts) over science, but previous evidence proves an overall improvement of high school students' academic performance. Since this research is concerned about STEM, in particular, a micro look at this field is important to reach valid conclusions.

Using six different longitudinal data sets (NLS72, NLSY79, HS&B, NELS88, B&B93, NLSY97) Lowell et al. (2009) tracked the percentage "flow rate" of a given cohort over time. The study compared cohorts or data sets, from one phase to another along the STEM pipeline, covering thirty years of time, to spot a change or stability in the flow rate of students along the pipeline. For high school graduates, the retention rate in the STEM pipeline has stayed stable over time, hinting that overall the percentage of high school graduates who enroll in a STEM field did not change significantly over time (Lowell et al., 2009). It is worth noting though that only the retention rate of high school top achievers—those testing the highest on their SAT/ACT math exams—significantly dropped around the late 1990s; the same period where S&E market witnessed the turning point caused by third-generation globalization. The retention rate in the STEM pipeline for high school top performers significantly (p=.000) dropped from "28.7 percent in the 1992/97 cohort to 13.8 percent for the 2000/05 cohort" (Lowell et al., 2009, p. 18). The explanation may be the fact that high school top performers are usually from well-educated families who have the knowledge of market needs and thus involve in their children's postsecondary enrollment decisions. For example, in their interviews with engineering managers, Lynn and Salzman (2006) reported that "some managers said they would not recommend that their children go into engineering since they did not see it as a career with a bright future" (Lynn & Salzman, 2006, p. 78).

Overall, little change occurred in the percentage of high school graduates who enroll in a postsecondary institution, and the same apply to the STEM field. Only the cohort of high school top achievers witnessed a steep decline in its retention rate in the STEM pipeline. The trend for top performers in the STEM pipeline shows an increase in the retention rate for 1972/77 cohort to 1992/97 cohort from 21.4 percent to 28.7 percent respectively, but then a steep decline for the 2000/05 cohort; 13.8% (Lowell et al., 2009).

Second Transition Phase: Persistence to Graduation

At the college level, the great challenge is to attract students to STEM majors and retain them until graduation. Although there is an increased interest to pursue a STEM degree among high school graduates, that does not necessarily translate to actual enrollment in the STEM field. Every year, the Higher Education Research Institute (HERI) selects a national sample of first-year students in four-year postsecondary institutions and asks them through a survey known as the Freshman Norms Survey about their intentions to major in STEM fields. The freshman survey shows continuity in students’ desires to pursue STEM majors, but again what freshmen say they intend to do and what they, in fact, do differ on many occasions. Roughly speaking, there is equivalence in the percentage of students who expressed an interest in pursuing a STEM degree and students who obtained one (Lowell & Salzman, 2007). Further, the proportion of students graduating with a STEM bachelor degree has been growing over time (Figure 12), as well as the proportion of freshmen enrollment in STEM fields, and the proportion of STEM master and doctoral students (Lowell & Salzman, 2007).



SOURCES: U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System, Completions Survey; and National Science Foundation, Division of Science Resources Statistics, Integrated Science and Engineering Resources Data System (WebCASPAR), http://webcaspar.nsf.gov.

Figure 12. Number of S&E Bachelor's Degree awarded between: 1983-2011

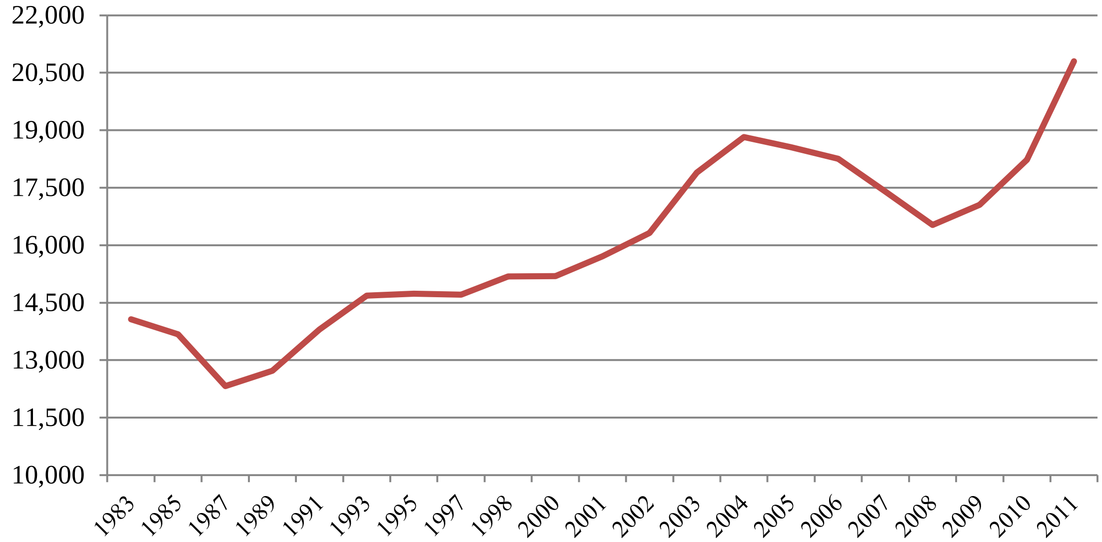
So far, measurements show no decline in the interest to pursue a STEM degree, an increase in the number of undergraduates finishing their STEM studies, and historical growth in the number of students pursuing a STEM graduate degree. The evidence presented so far shows no "shortage" of any kind in the first and second phase of the STEM pipeline; except possibly for high school top achievers, signaling that the STEM pipeline may face a lack of talent. Consequently, such lack of talent may lead STEM employers to complain about the inadequate supply of domestic STEM students. The only way to test the hypotheses of a domestic lack of talent is to look at the last phase in the STEM pipeline when students transit from college to the workforce. Also, the evidence so far did not show any leakage in the pipeline, hinting that the last phase may hold the missing link.

Third Transition Phase: College to Workforce

To address the explicit criticism, that there is an inadequate number of STEM graduates, a look at the employment rate in the STEM workforce may help in testing these claims. It is important to note though that not all STEM graduates have the interest to work in STEM careers, and for those who are interested, the number of job openings may not be equal to the number of STEM graduates who are pursuing a career in the STEM field. Also, even if we assume the supply is equal to the demand, some STEM graduates may not enter the STEM employment simply because they are under qualified for the STEM jobs that are available. The retention of STEM graduates in STEM fields-either working or pursuing graduate studies- increased from 1977/80 (31.5%) to 1987/90 (38.3%) to 1993/96 (52.8%), but then significantly declined (44.9%) in 1997/00 cohort (Lowell et al., 2009). The drop in the STEM retention rate found in all students regardless of their GPA scores; indicating that even STEM levels of preparedness could not moderate the significant reduction (Lowell et al., 2009). The chances of top STEM achievers to hold a STEM job as their first occupation are equal to average STEM graduates. In fact, Lowell et al. (2009) concluded that "college achievement does not predict STEM retention...higher achievers are not more likely to stay in the STEM pipeline, either at the first job or at mid-career, than average STEM college graduates" (Lowell et al., 2009, p.29). Further, the same period (1993-2001) witnessed high attrition where the percentage of STEM bachelor holders and master holders working in non-STEM fields is 45 percent and 31 percent respectively (NSF, 2006). So what is causing STEM graduates not to work or be unable to work in the STEM workforce? Is the high attrition at the end of the pipeline caused by poor math and science preparation during high school or poor quality of college education thus leading STEM graduates to exit the STEM pathway? As stated earlier, science instructional time in K-12 education dropped in recent years to reach an average of 2.3 hours per week, but could this explain the high attrition rate at the end of STEM pipeline? Previous studies concluded that once enrolled in a STEM major, neither prior science and math abilities nor the quality of college education were strong predictors of STEM attrition (Lowell & Salzman, 2007; Seymour, & Hewitt, 1997).

So the question then, is the decline in STEM graduates' retention (holding a STEM job after graduation) attributed to a shortage of STEM jobs? Alternatively, are there another type of employees (non-STEM holders) taking STEM jobs, especially when the period that witnessed a decline in the STEM graduates' job retention was the same period where STEM job market witnessed an expansion and growth? There are three different arguments in this regard.

First, the number of STEM graduates—bachelor, master, and doctoral levels—from 1985 to 2000 was around 435,000 annually (Lowell & Salzman, 2007). For the same period, the "net change" in STEM job market was about 150,000 annually, with disregard to a replacement for retirements or occupational quits (Lowell & Salzman, 2007). These numbers reveal that the average ratio of all STEM graduates relative to net occupational change is about three to one (Lowell & Salzman, 2007). This argument suggests that colleges and universities are providing a more than adequate supply for the demand; hence "there are 15.7 million workers who report at least one degree in an S&E field but 4.8 million work in an S&E occupation" (Lowell & Salzman, 2007, p. 34). The second argument claims that STEM degree holders are not facing employment difficulties, but the fact is the majority, especially top-achievers, have been lured to non-STEM related occupations where there is a substantial demand for STEM-related knowledge, such as a patent lawyer or a medical salesperson. For example, some financial firms have been hiring top-achieving STEM graduates by offering incentives and much higher salaries than those offered by STEM occupations (Bernstein, 2008; Derman, 2004; Lowell et al., 2009; Overbye, 2009). So even if STEM graduates are working in jobs classified as non-STEM, they are still using their STEM knowledge; the issue is simply with formal occupational classifications (Lowell et al., 2009). Third, there is the argument that claims non-STEM degree holders are taking STEM jobs. Lowell et al. (2009) reported in their study a strong evidence of non-STEM graduates moving into the STEM workforce; from 1977/80 cohort to 1997/00 cohort the percentage of non-STEM workers working in formal STEM occupations increased from 2.5 percent to 7 percent (Lowell et al., 2009). Further, the percent of STEM occupations held by non-STEM graduates increased from 16 percent in 1987/90 to 40 percent in 1997/00 (Lowell et al., 2009). This rapid increase can be explained as Lowell et al. (2009) suggested by the substantial increase of non-STEM workers in the information technology sector which was a booming sector in the late 1990s. Further, the same period witnessed a large number of immigrants holding a substantial share of the STEM labor market. The U.S. witnessed an increase in the number of students with a temporary visa graduating with a STEM bachelor's degree (Figure 13) who may compete for STEM jobs with their U.S. counterparts (Salzman, 2007). Figure 13 shows a rapid increase in foreign students graduating with a U.S. bachelor's degree in STEM majors. The past three decades witnessed a 67 percent increase in the number of students on temporary visa graduating with a U.S. STEM bachelor degrees; from 14,071 degrees awarded in 1983 to 20,798 awarded in 2011 (NSF, 2013).



SOURCES: National Center for Education Statistics, Integrated Postsecondary Education Data System, Completions Survey; and National Science Foundation, National Center for Science and Engineering Statistics, Integrated Science and Engineering Resources Data System (WebCASPAR), http://webcaspar.nsf.gov.

Figure 13. Total number of S&E bachelor degrees awarded to students on temporary visas between 1983- 2011

The evidence so far suggests that the school-to-work STEM attrition is neither due to an inadequate supply of STEM graduates nor due to poor educational preparation. In fact, the evidence reveals that the leakage could be due to the failure of the occupational classification system to identify the extent of jobs a STEM major can reach. Also, the growing share of non-STEM graduates, foreign STEM graduates, and immigrants working in the STEM marketplace is undoubtedly contributing to the STEM pipeline attrition rate (Lowell & Salzman, 2007; Lowell et al., 2009). All the evidence reviewed so far point at the "demand-side" as a possible cause of the STEM pipeline leakage. Thus, a close analysis of the nature of the STEM marketplace is critical at this stage to pinpoint the "real" shortage.

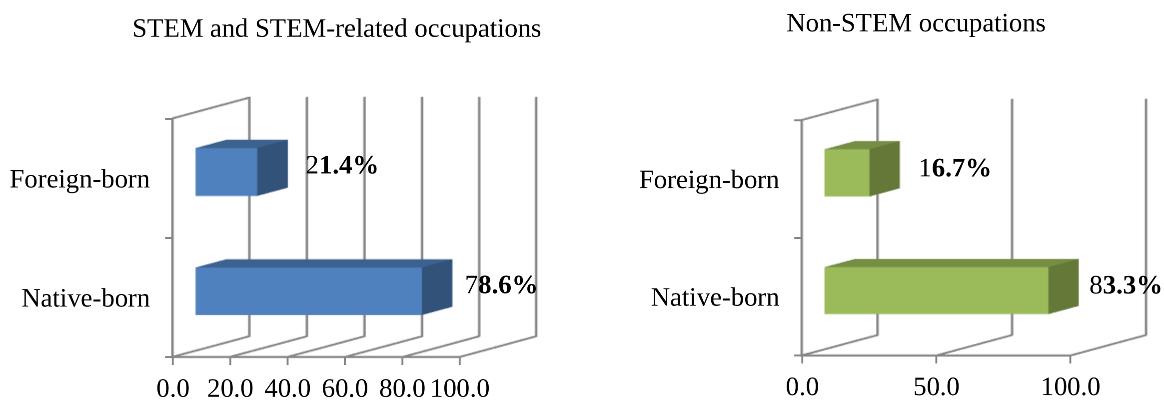
The Nature of the STEM Demand

Structural Changes: New frameworks

Before looking at the nature of the STEM market's demand, it is important to understand the recent structural changes caused by the shift in globalization patterns to understand better the demand side. Changes occurred both in human capital flows and firms structures, along with innovation changes in emerging economies enabling them to step up as pioneers in technological developments (Bartlett, 2000; Bartlett & Ghoshal; 1988, 1989; Choy, 2007; Salzman, 2007). STEM market structural changes caused by changes in globalization patterns can cluster in three areas as Salzman (2007) suggests.

First, the *"internationalization of the STEM field"* is now clearer in the U.S. universities and workforce than two decades ago. As mentioned earlier, the number of students on temporary visas seeking bachelor degrees in S&E fields has been steadily growing since the 1980s. That number is even larger in graduate programs where in some fields, such as petroleum engineering 75 percent of graduate degrees awarded were to students on temporary visas since the late 1980s (Salzman, 2007). Further, the percentage of doctoral degrees in S&E awarded to students on temporary visas has roughly grown by 62 percent for the period from 2000 to 2009 (NSF, 2009). Students on temporary visas (both graduate and undergraduate) have been entering the U.S. STEM workforce as scientists and engineers representing a relatively large proportion of STEM occupations where that proportion increase/decrease by type of industry. Nowadays, these scientists and engineers have climbed the work ladder, working in upper-level management and involved in decision-making processes (Salzman, 2007). Figure 14 shows how for the year 2011, foreign-born workers represented 21.4 percent of the total number of employees in STEM and STEM-related occupations compared to 16.7 percent of their representation in non-STEM jobs;

showing an overrepresentation of foreign-born STEM workers in STEM and STEM-related jobs compared to non-STEM occupations (U.S. Census Bureau, 2011).



Source: U.S. Census Bureau, 2011 American Community Survey.
Calculation by Author

Figure 14. Employment in STEM, STEM-related, and non-STEM occupations by citizenship: 2011 (percentage)

Recent trends of *"deconstructing"* the firm's organizational forms demonstrate the second structural change. In the past, companies were rooted in their home countries and bound by geographic limits reflecting the economic performance of the country where they reside (Bartlett, 2000). Then a structural shift occurred due to third-generation globalization; firms started outsourcing their production, buying rather than making products. At first, companies outsourced low-level commodity parts but then moved to outsourcing high-value functions to external enterprises. The new strategy soon expanded to reach many industries causing, as a result, less integration among domestic organizational forms, and more globalization of the STEM workforce where many international markets supplied the needs of U.S. firms in the form of labor, knowledge, and experience (Salzman, 2007).

The nature of innovation witnessed the third structural change that caused three types of innovation shifts that benefited emerging economies. First, in the field of Information Technology, offshoring initially started with low-level activities such as product development and services. As Information Technology field prospers and advances, offshoring developed to the point where companies at emerging economies highly structured and systematized methods of product process and software development causing an innovation shift (Salzman, 2007). The second innovation shift is in the types of innovation. In the first- and second- generation globalization, innovation aligned with existing products that adhere to local conditions, that type of innovation does not suit the current third generation globalization. The current local innovation must adapt to local environments as well as global demands (Salzman, 2007). Lastly, the innovation market in the past captured only high-end technology whereas nowadays both high- and low- end technological innovations are occurring. Slazman (2007) gives a simple, yet thoughtful, example to explain this third shift in high-end and low-end innovation:

> The high-end IPhone is predicted to capture something less than 1 percent of the global market (under 10 million units), whereas developing an innovative, cheap cell phone has potential sales in the hundreds of millions (China Telecom is already the largest cell phone company in the world with an estimated 300 million subscribers). (p. 6)

Further, just because U.S. based firms are innovation leaders in some technical areas, does not necessarily mean the innovation or its benefits will advantage the United States, and that is because many U.S. companies are offshoring their innovation development whether it is on high- or low- end levels (Salzman, 2007). An understanding of the dynamic of offshoring and outsourcing of STEM workforce through an analysis of multi-level perspective both on firm-level strategies and national policy-making will help in strengthening the analysis of this research.

The Dynamic of Offshoring and Outsourcing

Offshoring refers to the process of sending abroad and coordinating business tasks and functions to emerging economies to cut costs and boost benefits (Manning, Massini & Lewin, 2008). Two trends of offshoring emerged in the past decade. First, offshoring is no longer driven by cost efficient causes, but search for highly talented individuals is the new key role driver. Second, offshoring abandons its simple initial role of low-level IT processing and production to reach products development and design and even some areas of R&D (Bunyaratavej, Hahn & Doh, 2007; Engardio, Einhorn, 2005; Farrell, Laboissiere, & Rosenfeld, 2006; Manning et al., 2008). The shift in offshoring structures led to the global sourcing of STEM's highly talented individuals, meaning in the past decade companies developed their product functions at home (U.S.) through domestic STEM talent. However, the case is different now where many U.S. firms are hiring talented STEM employees around the globe at their global locations (Manning et al., 2008). The annual Offshoring Research Network (ORN) survey, initiated in 2004 by Duke Center for International Business Education and Research (CIBER) follows offshoring trends and global sourcing strategies and drivers of more than 1,600 U.S. and European companies. It noted that for the 2004-2006, results indicate that access to highly talented individuals come second as main reasons for offshoring decisions after cost savings and that product development including software development and product design along with some R&D services were the second most offshoring services after IT. In 2010, sixty-three percent of companies engaged in innovation offshoring where their main destination, with countries such as India and China taking about 33 percent and 27 percent respectively of innovation services (CIBER, 2010). Such trend will likely to continue in the upcoming years as more services provided by emerging economies, and as more manufacturing companies continue to search for new ideas (talent) and new business models and technologies (innovation).

Offshoring and outsourcing are two terms that are often confused and used interchangeably. While offshoring refers to sending business tasks abroad while coordinating and supervising such tasks domestically, outsourcing, on the other hand, refers to the delivery of tasks by external providers (domestically or abroad) that have no affiliation with companies that receive such tasks (Manning et al., 2008). Offshoring concerns development and production that support local operation (home-based) where the benefit may go to global or domestic ends, while outsourcing completely supports and benefits the provider. With the continuing trend of offshoring and outsourcing, new providers emerged, with coordination with domestic firms, they provided an array of technological and R&D services. Providers then, in the longer term, expanded and advanced their corporate networks and centers of excellence where the line between domestic and foreign slowly faded away (Holm & Pedersen, 1999). Thus, product development and R&D services witnessed an internationalization trend where STEM talent needed to perform such functions has to be sourced globally (Manning et al., 2008). Sending production, design, and R&D services abroad is not a new phenomenon; United States firms outsourced low-level tasks for decades. What is unique about the offshoring and outsourcing that is occurring recently in third-generation globalization is, as mentioned earlier, the relocation of the high-level process and administrative services to emerging economies, and the rapid improvement of technology that enabled a variety of delivery forms (Manning et al., 2008).

As mentioned earlier in this section, companies are no longer driven only by cost savings when making offshoring decisions— in fact, there is an acceleration in wage inflation in offshore locations. As more high-end STEM work sourced globally, search for the global talented, skilled workers "global race for talent" becomes the norm (Athey, 2008; Bunyaratavej et al., 2007; Frymire, 2006; Salzman, 2007; Manning et al., 2008). Even for STEM tasks that are difficult to accomplish in an asynchronous matter, U.S. firms react to such limitation by restructuring the nature of the work or even sourcing the entire task to offshore locations (Salzman, 2007). Offshoring and outsourcing have challenges of their own. The Offshoring Research Network (ORN) survey indicated that U.S. companies involved in offshoring activities are concerned about wage inflation, maintaining a consistent quality, efficiency in operational functions, offshore employee shortages and turnovers, and loss of managerial control (ORN, 2006). Further, with the growing tendency to offshore and outsource STEM jobs, an imminent threat to high-end STEM tasks is not here yet, simply because U.S. firms are not willing to completely abandon their domestic locations due to their investments in facilities and human capital that is hard to replicate elsewhere (Salzman, 2007). Also, the United States is still a pioneer in its high-level knowledge production through its universities that most of the emerging economies lack though they may catch up in the not-too-distant future. The recent trend of globalizing U.S. universities by founding centers of excellence around the world supports this trend. Notably, in the future growth in high-task STEM jobs is more likely to shift to offshore locations based on the current globalization pattern. Thus before boosting the supply of STEM-educated workforce entrants, policymakers need to validate the current demand for such workers otherwise increasing the supply will shrink the demand, stagnate wages, reduce the quality of STEM jobs, and eventually discourage future students from pursuing STEM jobs.

The previous section reviewed factors in both the supply and the demand side that might impact the attrition rate at the end of the STEM pipeline. STEM graduates (potential STEM workers) can as well affect the current issue. It seems that recent graduates' degree type and field along with their demographic characteristics can predict their employability in the STEM workforce. The following graph (Figure 15) illustrates the current issue faced by recent STEM graduates.

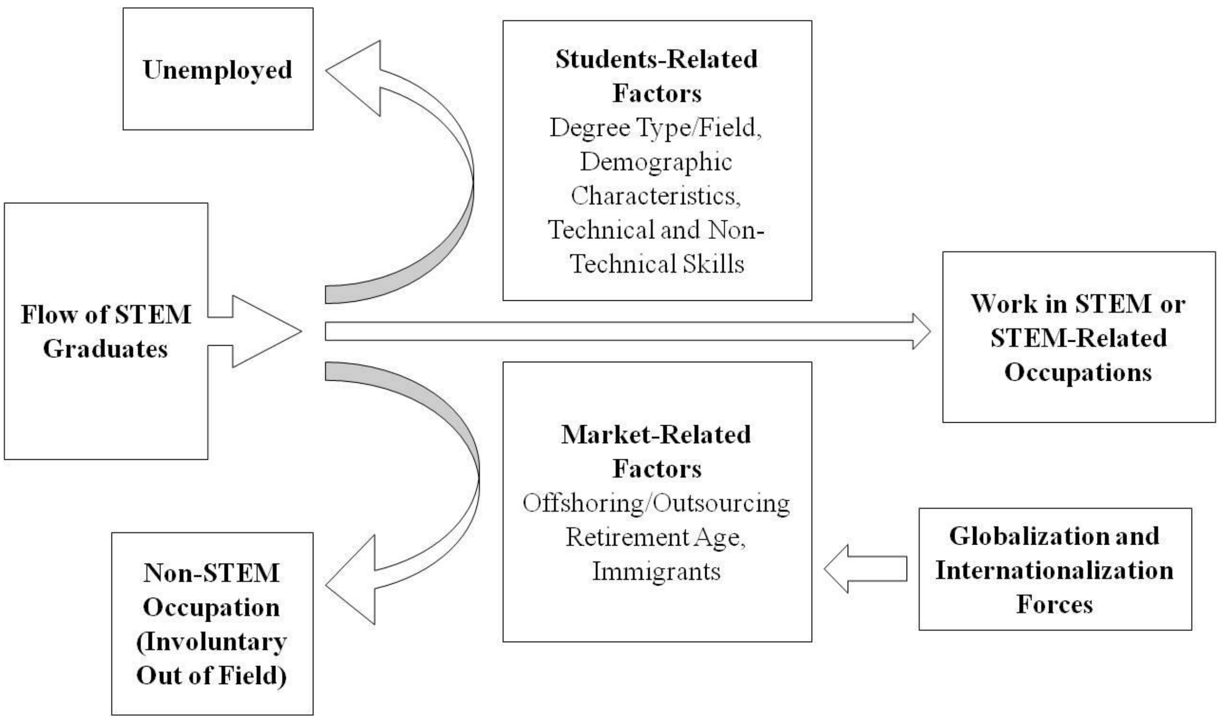


Figure 15. Illustration of the flow of recent STEM graduates

As seen in Figure 15, recent STEM graduates are faced with obstacles related to both their characteristics and the characteristics of the workforce where they are seeking employment. Some graduates successfully secure a job in their field or related field, while others struggle to find a job. The percentage of recent STEM graduates involuntary working out of their field is increasing lately along with the percentage of those who are still looking for a job (unemployed). Recently the STEM workforce changed rapidly as a response to globalization forces where both human capital flow and firms structures changed. It is time for U.S. universities to respond to globalization demands by preparing their students, especially those who will be most affected by these forces (STEM graduates), and equip them with the needed skills in such globalization time.

Graduates Shortage or Skills Shortage?

To date, claims regarding STEM deficiencies were directed to primary, secondary and postsecondary STEM education as the primary reason for employment shortage (Lowell & Salzman, 2007; Lowell et al., 2009; Teitelbaum, 2014). Without much evidence, many "alarmed" the general public and policymakers of a "crisis" that may cause the U.S. to lose its global position as innovation, R&D, and technological leader (Charette, 2013; Salzman, Kuehn & Lowell, 2013; Teitelbaum, 2014). As Salzman (2007) points out, it is important to distinguish between employment difficulties U.S. firms are encountering, and an actual workers shortage. So far, data along with evidence cited in various policy reports point at STEM workforce as a cause of the perceived STEM crisis. Many firm managers assert that the number of domestic applicants is sufficient, and they are more than qualified when it comes to their STEM knowledge and technical skills. A repeated complaint by firms where about the lack of years of experience of new entrants, and dissatisfaction about the need to train them; companies do not want to bear the cost of training new STEM-graduates and have been asking higher education to shoulder the cost (Salzman, 2007). This highlights the critical importance of experience; in fact the same concern was raised in the sixties when the number of technicians working as engineers increased rapidly (Freeman, 1971). Non-degree holders can take a few academic courses in an educational institution, along with considerable on-the-job training and work experience and then easily compete with degree holders. Furthermore, graduates' lack of non-technical skills, "soft-skills," seems to surface frequently as a complaint by firms, especially in a world where geographic boundaries are fading due to globalization forces. Thus cross-cultural skills such as communication and cultural appreciation are critical. Several managers stated that technical skills are not a distinguishing factor when considering STEM applicants, where abilities to communicate ideas in a diverse setting of co-workers along with different social skills are the criterion that set applicants apart (Lynn & Salzman, 2006; Salzman & Lynn, 2010).

Universities must go beyond academic qualifications to teach cross-cultural non-technical skills to maintain global competitiveness. Policies must focus on the quality of STEM-graduates taking into account technical and non-technical skills together, rather than only the number of STEM graduates. The focus needs to shift to the current mismatch between what employers need and are looking for, and what STEM graduates have to offer. Policies need to address the development of cross-cultural non-technical skills to enhance STEM graduates effectiveness at working across organizational borders in both settings; domestic and global. The current mismatch originates from the difference between what the demand needs and what the supply offers in term of soft skills (Salzman &Lynn, 2010). Unfortunately, the vast majority of STEM graduates do not have sufficient levels of soft skills that make them valuable to firms and meet the demand of the global workplace (Salzman & Lynn, 2010).

Currently, U.S. colleges and universities are not responsive to market needs in a time that is highly impacted by third-generation globalization forces that causing massive structural shifts in firms, innovation patterns, and even offshoring trends. There is little evidence of a deficit in K-12 education, STEM postsecondary technical education, and in the STEM market. However, a deficit does exist, and it might be a "soft skill" deficit (American College Testing, 2013; Butz et al., 2004; Freeman, 2006; Lowell & Salzman, 2007; NSF, 2012; Salzman et al., 2013).

Theoretical Framework

This section reviews theories and models that impact the current discussion on the STEM mismatch starting with the Economic Theory of Occupational Choice, which deals with economic factors affecting the career decision-making process, and then moving to Sattinger's Assignment Theory; a theory that explains how the labor market assigns workers to jobs. Next, is a discussion of Freeman's Cobweb Model; a model that deals with the supply and demand cycle. The final section of this chapter addresses two theories; the theory of Globalization and how it relates to the STEM workforce along with Lent, Brown and Hackett's (1987) Social Cognitive Career Theory (SCCT).

The Economic Theory of Occupational Choice

In the occupational choice process, decision making differs according to preferences; both monetary and nonmonetary. When choosing a career from a set of mutual alternatives, individuals tend to take the "all-or-nothing" approach; meaning that individuals tend to limit themselves to a single occupation (Freeman, 1971). That could be because the time needed to master the skills of the new career is long enough to hinder the process of learning other specialties' skills (Freeman, 1971). On the other hand, the attempt to develop a variety of skills that would suit different occupations may lead to an inability to compete with specialized individuals, or as Ben-Porath (1967) summarizes "jack of all trades and master of none." When making career choice decisions, two sets of factors influence the process: individual's abilities and preferences and job characteristics (Ben-Porath, 1967; Freeman, 1971). Within the limitations of the two sets (individual abilities and market characteristics), the Economic Theory of Occupational Choice posits that individuals choose careers that maximize their "utility function" (Freeman, 1971). In other words, when a person chooses an occupation, the decision is based on the expected income to earned throughout a lifetime of working in that career or relevant careers. One then compares the "utility of the commodities" purchased with the potential career's income and other non-career incomes (e.g. family wealth) to the non-monetary value that he/she may get when working in the potential job. Then a career selection is grounded on the one that maximizes the total utility (Freeman, 1971).

The theory suggests that those with a wealthy background (upper-middle-, upper-class) who have non-career incomes tend to choose different careers than individuals with different socioeconomic backgrounds. Career wages may not lead, or at least are not a major factor in the career decision-making process; the wealthy may choose careers with higher non-monetary rewards (Freeman, 1971). Thus, socioeconomic backgrounds (along with the availability of nonwage income) may become a key factor in STEM graduates' career choice decisions on which graduates from affluent backgrounds may consider values other than monetary factors. Such graduates may voluntarily opt-out of the STEM field because they are seeking non-monetary rewards.

Further, since the theory indicates that individuals make their decisions based on expected future income and job stability rather than current income, job expectations and market conditions are two interrelated factors. If a job seeker feels uncertain about a work environment; e.g. highly susceptible to offshoring and highly competitive such as the STEM workforce, the rewards of such environment can be at risk. Thus, job expectations influence current and future labor market behavior and the process of career choice decision (Freeman, 1971). Under the Economic Theory of Occupational Choice, career decisions are made largely based on individuals' perceptions and attributes.

The Assignment Theory

The Assignment Theory developed by Sattinger (1993) asserts that returns to human capital investments depend largely on the match between the worker's qualifications (education and skills), and the occupation requirements (Sattinger, 1993). Mismatches between the two (worker-job) result in weighty costs to workers; they either have skills that go underutilized or they are unable to fulfill job requirements (Bender & Heywood, 2009; Sattinger, 1993). These mismatches simply waste educational investments which, in the long run, results in frustration and job dissatisfaction (Allen & Van der Velden, 2001; Sattinger, 1993; Solomon, Kent, Ochsner & Hurwicz, 1981; Tsang, 1987) and low wages (Bender & Heywood, 2009; Sattinger, 1993). It also results in high turnovers, absenteeism, and quit rates (Clark & Oswald 1996; Freeman 1978; McGoldrick & Robst, 1996; Sattinger, 1993). This is so even after controlling for other explanatory variables (Bender & Heywood, 2009). Several arguments came to explain why the mismatch between workers and jobs continues to persist. First, when looking for a job, wage offers drive job seekers' decisions to accept a job offer or not; in alignment with the Economic Theory of Occupational Choice that potential future monetary gains drive career choices. However, because the search process is costly, a worker may stop searching and accept a job that pays less than what a continued search may generate (Sattinger, 1993). Further, workers may remain mismatched because it is still cheaper and less risky to stay in a mismatched career than starting a search for new "better" alternatives. Similarly, though job productivity depends on workers' qualifications, employers tend to fill jobs as quickly as possible (regardless of finding the ideal worker) because it is costly to leave the job vacant for so long. Thus, the worker's qualifications and jobs are not perfectly matched; disadvantaging both the employee and the employer (Sattinger, 1993).

Another argument explaining the persisted mismatch between workers and jobs notes that it is a result of government subsidization that generated overeducated individuals with levels of educational attainment that exceed what the workforce demands (Freeman, 1976). Overeducated individuals suffer a 14 percent earnings penalty (Groot, 1993). The resultant earning penalty from the mismatch goes beyond "too much" education to reach individuals working out of their fields in jobs not directly related to their degrees. Such IOF workers suffer significantly diminished earnings as a result of wages-skills mismatch (Allen & Van der Velden, 2001). It seems that mismatched workers disadvantage differently based on the level of skills they have or required by occupations. For instance, the STEM field requires high skills that change rapidly depending on the discipline, technological changes, globalization, and workforce changes, and thus scientists are more likely to be mismatched. The penalty of mismatch grows as career life progresses and new more advanced skills emerge (Bender & Heywood, 2009).

Two kinds of workers' mismatch are identified by Sattinger (1993); short-run mismatch and long-run mismatch. The cause of short-run mismatch, as mentioned earlier, is from the perceived cost of job searching while the cause of long-run mismatch is globalization forces. The consequences of short-run mismatch are lower wages, lower productivity, lower job satisfaction, and a decline in cognitive abilities. While the consequences of long-run mismatch are a loss of return on human capital investment, loss of workers' investment in education, loss of time spent on job training, and inadequate labor force for firms' expansion and growth (Sattinger, 1993). Some may argue that changing careers can solve the short-run mismatch, but not all mismatches can be resolved by individual workers and there always will be new entrants who will begin their careers with mismatches (Sattinger, 1993). Though they are beyond complete elimination, short-run mismatches can be substantially reduced through policies that ensure efficient matching. An example of an intervention to reduce short-run mismatches is through the labor market's intermediary agencies that help to place workers in jobs more efficiently. Another example can be through conducting research and analyzing data that help understand how the labor market assigns workers to jobs, and how workers' attributes, educational attainments, and skills level affect the mismatch susceptibility (Lowell, Salzman, Bernstien, & Henderson, 2009). Recent graduates face difficulties transitioning to the labor market and often accept jobs for which they are overqualified as a method to secure employment until they locate a stable occupation (Quintini & Manfredi, 2009). Exposing recent graduates to apprenticeships during their degree minimize the time needed to locate stable employment and ensure smooth and quick transitioning to the labor force, thus reducing the short-run mismatch that will eventually reduce the long-run mismatch.

The Cobweb Model

When choosing a college major, students make their decisions based on the perceived value of their degrees, or the expected rewards (wages) in the corresponding professional sectors (Diebolt & El Murr, 2004; Freeman, 1975). Further, a certain field of study may receive considerable attention and interest from students when a shortage (or perceived shortage) occurs in a particular profession. Once the professional sector's shortage is gone, the shortage notion continues because of the delay in the perception of the actual market's conditions by young college entrants (Freeman, 1975). As a result, a gradual overproduction (surplus) of qualified young graduates holding degrees in fields that once experienced a labor shortage starts flooding the workforce causing unbalanced supply and demand. Consequences of the unbalanced supply and demand can result in stagnant or lower wages and high unemployment and IOF rates. Thus, new students start to divert from these fields of study to other sectors causing, in the long run, a new shortage and a continuous cyclical movement that follows job conditions (Diebolt & El Murr, 2004; Freeman, 1975). Such cyclical movement is called the Cobweb Model, and it can appear in all educational sectors depending on market dynamics and jobs availability (Freeman, 1975). The cobweb model, an economic model, is based on the time lag between supply and demand. For example, the time lag between enrollment and graduation in field X may increase the time of job vacancy that requires an X degree, and thus a worker shortage appears on the demand side. The shortage results in high demand for workers with the X degree, and when strong demand is expected to continue, more students decide to enroll in the X field compared to other fields. Therefore, considering the time lag, a surplus of students holding the X degree will flood the market resulting in low demand, low wages, and high unemployment rate. Again when the weak demand is expected to continue in that particular field, new students will divert from the field, resulting in a repeated shortage and high demands for potential employees from the field.

The STEM field has witnessed these cyclical cobweb patterns in different disciplines across different periods of time. For example, after a substantial growth in the number of engineers in late 1960s and early 1970s engineers experienced a steep decline in starting salaries because of low market demand where the number of new students seeking an engineering degree fell sharply (Freeman, 1975). The cobweb model reveals the supply sensitivity to economic indicators and it can be a measure of supply-demand equilibrium and a prediction tool to help labor market decision-makers and human resources managers to predict future market needs. Patterns of cyclical behaviors drawn from cobweb models may be useful in forecasting future market trends and provide future postsecondary students with appropriate guidance and market information.

The Globalization Theory

The idea of globalization is that many of the current problems cannot be fully understood at the national level while separated from the entire globe (Sklair, 1999). Instead, in solving contemporary problems, many argue for full consideration of international forces of transnational corporations, globalization of beliefs and ideologies, and other global forces as they become so powerful (Ohmae, 1990). When analyzing national problems, many globalization theorists assert that the nation-state analysis approach is no longer the only critical unit of analysis. In fact, some theorists even consider that the nation-state unit of analysis is now even less important compared to other global units (Sklair, 1999). Globalization resulted in two unique phenomena; the first is where new systems of production and consumption appeared as a consequence of the emergence of a globalized economy, and the second is the emergence of a global culture (Sklair, 1999). The U.S. for years dominated technological innovations and became the preeminent market economy. However, its global dominance started eroding lately and will continue eroding, probably forcing the U.S. to accept a position as one of many centers of excellence (Freeman, 2006). This can be explained through forces of globalization where the number of foreign science and engineering graduates increased as a result of enrollment expansions in their countries, the increasing number of international students on U.S. campuses, and the spread of U.S. centers of excellence around the world. For example, in 1975 China graduated almost no S&E doctoral students, but in 2003 Chinese universities awarded 13,000 PhDs where nearly 70 percent were in science and engineering (Freeman, 2006).

The major impacts of globalization can be seen in market changes, as mentioned earlier in this chapter, offshoring and outsourcing are two of the most tangible effects. Although the U.S. government does not keep a record of the number of jobs or tasks that are off-shored, many business consultants say that the number is not negligible and estimate a 10 to 15 percent of U.S. jobs as potentially offshorable (Bardhan & Kroll 2003; Hira & Hira 2005). The fact is research and technological developments are moving where the people are; whether they are in the U.S. or across the world. Qualified individuals with skills that match the market's needs are in high demand, and market leaders are seeking them whether nationally or globally. This theory shed light on how the mismatch between worker and career can be influenced, in an indirect way, by global forces, thus highlights the importance of monitoring the demand side and preparing graduates with skills needed to succeed in such globalized market.

The Social Cognitive Career Theory

The Social Cognitive Career Theory (SCCT) devolved by Lent, Brown and Hackett in 1987 derives from Bandura's (1986) general social cognitive theory. The SCCT focuses on the relationship between self-efficacy, expectations and personal goals, and how the combination of these relationships affect individual's career choice (Lent, Brown, & Hackett, 2002). The SCCT notes that individuals' beliefs influence career choices where such beliefs develop through four contextual factors that work together as a self-system: personal accomplishments, social persuasion, physiological status, and vicarious learning. Individuals express interest in a particular occupation if they think they will perform well in it, and if working at that particular job will lead to desired outcomes and offer valued compensation (Lent et al., 2002). The four contextual factors work together in the career development process and refine and reinforce individuals' career choices and perception of success. The success of the process depends on individuals' views and perceptions of their abilities to succeed. Most job applicants have a sense of their competence and hold certain beliefs or perception about career outcomes that inherently influence the career choice process.

In SCCT, career interest is regulated by one's belief about the ability to compete and success (self-efficacy) and by outcome expectation; the consequences of performing a specific task, e.g. an occupation (Lent et al., 2002). If a person perceives that a certain occupation will not lead to the desired outcome then the person will not seek employment in that job nor that he/she will express interest. Similarly, if a person has low confidence in performing a certain task, he/she will not perform such a task. Accomplishments depend, in part, on how people perceive their abilities to accomplish (Bandura, 1986). Thus, self-efficacy is a co-determinant of performance and can impact how effectively people deploy their talents (Lent et al., 2002). Competency level depends on both actual capabilities and the sense of personal efficacy, where both can explain performance attainments and overall success (Lent et al., 2002). Individuals are more likely to face issues (e.g. employment issues) when they either do not have sufficient skills needed for a particular task/occupation or when they underestimate their self-efficacy. These lead them to give up (unemployed), set lower goals (working out-of-field) or suffer from anxiety and disappointment (job dissatisfaction) as a consequence (Lent et al., 2002). In short, SCCT posits that abilities, self-efficacy, goals, and outcome expectations influence occupational and academic performance, where self-efficacy plays a major role on how individuals exploit their skills. Occupational failure may result from the unsuccessful match between personal abilities and occupationally required abilities, or when there is substantial underestimation of workers' self-efficacy.

The Mismatch Process

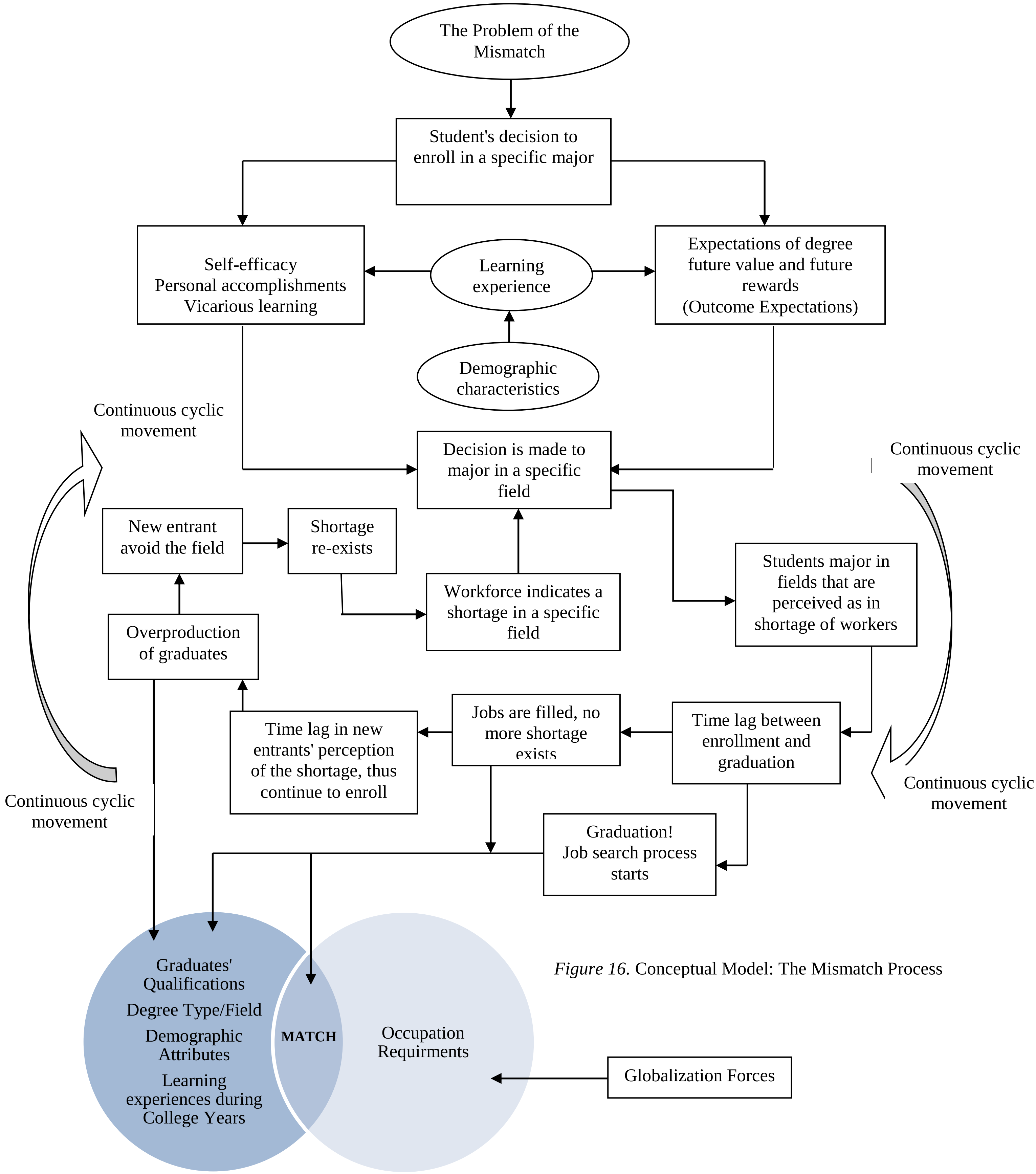


Figure 16. Conceptual Model: The Mismatch Process

As seen in Figure 16 above, the problem of the mismatch is so complicated and involves many components that could start as early as major decision making. When students are trying to make a decision to enroll in a specific field (e.g., STEM), their decisions are regulated, based on the SCCT, by their self-efficacy (Lent, Brown, & Hackett, 2002), and outcome rewards (Diebolt & El Murr, 2004; Freeman, 1975). Self-efficacy and outcome expectations are both affected by students' personal accomplishments and their previous learning experiences; factors that greatly differ by demographic characteristics. After a decision to major in a particular field, these decisions are based in part on the perception of workers' shortage (Freeman, 1975).

Due to the time lag between enrollment and graduation, and the delay in students' perception of the actual market's condition, a surplus of qualified graduates floods the workforce. The result is an overproduction of young professionals seeking a job in a field that once experienced a shortage (Freeman, 1975). Employers only hired graduates with credentials that match job requirements in their desired careers (Sattinger, 1993). Graduates' credentials can vary by degree field/level, professional experiences, and personality traits. It is equally important to mention that the STEM workforce, focus of this study, is constantly changing as a result of forces of globalization and internationalization (Freeman, 2006). Workforce changes are requiring new skills that go beyond degrees' credentials.

CHAPTER III

METHODOLOGY

The aim of this study is to examine whether career self-efficacy and expectancy are related to the degree-job matching among recent STEM college graduates. To fulfill this aim, this chapter will outline the methodology used in this research, including the study's variables and dataset, steps that will be taken to prepare the data, and the statistical procedures that will be performed to analyze the data. It is important to note first, that in the absence of an accepted definition of STEM majors or STEM occupations, it becomes complicated to investigate the current claim of STEM shortage/surplus or to analyze trends in the STEM pipeline. The acronym STEM stands for the primary disciplines of Science, Technology, Engineering, and Math. However there is some disagreement on what precisely falls within the STEM criteria. For example, the Standard Occupational Classification (SOC) federal system considers social science occupations as STEM while the National Science Foundation (NSF) does not. The Department of Commerce includes some STEM-related managerial occupations as STEM occupations, unlike many federal agencies. The existence of a too broad classification (or too narrow in some cases) and the absence of a commonly agreed upon definition of what comprises a STEM occupation or a STEM field further complicates the current issue, thereby making comparison among datasets provided by different federal agencies and organizations infeasible.

In this study, a framework of what STEM fields include will be developed following the Classification of Instructional Programs (CIP) codes. Developed by the U.S. Department of Education's National Center for Education Statistics (NCES) in 1980, CIP provides classification codes of about 60 main fields of study. The Education Longitudinal Study of 2002 (ELS:2002), the dataset used in this research, follows CIP classification codes where fifteen of the majors listed by ELS:2002 can be considered to be STEM majors following NSF's STEM CIP crosswalk (see Appendix A). These majors are agriculture, natural resources and conservation, communications technologies, computer and information sciences, engineering and engineering technologies, life/biological and biomedical sciences, mathematics and statistics, physical sciences, science technologies, and health professions and related clinical sciences.

Further, guided by the Census Bureau more majors can be added to the above list: social science, psychology, family sciences, architecture and related services, mechanic and repair technologies/technicians, human sciences and interdisciplinary studies such as nutrition sciences, behavioral sciences, and gerontology. To consider both NSF and Census Bureau classifications, this research will approach the STEM classification differences in the following way: first, a sample that combines both NSF's and Census Bureau's will be used when analyzing the dataset. Second, the academic major classification variable will be recorded into two categories: 1= Hard STEM and 0= Soft STEM. In that variable, Hard-STEM fields include Science and Engineering, and Soft-STEM fields include other STEM majors. By doing so, all possible STEM majors definitions will be taken into account by this study and further allowing for comparison among hard and soft STEM.

Research Questions

As stated earlier in chapter one, the following research questions, which are derived from Lent, Brown and Hackett's (1987) Social Cognitive Career Theory (SCCT), guided this study:

(Demographic Characteristics)

1) How do demographic characteristics of recent STEM graduates influence the match between their degree and their current job?

(Institutional Characteristics)

2) Controlling for demographic characteristics, how do institutional characteristics (i.e., selectivity and control) influence recent STEM graduates' current degree-job match?

***(**College Attributes)*

3) While controlling for both demographic and institutional characteristics:

- How do a graduate's major and academic cognitive abilities relate to the match between degree and current job?
- Does participating in hands-on learning opportunities (e.g., internship and onsite training) during college years increase the odds of match between STEM graduates' degree and current job?

(*Career Self-efficacy and Outcome Expectations*)

4) Controlling for demographic characteristics, institutional characteristics, and college attributes, to what extent do individuals' career self-efficacy and expectancy predict the odds of match between degree and job for recent STEM graduates?

Research questions were built on the following model:

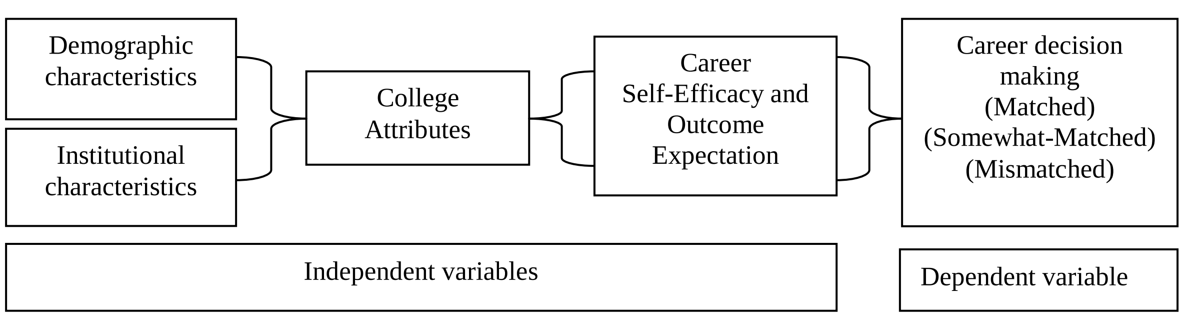


Figure 9. Research Model for Predictors of Degree-Job Match among Recent STEM Graduates

Data Source and Sample

This study will use the National Center for Education Statistics (NCES): the Education Longitudinal Study of 2002 (ELS: 2002). It is based on three preceding studies collected by NCES; the National Longitudinal Study of the High School Class of 1972 (NLS: 72), High School and Beyond (HS&B: 80), and the National Education Longitudinal Study of 1988 (NELS: 88). ELS: 2002 is the most recent study that follows a national sample of American students from secondary education to postsecondary years, and finally to the workforce. ELS: 2002 allows a deep insight into a decade of American students and their educational experiences and outcomes. ELS:2002 base year data (BY 2002) collected while students were in the tenth grade, was followed by a first follow-up (F1) two years later, in 2004, when most students were in their senior year of high school. In 2006, a second follow-up (F2) collected data from students who responded to both the base year and the first follow-up; students at that time were either in their second year of college, did not go to college, or joined the workforce (NCES, 2013). The third and final follow-up (F3), the focus of this study, was released in 2014 and surveyed students during the year of 2012; or six years after the second follow-up. The third follow-up (F3) provides information about participants' graduation status, whether they continued with graduate studies, their employment histories, their marital status, their families, and their job satisfaction if they are employed, and much more valuable information.

ELS:2002 is the most suitable data source for this study for the following two reasons: (1) released in 2012, it is the most up-to-date dataset about college graduates, (2) the depth of information given by ELS:2002 dataset is more comprehensive than other datasets that specifically follow STEM graduates. For example, the National Science Foundation (NSF) National Survey of Recent College Graduates (NSRCG) was released in 2010. Although this is the most current dataset of recent STEM graduates and is useful, many of its main variables are also found in the ELS:2002 dataset. The reason for ELS:2002 selection over (NSRCG) is that ELS:2002, besides the commonly found variables like demographic attributes, fields of study, GPA, and so on, provides many social cognitive skills measurements. For instance, in its third follow-up, ELS:2002 includes seven different scales that based on the Social Cognitive Career Theory (SCCT); these items were created specifically for its third follow-up. These scales have an internal reliability estimate that ranged from 0.79 to 0.93. After data collection and analysis, ELS:2002 statisticians decided to include only three of the SCCT scales due to high skewness in other scales that can inaccurately influence results. The trait-like scales included in ELS:2002, are support, satisfaction, and commitment. These three components are useful for this study and are part of the conceptual framework. Given these advantages, this study selected ELS data over other data.

This study will consider individuals who participated in the third follow-up study and who graduated with a STEM bachelor's degree as their highest level of education, have joined the workforce, and thus have employment. Since this study looks at predictors of the mismatch between degree and job, only students with a STEM degree holding a full-time job by June 2012 will be included in the sample. Since ELS data follows its participants for about three years after they earned their bachelor's degree, individuals who continued their graduate studies and were pursuing a master or a doctoral degree will not be included in this study. That is because measuring attributes to degree-job match is not feasible when many of these individuals are still students pursuing a higher degree and when there are no more follow-ups with ELS data to measure their future career outcomes.

Missing Data

Missing data will be handled using a multiple imputation method (MI) which is a desirable method over other traditional approaches to working with missing values (Acock, 2005). Other traditional approaches may include listwise deletion (delete cases with mission values), or mean substitution (replace missing values with the mean of non-missing values) which could produce seriously biased estimates, increase Type II errors, or either reduce or increase statistical power; leading to invalid conclusions (Acock, 2005). Multiple imputations, on the other hand, allow for an improved parameter estimate and standard errors through 5-10 imputed data sets and then pooling the results (Acock, 2005).

Researchers have argued whether to impute/include in the imputation the dependent variable (von Hippel, 2007). Many researchers (e.g., Allison, 2002) recommend the inclusion of the dependent variable in the MI procedure. Statisticians have argued (e.g., Allison, 2002) that when missing values exist in both the dependent and the independent variables, then the dependent variable must be included in the MI model. The rationale behind this is that if the imputation model does not use the dependent variable, then independent variables will be imputed as if they have no relationship to the dependent variable (Allison, 2002; Little, 1992; von Hippel, 2007). This will result in a biased estimate; the estimated slope of the dependent variable on the independent variable (Little, 1992). Including the dependent variable, even when it has missing values, in the imputation process of independent variables provides more information and improves the prediction of independent variables' missing values (Little, 1992). For these reasons, this study includes and imputes all variables with missing values (dependent and independent) in the MI model.

Validity and Reliability

As stated earlier, ELS:2002 is based on three preceding studies (NLS:72, HS&B:80, NELS:88) collected by NCES where numerous reports and empirical studies that used these datasets as a base for their findings and conclusions. Thus, the components found in these datasets are already established in the field.

Selection of Study Variables

The issue of degree-job match/mismatch has a theoretical importance as it draws attention to how and why individuals match with their careers; a concern of many policymakers and labor force specialists (Robst, 2007; Witte & Kalleberg, 1995). Theories and relevant studies in the field of career-choice literature are the basis for the selection of variables. For example, the Economic Theory of Occupational Choice, discussed in Chapter 2, notes that in the occupational choice process, decision making differs by preferences; both monetary and nonmonetary (Freeman, 1971). The theory also points out that individuals' career choices vary by socioeconomic backgrounds; noting that individuals with high socioeconomic status may accept a lower paying job (e.g., humanitarian job) because financial needs do not drive them. Under the Economic Theory of Occupational Choice, socioeconomic status may play a role in degree-job matching.

Furthermore, the Human Capital Theory notes that in addition to education, skills gained from experiences and training are critical to workers to be more productive and to perform complex tasks (Allen & De Wert, 2007). The theory concludes that skilled individuals usually end up with the best careers and the highest wages. The same was noted by Lynn and Salzman (2006) in their interviews with engineering managers where many managers highlighted the importance of technical and non-technical skills when hiring new employees. Salzman (2007) also noted in his research the importance of a STEM graduate's experience since firms do not want to burden the cost of training new STEM graduates and have been asking higher education to shoulder the cost. For such reasons, learning experiences gained from participations in on-site training and internships during college years, for example, is a major factor recognized by many scholars, theorists, and workforce specialists to play a role in graduates' career placement.

Many empirical studies have documented variations in the career choice process based on graduates' field of study where occupation-specific fields are found to have a much higher degree-job match than fields with general skills (Garcia-Espejo & Ibanez, 2006; Grayson 2004; Robst, 2007; Storen & Arnesen, 2006). Such findings warrant the importance of considering the graduates' majors when investigating attributes to degree-job match/mismatch.

There has been a consensus in empirical research that academic performance is almost always a strong predictor of desirable outcomes. Many scholars concluded that academic performance during college years can affect the degree-job match/mismatch (Boudarbat & Chernoff, 2010; Garcia-Espejo & Ibanez, 2006; Grayson 2004; Storen & Arnesen, 2006).

There are mixed conclusions about the relationship between demographic attributes and degree-job matching (Boudarbat & Chernoff, 2010). For instance, some scholars (e.g., Krahn & Bowlby, 1999) found that older workers are more likely to match with their careers than younger workers; a conclusion that contradicts other scholars' findings (e.g., Robst, 2007; Witte & Kalleberg, 1995; Wolbers, 2003). As for gender, some scholars (e.g., Robst, 2007; Wolbers, 2003) found that being female increases the likelihood of the degree-job match. On the other hand, other researchers (e.g., Krahn & Bowlby, 1999) found that the males have higher chances of matching with their careers, and some scholars found no significant difference by gender (e.g., Boudarbat & Chernoff, 2010; Garcia-Espejo & Ibanez, 2006; Storen & Arnesen, 2006).

Moreover, many researchers consider racial backgrounds to be a key to degree-job match/mismatch (Boudarbat & Chernoff, 2010). White and Asian workers are less likely than African Americans and Hispanics to match with their careers (Robst, 2007). This study includes demographic backgrounds as an independent variable in the analysis.

Institutional characteristics are aspects that should be involved since many empirical studies found that postsecondary institution characteristics such as sector, control, and selectivity can be important predictors in explaining variations in student educational outcomes (Astin, 1993; Bandura, 1986; Lent et al., 2002; Tinto, 1975, 1987).

Career self-efficacy and outcome expectations refer to students' perceived confidence in their abilities to plan and execute future careers that they perceive as having desirable and rewarding outcomes (Lent et al., 2002; Peterson, 1993). Many scholars note the significant relationship between career goal identification and retention in the field (Astin, 1975; Beal & Noel, 1980; Lent et al., 2002; Sprandel, 1986). Further, there is evidence to support a relationship between career self-efficacy expectations and persistence (Brown, Lent, & Larkin, 1989; Lent, Larkin, & Brown, 1989; Lent et al., 2002). Thus, career planning and the perceived abilities to execute such plans (career self-efficacy) might be a critical factor in explaining degree-job match. In the present study, such component will be measured by comparing respondents' expected age-30 occupation as reported in the third follow-up (after postsecondary graduation) to their expected age-30 occupation as reported in the first follow-up (when participants were high school seniors). Such variable allows for an insight into individuals' career self-efficacy and outcome expectations. Participants will expect to work in certain jobs if they perceive these jobs as having satisfying results and if they are confident in their abilities to pursue such careers. Participants whose career self-efficacy and outcome expectation remained the same (or even increased), before and after college years, meaning they are still expecting the same age-30 occupations, are the ones with high career self-efficacy and outcome expectations because their perceived abilities persisted throughout the college years. In contrast, individuals with lower expected age-30 occupation as compared to their expectations during high school are hypothesized to have less confidence in their abilities to execute their career goals, and thereby possessing less career self-efficacy and outcome expectation.

Study Variables

Variables in this study include an outcome variable, and a set of independent variables grouped into four categories: individual's characteristics, institutional characteristics, college learning experiences, and career self-efficacy and outcome expectations. Details about variables description, labels, and recording are in Appendices B and C.

Outcome Variable

The outcome variable in this study is the primary measurement of the mismatch, and it comes from participants' response to one of the third follow-up (F3) questions, asked in 2012. The question is "How closely related is your current job to the major or field of study you had when you were last enrolled in college?" Responses vary between "1=closely related," "2=somewhat related," or "3=not related." Matched individuals will probably answer "closely related," and somewhat matched are more likely to choose "somewhat related," where mismatched individuals will probably answer "not related." Thus, the outcome variable will be coded as a nominal variable where "closely related" is coded as 1=closely matched, "somewhat related" is coded as 2= somewhat-matched, and "not related" is coded as 3=mismatched; with "closely matched" as the reference category.

Responses to the outcome variable chosen in this research might be considered by some to be subjective where alternatives such as comparing the degree field with the current occupation field might be a better approach to measuring degree-job matching. It is, however, important to note that in this research the degree-job matching is considered to be the match between, not only degree field but also degree knowledge and skills, to career. With the current classification issue within STEM fields and occupations, there might be some STEM graduates who are working in careers not classified as STEM. These individuals, such as patent lawyers and medical consultants, use their degree knowledge and skills on a daily basis. The issue arises from formal occupational classifications (Lowell et al., 2009). Further, many universities are now providing students with a broad range of skills that go beyond their degrees' fields to be able to compete in a competitive job market (Robst, 2006). For these reasons, it is not viable to simply compare degree field to occupation field and ignore whether employees apply their academic knowledge and skills or not. Consequences of the mismatch result mainly from feelings of loss in return on educational investments (Sattinger, 1993, 2012); when employees use their academic knowledge and skills they acquired from a college education, it is unlikely that a sense of loss in return on investment in education will occur. Thus, individuals' assessments, while it might be subjective, could be a valid measure of the degree-job matching.

Independent Variables

Independent variables are grouped into set of blocks under four major constructs.

Participants' Characteristics:

- Gender: A categorical variable indicating participant's gender. In this research, the variable will be recoded into a dichotomous variable with Male as the reference group.

- Race: A categorical variable indicating participant's race/ethnicity. The variable will be recorded into a set of dummy variables, in which White will be considered as the reference group.
- Socioeconomic status composite: A continuous variable which is a composite of parental education and income.
- Cognitive abilities: A continuous variable that is the transcript reported cumulative GPA for the last degree obtained.
- Field of study: A categorical variable indicating whether participant's field of study is within the hard or soft STEM majors. The variable will be coded as a dummy variable in which hard STEM is considered as the reference group.

Institutional Characteristics:

- Institution control: A categorical variable indicating the control of the respondent's attended postsecondary institution. The variable will be recorded as a dichotomous variable with public institutions as a reference group.
- Institution selectivity: A categorical variable indicating the selectivity of the respondent's attended postsecondary institution (based on 2005 Carnegie Classification System). The variable will be recorded into a set of dummy variables, in which Very Selective will be considered as the reference group. Appendix B further clarifies definitions of each selectivity category.

College Experiences:

- Participation in hands-on learning opportunity: A categorical variable indicating if a graduate participated in an internship, field experience, student teaching, or clinical assignment during college.

Career Self-efficacy and Outcome Expectation:

- Career self-efficacy and outcome expectation: A categorical variable indicating whether the respondent's expected age-30 occupation as reported in the third follow-up is higher than, equal to, or less than the respondent's expected age-30 occupation as reported in the first follow-up.

Data Analysis

Due to the categorical nature of the outcome variable, a hierarchical multinomial logistic regression analysis will be used in this research along with descriptive statistics to analyze the dataset. Built upon the SCCT, independent variables can cluster in four categories resulting in four blocks of predictors; individuals' characteristics, institutional characteristics, college experiences, and career self-efficacy and outcome expectation. Each block of predictors will be entered in the logistic model where, based on the SCCT, individuals' backgrounds will be entered first followed by institutional characteristics, then by college experiences and lastly career self-efficacy and outcome expectation.

Why Multinomial Logistic Regression?

Hierarchical multinomial logistic regression analysis is the appropriate type of inferential analysis for this study considering the nature of the dependent variable (three outcomes). When testing institutional characteristics, Hierarchical Linear Modeling (HLM) might be more advantageous over Multinomial Logistic Regression (MLR) since MLR does not allow institutional characteristics to vary within institutions (Astin & Denson, 2009). When using MLR, institutional characteristics' degrees of freedom are based on the number of students when it should be based on the number of institutions (Astin & Denson, 2009). Such case results in a tendency to commit more Type I errors (rejecting the null hypothesis when it is true) when measuring the effects of institutional characteristics (Astin & Denson, 2009). The aim of the study is not to measure how individual predictors vary across institutional units (cross-level effects) which in that case HLM may not offer any other advantages over MLR (Astin & Denson, 2009). The study considered the issue of clustering in the data, and HLM software will be used to calculate the interclass correlation coefficient (ICC) for the data. This allows for the calculation of the between group variance that can be explained by differences in level two predictors; in this study, postsecondary institutions' variables. Performing this step; testing the null model and calculating the ICC, indicates whether multilevel modeling is warranted (Lee, 2000). Before doing so, the sample under consideration needs to meet certain assumption; HLM is not only affected by the size of the student sample but also the size of the organizations at level-two. Too few institutions and/or too few students within each institution may not be sufficient to run HLM (Snijders & Bosker, 1999). Though there is no general rule on the number of institutions and/or the number of students in each institution needed to perform HLM, at least 50 institutions along with 20 students in each institution is essential.

Education Longitudinal Study (ELS) dataset has students who attended 2,470 different postsecondary institutions (Núñez & Bowers, 2011). In the current sample, students have attended 970 different institutions. Although the number of institutions is more than adequate for HLM, the number of students in each institution does not make HLM analysis feasible. Ninety-three percent of institutions in the sample have only one student within them which is reasonable considering the criteria used to narrow the sample size and target the particular group. Since level-two is critical in HLM analysis, excluding institutions with only one student is a must because variances cannot be calculated for institutions with only one student (Snijders & Bosker, 1999). Such action will result in excluding 93% of institutions in the sample which will significantly reduce the sample size, making HLM less favorable compared to other statistical approaches. On a final remark, logistic regression analysis is proven to be a very robust method with a good fit even if it does not satisfy all of its assumptions, such as homoscedasticity and linearity (Bohrnstedt & Carter, 1971; Hanushek & Jackson, 1977).

After excluding the possibility of using HLM due to lack of appropriate data and since nesting in the data exists, to exercise caution and to avoid committing Type I error many researchers recommend assigning a smaller p-value to determine the statistical significance of institutional variables. A general approach used by many is a stringent p-value of $p < .001$ (e.g., Austin & Denson 2009; Thomas & Heck, 2001; Park, 2009).

The multinomial logistic regression model is based on the following equation:

$$\log \frac{Pr\ (Y=j\ )}{Pr\ (\ Y=j')} = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \qquad \text{Equation 1}$$

where j is the identified outcome (somewhat-matched/mismatched)

and j' is the reference outcome (matched)

In this research, the model of degree-job matching between three outcomes can therefore be represented using two logit models as follow:

$$\log \frac{Pr\ (Y=undermatched\ )}{Pr\ (\ Y=matched)} = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

Equation 2

$$\log \frac{Pr\ (Y=mismatched\ )}{Pr\ (\ Y=matched)} = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

As shown above in Equation 2, to model which of the three degree-job outcomes is likely to be influenced by explanatory variables, two logit models are computed; one comparing outcome (somewhat-matched) with the reference category (matched) and one comparing outcome (mismatched) with the reference category (matched). The two logit models provide two estimates for the effect that each explanatory variable (X_k) has on the response (e.g., the effect of X_{gender} on the degree-job outcome between somewhat-matched and matched, and the effect of X_{gender} on the degree-job outcome between mismatched and matched) and also for the model as a whole (e.g., the effect of X_{gender} across all degree-job outcomes in the sample) (Moutinho & Hutcheson, 2007).

Descriptive statistics (using both frequencies and cross-tabulations) allow for data exploration and comparison of participants' characteristics, and against the outcome variable, while inferential statistics (e.g., multinomial logistic regression) allow for findings generalization to the general population (Gay, Mills, & Airasian, 2009). Before proceeding with data analysis, a few steps will be taken to prepare the dataset. First, as mentioned earlier, multiple imputations will be used to handle missing values. Second, the sample will be weighed using the adjusted weight from the appropriate weight panel (F3QWT) which accommodates sample members who participated in the 2012 third follow-up questionnaire; allowing for the generalization of results to the cohort of the study; 2002 high school sophomores. Third, the Variance Inflation Factor (VIF) will be tested for independent variables in the multinomial logistic model as a measurement of multicollinearity within the model. If predictors have VIF values that are less than 10, then none of the predictors are highly correlated (Marquardt, 1970). Fourth, to examine the fit of the multinomial logistic regression models against the outcome variable, Hosmer–Lemeshow (H–L) goodness-of-fit test will be used where insignificant results (p > .05) are an indication that the models are well fit to the data (Peng, So, Stage, & St. John, 2002). Using block sequential modeling, participants' characteristics will be entered first in the hierarchical multinomial logistic regression model, followed then, in the second block, by institutional characteristics, and in the third block by college attributes, and finally, in the fourth block, by career self-efficacy and expectancy measurement.

Why Hierarchical Regression as the Data Analysis Strategy?

The desire to examine specific theoretically-based hypotheses drives the decision to use sequential block entry of variables (hierarchical regression). The aim was to test if the hypnotized Degree-Job Match Model proposed by the study, based on the SCCT, can be used as a model to predict degree-job match among recent STEM graduates. Simultaneous regression is used to maximize prediction and determine the "optimal" set of predictors while hierarchical regression is used to examine theory-based hypotheses (Aron, 2012; Cohen, 2008; Petrocelli, 2003).

Also, hierarchical regression allows for testing the predictability associated with independent variables that were entered later in the analysis over and beyond that contributed by predictors entered earlier in the model (Petrocelli, 2003). In doing so, the relative importance of predictors entered later in the analysis can be judged based on how much prediction of criterion they add over and above predictions accounted for by other predictors (Petrocelli, 2003). Considering that some predictors (e.g., demographic) were proven by previous empirical research to influence career outcomes, this study wanted to test other predictors over and above that of preexisting predictors. In such a case, hierarchical regression analysis would be appropriate provided that preexisting variables be entered into the analysis first (J. Cohen, P. Cohen, West, & Aiken, 2013; Petrocelli, 2003). For instance, the interest of this study is to examine the effect of career self-efficacy and expectancy as a predictor independent of the effects of other preexisting predictors (e.g., demographic and institutional variables). The study used logical reasoning driven by theoretical grounding in specifying the order of block entry of variables. This is a strongly recommended approach since results may depend largely on the entry order of predictors into the model (J. Cohen et al., 2013; Petrocelli, 2003).

Variables Coding Scheme

Table 3 presents the variable's coding scheme used in the hierarchical multinomial logistic regression model.

Variance Inflation Factor

The study tested the Variance Inflation Factor (VIF) for all independent variables as a measurement of multicollinearity within the model. Table 4 presents the VIF values for all predictors in the model. None of the study predictors have a VIF value that is greater than 10; the range of VIF values is 1.02 to 1.61. This range is an indication that predictors are not highly correlated, and thus, a multicollinearity issue does not exist for the model (Marquardt, 1970).

Table 3

Variable Coding Scheme

Variables	Coding Scheme
Individuals' Characteristics	
Gender	1= Female; 0= Male
Race/ethnicity	
African American	1= African American; 0= Other
Hispanic	1= Hispanic; 0= Other
White [a]	1= White; 0= Other
Asian	1= Asian; 0= Other
Other Races	1= Other Races; 0= Race Specified
Socioeconomic Status (Quartile)	
Low SES Quartile	1= Low SES; 0= Other
Mid SES Quartile	1= Mid SES; 0= Other
High SES Quartile [a]	1= High SES; 0= Other
STEM Cognitive Abilities	
GPA for all known STEM courses †	Continues Scale
STEM Major	1= Hard STEM; 0= Soft STEM
Institutional Characteristics	
Institution Control	1= Public; 0= Private
Institution Selectivity	
High Selectivity [a]	1= High Selectivity; 0= Other
Moderate Selectivity	1= Moderate Selectivity; 0= Other
Inclusive Selectivity	1= Inclusive Selectivity; 0= Other
Selectivity not Specified	1= Selectivity not Specified; 0= Other
Learning Experiences	
Participation in hands-on learning opportunities (e.g., internship and onsite training) during college years	1= Yes; 0= No
Career Self-efficacy and Outcome Expectations	Continues Scale
Outcome Variable	
Relationship between current job and field of study	
Matched	1= Closely Related; 0= Other
Somewhat-Matched	1= Somehow Related; 0= Other
Mismatched	1= Not Related; 0= Other

[a] Reference Group
† Using NSF definition of Science, Engineering, and related fields

Limitations

Several limitations should be noted when considering results from this study. First, every effort was made to ensure proper classification of STEM majors. However, in the absence of an agreed upon definition of what STEM includes, some may criticize the classification procedure followed in this research. Some majors considered in this research as STEM might be regarded by others as non-STEM. Likewise, there might be some majors that are not included in this research as STEM when many others consider them as STEM. Second, the dataset used in this study (ELS:2002) follows participants for about three to four years after their graduation (or six years after the second follow-up). Thus, an analysis of participants' long-run career outcomes was not feasible in this study limiting findings to only short-run career outcomes. Third, employment history was not considered in this research, nor individuals employed previously but are currently looking for a job. However, it would be interesting to see if somewhat-match/mismatch status is influenced by the length of past unemployment or by the number of times individuals were unemployed. Fourth, it is important to note that some STEM graduates may choose to work outside their field of study simply because they lost interest in their previous field, or have goals that can only be fulfilled by working outside their field of highest degree. This study did not include this factor due to data limitation. Fifth, the model in this study, used one component to measure career self-efficacy and outcome expectation as a predictor of degree-job match, integrating more than one component to assess career self-efficacy and outcome expectation was not feasible due to data limitations.

An additional consideration is the potential influence of pre-college attributes (e.g., interest in STEM, high school math and science preparation) on the degree-job matching phenomenon. Empirical studies on major choice and college retention have noted the importance of pre-college variables in influencing graduation and career placement (Clotfelter, 2010; Trusty, 2002). Pre-college attributes were not integrated in this study partly because the primary intention of this study was to examine the predictability of college factors for degree-job matching (e.g., collegiate experience, career self-efficacy, institutional characteristics).

Finally, this study used ELS:2002 dataset where results are reflective of the 2002 high school sophomore cohorts. Other national datasets, such as Baccalaureate and Beyond (B&B), may provide a more comprehensive representation of U.S. college graduates. B&B follows several cohorts of college students over time focusing on bachelor's degree graduates' education, undergraduate experiences, and employment outcomes.

Table 4

Variance Inflation Factor (VIF) for Independent Variables (N=1864).

Predictor Variables	Variance Inflation Factor
Individuals' Characteristics	
Gender	1.06
African American	1.12
Hispanic	1.09
Asian	1.06
Other Races	1.03
Low SES Quartile	1.29
Mid SES Quartile	1.24
GPA [a]	1.12
Institutional Characteristics	
Institution Control	1.07
High Selectivity	1.61
Moderate Selectivity	1.42
Inclusive Selectivity	1.19
Learning Experiences	
Participation in hands-on learning opportunities during college years	1.05
Career Self-efficacy and Outcome Expectations [b]	1.02

[a] GPA for all known STEM courses (using NSF definition of science, engineering, and related fields).
[b] A scale that measures whether the prestige score associated with the respondent's expected age-30 occupation as reported in the third follow-up is higher than, equal to, or less than the prestige score associated with the respondent's expected age-30 occupation as reported in the first follow-up

Summary

In this chapter, a description of the dataset used in this study (ELS:2002) along with research variables were presented. In addition, the methodology that will be used to handle the dataset was outlined along with the research limitations. The following two chapters will present the results and discussion of findings along with implications and suggestions for policyholders and future research.

CHAPTER IV

Results

This research focuses on examining whether career self-efficacy and expectancy are related to the degree-job matching among recent STEM college graduates. Possible attributes include participants' background characteristics (such as race/ethnicity, gender, and socioeconomic status), academic performance, institutional characteristics, college attributes, and participants' career self-efficacy and career outcome expectation. The study limited the sample subjects to bachelor's degree recipients in a STEM field or related fields (based on NSF classification) who, at the time of the survey (June 2012), held a full-time job. This limit yielded a sample size of 1,864 participants. Handling missing values along with model fit tests were performed first to prepare the dataset. Descriptive and inferential statistics were then performed to look at relationships between predictors and the outcome variable (measured by degree-job match). The study presents the results along with related tables.

Missing Values

Multiple Imputation (MI) was used to handle missing values as it is the most recommended method by statisticians (Acock, 2005). No missing values were found for the demographic or the institutional variables. On the other hand, the following variables have missing values; GPA and Major have less than 1% missing values, Experience (6.5%), Self-Efficacy (41%), and the dependent variable has less than 7% missing values. One may argue that 41% of missing value found in the Self-Efficacy variable is not acceptable to perform statistical analysis. However, the existing line of research does not note a specific cutoff regarding an acceptable percentage of missing data to perform statistical inferences (Dong & Peng, 2013). Researchers do not focus on the amount of missing data, but rather on the missing data mechanisms and patterns (Tabachnick & Fidell, 2012). Three missing data mechanisms can occur where one of them is MCAR or missing completely at random where missing values do not depend on the values of the dataset variables (Rubin, 1876). When missing values are MCAR, the response mechanism is ignorable and concerns over having biased estimates of parameters or increased standard errors should no longer exist (Pigott, 2001). Little's MCAR test was performed to test whether the 41% missing values of the Self-Efficacy variable are MCAR. The result was found to be not statistically significant ($p = .304$) indicating that the data is MCAR in which there is no pattern exists for the missing values, and thus allows for MI (Little,1988).

Missing values, including those found in the dependent variable, were imputed using MI as this technique found to be desirable by multiple researchers (e.g., Allison, 2002; Little, 1992). The study created five imputed datasets with interpretation of the pooled data. No consensus in empirical research on whether to include the dependent variable's (DV) imputed values in the analysis. Von Hippel (2007) described an accepted practice known as Multiple Imputation then Deletion (MID) where MI includes missing values of DV, but delete these before analysis. This is, as von Hippel (2007) notes, because adding imputed DV values to the analysis add "unnecessary noise," and inflate the standard error (von Hippel, 2007). That might be true when (1) there are a small number of imputed datasets, less than 5, or when (2) DV has a high percentage of missing values; over 20% (Sullivan, Salter, Ryan, & Lee, 2015; Young & Johnson, 2010). When none of the two conditions exist, MID may not offer any more advantage than standard MI (Young & Johnson, 2010). Since the DV in this study has less than 7% missing values and since five imputations generated, the standard method of MI was chosen over MID; meaning retention of DV imputed values in the analysis. With that said, a sensitivity test was performed to compare outcomes obtained from standard MI and MID. The test showed no significant difference between the two methods, validating the decision to use standard MI and retain 7% of the data.

Goodness of Fit Test

When testing the fit of a multinomial logistic regression model, many researchers recommend treating the model as if it was a series of binary logistic regression models; where each outcome is tested against the reference outcome, thus testing the fit of each model separately (Begg & Gray, 1984; Hosmer & Lemeshow, 2000; Goeman & Le Cessie, 2006; Pigeon & Heyse; 1999). In doing so, two binary logistic regression models were created (matched and somewhat-matched) to test the goodness of fit of each model against the reference outcome (mismatched). Using Hosmer-Lemeshow goodness of fit test, both models proved to be insignificant ($p > .05$) indicating that both models fit the data very well (Hosmer & Lemeshow, 2000) as shown in Table 5.

Although R^2 values are a desired method of testing a model power or goodness of fit, this method is not recommended for use with logistic regression models (Hosmer & Lemeshow, 2000). R^2 measures compare the predicted values from the fitted model to the null model (the no data model) when the comparison should be between the observed and the predicted values from the fitted model (Hosmer & Lemeshow, 2000). Thus, R^2 in logistic regression models is not an adequate method of the goodness of fit or power. With that said, this study tested models using the R^2 test where values seemed to be low (ranging between 2.5% to 15%). However, low R^2 values are the norm in a logistic regression where the test might be helpful in model building, but not model assessing (Hosmer & Lemeshow, 2000). Thus, this study used R^2 values only to test variables' contribution to the model, but not the goodness of fit since the Hosmer-Lemeshow test served that purpose.

Table 5

Hosmer-Lemeshow Goodness-of-Fit Test for MLR Models

MLR Outcome	Model 1	Model 2	Model 3	Model 4
Matched	0.974	0.243	0.093	0.138
Somewhat-Matched	0.862	0.774	0.491	0.247

Note: As shown, all models are found to be insignificant ($p > .05$) indicating a good fit

Descriptive Statistics

Table 6 summarizes the descriptive statistics of the dependent variable, where Table 7 presents the descriptive statistics of the categorical independent variables, and Table 8 shows descriptive statistics of the continuous independent variables including the weighted mean, standard deviation, and range.

As noted in Table 6, more than half of the study sample (53%) stated that their field of study is closely related (matched) to their current job while only 24% noted that their degree is somewhat related to their current job (somewhat-matched). On the other hand, 23% of the sample reported that their current job is unrelated to their field of study (mismatched).

Table 6

Descriptive Statistics of the Dependent Variable (N=1864).

Variable	Weighted Percentages (%)
Matched	53
Somewhat-Matched	24
Mismatched	23

Moreover, as shown in Table 7, female participants represent more than half (57%) the STEM bachelor’s degree recipients in the sample. However, male participants have a significantly higher representation in hard STEM fields; 91% in Engineering and 84% in

Computer Science for example. Female participants are more represented among soft STEM majors; for example, they represent 83% of those majored in Psychology.

Table 7

Descriptive Statistics of Categorical Variables (N=1864).

Variables	Weighted Percentages (%)
Individuals' Characteristics	
Gender	
Male	43
Female	57
Race/Ethnicity	
White	64
African American	10
Hispanic	10
Asian	11
Other Races	5
Socioeconomic Status	
High SES Quartile	41
Mid SES Quartile	45
Low SES Quartile	14
Major	
Hard STEM	61
Soft STEM	39
Institutional Characteristics	
Institution Control	
Public	70
Private	30
Selectivity	
High Selectivity	34
Moderate Selectivity	27
Inclusive Selectivity	8
Selectivity not Classified	31
Career-Related Experiences during College	
Participation in hands-on learning opportunities	
Yes	63
No	37

The sample comprised 64% White participants, 10% African Americans, 10% Hispanics, 11% Asians, and 5% other minority groups. Further, the socioeconomic status of participants seems to be equally distributed between high and mid socioeconomic quartiles, 41% and 45% respectively, whereas participants from the low socioeconomic quartile only represent 14% of the total sample. Further, 61% of participants have their degree in a hard STEM major compared to 39% in a soft STEM major. Seventy percent of the sample received their education at a public institution compared with 30% who graduated from private institutions.

Also, it is worth noting that 34% of the graduates in the sample received their degree from highly selective institutions compared with 27% who received it from moderately selective institutions and 8% who received from institutions with inclusive selectivity. As shown in Table 7, 63% of the sample stated that they had participated in hands-on learning opportunities (e.g., internship and field experience) during college years.

Regarding descriptive statistics of continuous independent variables; Table 8 shows that the Grade Point Average (GPA) for all participants in the sample has a mean value of 3.03 with a standard deviation of 0.552. The career self-efficacy measurement in the total sample has a mean value of 2.12 with a standard deviation of 0.648.

Table 8

Descriptive Statistics of Continuous Variables (N=1864).

Outcome	Variables	Weighted Mean	SD	Min	Max
Matched	GPA for all known STEM courses	3.10	.504	1.25	4.00
	Career Self-efficacy [b]	2.06	.612	1	3
Somewhat -Matched	GPA for all known STEM courses	3.00	.583	.75	4.00
	Career Self-efficacy [b]	2.15	.661	1	3
Mismatched	GPA for all known STEM courses	2.87	.564	.50	4.00
	Career Self-efficacy [b]	2.23	.736	1	3
Total Sample	GPA for all known STEM courses	3.03	.552	.50	4.00
	Career Self-efficacy [b]	2.12	.648	1	3

[b] A descending scale that measures whether the prestige score associated with the respondent's expected age-30 occupation as reported in the third follow-up is higher than, equal to, or less than the prestige score associated with the respondent's expected age-30 occupation as reported in the first follow-up.

Table 8 also presents descriptive statistics of continuous variables by each category of the dependent variable. GPA within the Matched outcome has a mean value of 3.10 and a standard deviation of 0.504 while career self-efficacy within the same model has a mean value of 2.06 with a standard deviation of 0.612. In the Somewhat-Matched outcome, GPA has a mean value of 3.00 with a standard deviation of 0.583, whereas career self-efficacy has a mean value of 2.15 with a standard deviation of 0.661. In the third outcome, Mismatch, GPA has a mean value of 2.87 and a standard deviation of 0.564 while career self-efficacy has a mean value of 2.12 and a standard deviation of 0.648.

One-Way ANOVA

The study performed a one-way analysis of variance (ANOVA) to test if there is a statistically significant difference between the groups' means presented in Table 8. As shown in Table 9, there was a statistically significant difference in GPA between groups as determined by one-way ANOVA ($F(2,1725) = 24.559$, $p = .000$). To determine which of the specific groups differed, the study applied a Tukey posthoc test. It revealed that GPA was significantly higher for the matched participants ($3.10 \pm .50$, $p = .004$) compared to somewhat-matched and mismatched, and for the somewhat-matched ($3.00 \pm .58$, $p = .004$) compared to the mismatched ($2.87 \pm .56$, $p = .004$), see Table 10. However, as shown in Table 9, there were no significant differences between the career self-efficacy groups as determined by one-way ANOVA ($F(2,1019) = 2.780$, $p = .063$).

Table 9

One-Way Analysis of Variance of Degree-Job Match by Continues Independent Variables

Variable		SS	df	MS	F	Sig.
GPA	Between Groups	14.238	2	7.119	24.559	.000
	Within Groups	500.024	1725	.290		
	Total	514.263	1727			
Self-Efficacy	Between Groups	2.339	2	1.170	2.780	.063
	Within Groups	428.740	1019	.421		
	Total	431.079	1021			

Table 10

Tukey Post-Hoc for the Depended Variable GPA

Match Level		Mean Difference	Std. Error	Sig.
Match	Somewhat-Match	.10320	.03189	.004
	Mismatch	.22292	.03225	.000
Somewhat-Match	Match	-.10320	.03189	.004
	Mismatch	.11972	.03770	.004
Mismatch	Match	-.22292	.03225	.000
	Somewhat-Match	-.11972	.03770	.004

Cross-Tabulation

The cross-tabulation analysis compared the characteristics of the sample participants by the outcome variable. Table 11 indicates differences among participants by predictors. First, female participants are more represented (60%) among matched individuals whereas male participants are more represented in the somewhat-matched group (48%). Further, differences are also found among different races; for example, White participants are more represented (71%) among matched groups while other minority groups, such as African-Americans, are more represented in the somewhat-matched and mismatched groups compared to the matched group (see Table 11 for further racial differences).

Further, participants from low socioeconomic quartile have more representation in the mismatched group than the matched or the somewhat-matched whereas those from the middle socioeconomic quartile have a slightly higher representation in the somewhat-match and mismatch groups than the match. Graduates with a degree in hard STEM are more represented in all degree-job match outcomes, with higher representation (71%) in the somewhat-matched group. The breakdown by institutional type in the total sample (70% public, 30% private) seems to remain stable across all degree-job match outcomes. Also, institutions with "no selectivity specified" have more graduates (41%) working in jobs unrelated to their fields of study;

compared to the representation in the total sample. It is also worth noting that 70% of matched individuals stated that they have participated in hands-on learning opportunities during college years compared with 55% of somewhat-matched and 50% of mismatched participants, suggesting the importance of hands-on activities during college years and prior experiences.

Table 11

Cross-Tabulation Statistics by Participants' Characteristics and the Outcome Variable

Variables	% of the total sample (*N=1,864*)	% of matched sample (*n=986*)	% of somewhat matched sample (*n=444*)	% of mis-matched sample (*n=434*)
Individuals' Characteristics				
Gender				
Male	42	40	48	45
Female	58	60	52	55
Race/Ethnicity				
White	64	71	66	68
African American	10	9	11	12
Hispanic	10	11	11	13
Asian	11	5	8	4
Other Races	5	4	4	4
Socioeconomic Status				
High SES Quartile	41	37	40	33
Mid SES Quartile	45	47	49	49
Low SES Quartile	14	16	11	18
Major				
Hard STEM	61	57	71	60
Soft STEM	39	43	29	40
Institutional Characteristics				
Institution Control				
Public	70	74	74	70
Private	30	26	26	30
Selectivity				
High Selectivity	34	28	34	28
Moderate Selectivity	27	29	27	24
Inclusive Selectivity	8	9	11	7
Selectivity not Classified	31	34	28	41
Career-Related Experiences during College				
Participation in hands-on learning opportunities				
Yes	63	70	55	50
No	37	30	45	50

Multinomial Logistic Regression Analyses

The Categories

This section presents the Multinomial Logistic Regression (MLR) analyses along with relevant tables. The study performed a hierarchical multinomial logistic regression analysis to determine the relationship between predictor variables (students' background characteristics, institutional characteristics, college attributes, and career self-efficacy) and the outcome variable (degree-job match).

The study examines student expectations for academic major and job match in the STEM field operationalized as a multi-categorical variable: matched, somewhat-matched, and mismatched. Multinomial logistic regression is the appropriate analytical method for multiple response categories such as those used in this study for matched types between job and field of study.

The hierarchical method was implemented in the multinomial logistic regression analysis to account for the effect of background and institutional characteristics on the criterion variable. Independent variables divided into four blocks were entered into the multinomial logistic regression equation in an order based on block sequential modeling per Lent, Brown and Hackett's (1987) Social Cognitive Career Theory (SCCT):

- Block 1: Participants' demographic characteristics represented in race/ethnicity, gender, and socioeconomic level (composite of parental education and income).
- Block 2: Institutional characteristics represented in control (public or private), and selectivity (based on 2005 Carnegie classifications).

- Block 3: College attributes represented in major (hard or soft STEM based on NSF classification), career-related experiences during college, and STEM cognitive abilities (measured in GPA for all known STEM courses).
- Block 4: Career self-efficacy and expectancy.

Table 12 presents the findings of the MLR analysis and model evaluation. Odds ratio were used to determine the predictability of factors in each category. In Table 12, an odds ratio greater than one indicates that participants in that category (closely-related/matched, or somewhat-related/somewhat-matched) have a higher odds than participants in the reference category (not-related/mismatched) to be classified as 'matched or somewhat-matched' (Osborne, 2008).

The "Matched" Outcome: Category Results

As shown in Table 12, Model One, within the Matched Outcome, introduces demographic variables (gender, race, and socioeconomic status) where none of these predictors was found to be statistically significant ($p > .05$). This indicates that demographic attributes, represented in race, gender, and socioeconomic status, have no statistically significant relation to the odds of STEM graduates being matched or mismatched.

In Model Two, after controlling for demographic variables, institutional characteristics (control and selectivity) were added to the category. Like the previous model, none of the institutional attributes were found to be statistically significant ($p > .05$). This indicates that institutional characteristics have no statistically significant relation to the odds of STEM graduates to be matched or mismatched with their jobs.

On the other hand in Model Three, and while controlling for demographic variables and institutional characteristics, college attributes were entered into the model. College attributes variables entered in this model include GPA, career-related experiences during college, and major (hard-STEM or soft-STEM). In this model, academic performance during college (represented in GPA for all know STEM courses) found to be statistically significant (OR = 2.206, $p < 0.001$) and positively related to being matched. This indicates that the odds of a STEM graduate being matched (as opposed to mismatch) were two times greater for participants with higher GPA; measured by a 0.25 point grading scale. In other words, a one unit increase in GPA, or a 0.25 increase, is associated with a 20% increase in the odds of STEM graduates to be matched with their jobs than being mismatched, controlling for all factors included in the model. For instance, the odds of a STEM graduate with a 3.75 GPA to be matched rather than mismatched are 60% higher than a STEM graduate with a 3.00 GPA. By the same token, controlling for other predictors, a STEM graduate with a 3.25 GPA is four times more likely to work in a job that is not related to his/her degree (mismatched) than a STEM graduate with 3.75 GPA.

Career-related experiences during college years was found to be a statistically significant predictor of participants' degree-job match (OR = 2.102, $p < 0.001$). This finding indicates that the odds of being matched (as opposed to mismatch) are two times as high for graduates who participated in career-related learning opportunities (e.g., internship and onsite training) during college years; controlling for other variables in the model. Major, on the other hand, was found to be statistically insignificant ($p > .05$) indicating that STEM major (hard or soft) has no statistically significant relation to the odds of being matched or mismatched.

After controlling for demographic variables, institutional characteristics and college attributes, the career self-efficacy and expectancy measurement was introduced to the final block; Model Four. In this model, the career self-efficacy and expectancy predictor was not found to be statistically significant ($p > .05$) indicating that career self-efficacy and expectancy is not a significant predictor of STEM graduates' degree-job match.

In sum, findings from the Matched Category show that demographic characteristics, institutional characteristics, STEM major, and career self-efficacy and expectancy were all found to be not statistically significant predictors of the odds of a STEM graduate to be matched or mismatched with their jobs. On the other hand, findings from the same category suggest that graduates who have a relatively lower GPA and lack career-related college experience have higher odds of being mismatched with their jobs than matched compared to their peers with higher GPA and more career-related college experiences.

Table 12.

Multinomial Logistic Regression Model and Model Evaluation for Recent Bachelor STEM Graduates' Degree-Job Match (N= 1864)

Variables		Model One				Model Two				Model Three				Model Four			
		$\hat{b}$	S.E. $\hat{b}$	$\hat{\beta}$	Odds Ratio	$\hat{b}$	S.E. $\hat{b}$	$\hat{\beta}$	Odds Ratio	$\hat{b}$	S.E. $\hat{b}$	$\hat{\beta}$	Odds Ratio	$\hat{b}$	S.E. $\hat{b}$	$\hat{\beta}$	Odds Ratio
Dependent [a]	Independent																
	Gender	-.219	.136	-.026	.803	-.207	.137	-.025	.813	-.015	.142	-.001	.986	.005	.145	.000	1.005
	Hispanic	.160	.211	.012	1.173	.117	.211	.009	1.124	-.028	.217	-.002	.972	-.022	.224	-.001	.979
	African American	.346	.205	.025	1.413	.369	.208	.027	1.447	.000	.228	.000	1.000	.013	.235	.000	1.013
	Asian	-.231	.316	.012	.794	-.225	.319	-.012	.798	-.342	.333	-.019	.710	-.371	.330	-.020	.690
	Other Races	-.070	.367	.003	.933	-.045	.369	-.002	.956	-.210	.373	-.010	.811	-.192	.376	-.009	.825
	Mid SES quartile	-.120	.133	.014	.887	-.115	.139	-.014	.892	-.114	.144	-.014	.893	-.124	.144	-.015	.883
	Low SES quartile	-.220	.186	.019	.803	-.178	.195	-.015	.837	-.148	.202	-.013	.862	-.172	.206	-.015	.842
Matched	Institution control					-.223	.136	.024	.793	-.425**	.140	-.046	.654	-.423**	.141	-.046	.655
	Moderate selectivity					.171	.166	.018	1.187	.214	.172	.023	1.239	.206	.174	.022	1.228
	Inclusive selectivity					.296	.253	.020	1.344	.343	.261	.024	1.409	.368	.265	.025	1.445
	Selectivity not specified					-.152	.161	.017	.859	-.174	.183	-.020	.840	-.192	.187	-.022	.825
	STEM GPA									.791***	.130	.107	2.206	.766***	.136	.104	2.151
	Major									.163	.148	.089	1.177	.154	.152	.018	1.166
	Career-related experience									.743***	.143	.019	2.102	.735***	.147	.088	2.085
	Career self-efficacy													-.359	.223	-.057	.699
	Gender	.049	.152	.006	1.050	.056	.153	.006	1.057	.078	.159	.009	1.081	.091	.160	.011	1.096
	Hispanic	-.151	.234	-.011	.860	-.205	.235	-.016	.815	-.247	.239	-.019	.781	-.243	.243	-.019	.785
	African American	-.052	.251	-.003	.950	-.016	.260	-.001	.984	-.227	.274	-.016	.797	-.218	.275	-.016	.804
	Asian	-.685*	.325	-.037	.504	-.633	.328	-.035	.531	-.682*	.333	-.037	.506	-.700*	.332	-.038	.497
	Other races	-.206	.393	-.009	.814	-.173	.396	-.009	.841	-.262	.399	-.012	.769	-.252	.400	-.012	.777
	Mid SES quartile	-.201	.157	-.024	.818	-.140	.166	-.017	.870	-.092	.167	-.011	.912	-.097	.166	-.012	.907
	Low SES quartile	-.793**	.237	-.070	.452	-.654**	.247	-.058	.520	-.595*	.250	-.052	.551	-.605*	.251	-.053	.546
Somewhat Matched	Institution control					-.286	.165	-.031	.751	-.402*	.165	-.044	.699	-.402*	.166	-.044	.669
	Moderate selectivity					-.028	.191	-.003	.972	.037	.193	.004	1.038	.033	.193	.003	1.034
	Inclusive selectivity					.377	.290	.026	1.457	.504	.291	.035	1.656	.524	.294	.036	1.690
	Selectivity not specified					-.478*	.204	-.056	.620	-.315	.229	-.037	.730	-.327	.234	-.038	.721
	STEM GPA									.478**	.142	.065	1.614	.466**	.143	.063	1.593
	Major									-.309	.179	.021	.734	-.314	.177	-.037	.730
	Career-related experience									.182	.155	-.037	1.199	.173	.159	.020	1.189
	Career self-efficacy													-.210	.249	-.033	.810
Overall Model Evaluation																	
Negelkerke R^2		2.5%				4%				12%				14%			

[a] The reference outcome is Not-Related or Mismatched. Significant variables are presented with asterisks *p<.05, **p<.01, ***p<.001

$\hat{b}$ = unstandardized beta. S.E. $\hat{b}$ = standard error of unstandardized beta. $\hat{\beta}$ = semi-standardized beta weight using the mean predicted probability of 0.544 as a reference value.

The "Somewhat-Matched" Outcome: Category Results

As shown in Table 12, Model One, within the Somewhat-Matched Outcome, demographic outcomes represented in race/ethnicity (with White being the reference group), gender, and socioeconomic status (measured by parental education and family income) were entered in this model. Gender was not found to be statistically significant ($p > .05$) indicating that gender is not a significant predictor of a STEM graduate being somewhat-matched or mismatched. Further, Hispanics, African Americans, and multiracial participants were found not to be a statistically significant predictor of a STEM graduate being somewhat-matched or mismatched as compared to their White counterparts. On the other hand, Asians were found to be statistically significant (OR = 0.504, $p < 0.05$) indicating that the odds of being somewhat-matched as opposed to mismatched are 50% lower for STEM graduates identified as Asians compared to their White counterparts. In other words, White STEM graduates have higher odds of working in jobs that are somehow related to their degrees (as opposed to not related) compared to their Asian peers.

In the same model, Model One, the log of the odds of being somewhat-matched (as compared to mismatched) were negatively related to participants from the low socioeconomic quartile (OR = 0.452, $p < 0.01$) as compared to the high socioeconomic quartile. This means that the odds of working in jobs that are somehow-related to STEM graduates' field of study (as opposed to not-related) are about 45% lower for graduates with low socioeconomic status compared to their peers with high socioeconomic status.

In Model Two, within the Somewhat-Matched category, institutional characteristics were entered in the model (Block 2) while controlling for demographic attributes (Block 1). In this model, and since the study is considering a stringent p-value for institutional characteristics (p <

.001), none of the institutional characteristics were found to be statistically significant. Such result indicates that there is no statistically significant relation between institutional characteristics (represented in control and selectivity) and the odds of STEM graduates to be somewhat-matched or mismatched; holding background attributes as constant.

After controlling for demographic predictors and institutional characteristics (Block 1 and 2), and within the Somewhat-Matched category, Model Three introduced the college attributes variables (Block 3). Similar to the "Matched Category," academic performance represented in GPA for all known STEM courses was also found to be statistically significant ($OR = 1.614$, $p < 0.01$). This indicates that controlling for all other factors included in the model, a one unit increase in GPA (measured on a 0.25 grading scale) is statistically associated with an over 61% increase in the odds of STEM graduates being somewhat-matched with their jobs than being mismatched. However, major and career-related college experiences were not found to be statistically significant ($p > .05$) for the Somewhat-Matched category. This indicates that STEM major (hard or soft) and career-related experiences during college have no statistically significant relationship to the odds of being somewhat-matched or mismatched.

In the final model, and within the Somewhat-Matched category, Model Four adds the last block of variables (Block 4) while controlling for previous blocks. In this model, the measurement of career self-efficacy and career outcome expectations was introduced and found not to be statistically significant ($p > .05$) in predicting the degree-career match outcomes.

Combining the statistically significant explanatory predictors from the Somewhat-Matched Category, race, socioeconomic status, and academic performance represented in GPA were all found to be statistically significant predictors in increasing the odds of a STEM graduate to be somewhat-matched than mismatched. On the other hand, gender, institutional characteristics, major, career-related college experiences, and career self-efficacy were all found not to be statistically significant predictors.

In short, combining the statistically significant explanatory variables from both of the MLR categories a simple, yet robust profile emerges for a STEM graduate who is at the greatest risk of being mismatched with his/her career. This is an Asian, who comes from the low socioeconomic quartile, has a relatively lower GPA, and lacks career-related college experience

How Costly is the Mismatch?

Descriptive statistics are presented in Table 13. To test if there was a statistically significant difference between the groups' means given in Table 13, a one-way analysis of variance (ANOVA) was performed. The one-way analysis of variance (ANOVA) compared participants' earnings from employment, during the 2011 calendar year, by degree-job match. As shown in Table 14, there was a statistically significant difference between groups ($F(2,1725) = 24.559$, $p = .000$).

Table 13

Descriptive Statistics of Participants' Earnings from Employment (N=1864).

Outcome	N	Weighted Mean	SD	Min	Max
Matched	990	40325.80	23715.20	0	250000
Somewhat-Matched	443	38966.05	29117.86	0	250000
Mismatched	431	29990.51	22793.60	0	250000
Total Sample	1864	37612.24	25296.73	0	250000

Table 14

One-Way ANOVA of Degree-Job Match by Participants' Earnings from Employment

	SS	df	MS	F	Sig.
Between Groups	14.238	2	7.119	24.559	.000
Within Groups	500.024	1725	.290		
Total	514.263	1727			

To determine which of the distinct groups differed, a Tukey posthoc test was applied (Table 15). The test revealed that earnings from employment were statistically significantly higher for matched (\$40325.80 ± \$23715.20, p = .000) and somewhat-matched (\$38966.05 ± \$29117.86, p = .000) compared to mismatched (\$29990.51 ± 22793.60). However, there was no statistically significant difference between matched and somewhat-matched (p = .643). To conclude, STEM graduates who are mismatched with their jobs are suffering from a wage penalty of about 33% compared to matched or somewhat-matched STEM graduates.

Table 15

Tukey Post-Hoc for the Depended Variable Earning from Employment

Match Level		Mean Difference	Std. Error	Sig.
Match	Somewhat-Match	1318.799	1471.365	.643
	Mismatch	10938.05	1486.346	.000
Somewhat-Match	Match	-1318.799	1471.365	.643
	Mismatch	9619.256	1740.099	.000
Mismatch	Match	-10938.05	1486.346	.000
	Somewhat-Match	-9619.256	1740.099	.000

Summery

This chapter presented the statistical findings of both the descriptive and inferential analysis along with model evaluation techniques. A one-way ANOVA was as well conducted to test differences in earnings among degree-job match groups. The hierarchical multinomial logistic regression results of four models were discussed in depth in this chapter along with related tables. The following chapter concludes with the discussion and implication of findings along with recommendations for policyholders and future research.

Chapter V

Conclusions and Implications

Concerns over the lack of adequate numbers of qualified STEM graduates continue to dominate discussions about the U.S. global position as innovation preeminence (Butz, Kelly, Adamson, Bloom, Fossum, & Gross, 2004; Charette, 2013; Freeman, 2006; Freeman & Goroff, 2009; Lowell & Salzman, 2007; Lowell, Salzman, Bernstein, & Henderson, 2009; Lynn & Salzman, 2006; Salzman, 2007; Salzman & Lynn, 2010; Salzman, Kuehn & Lowell, 2013; Teitelbaum, 2014). Although the federal government and private agencies allocate substantial fiscal aid to the STEM field, the quality and competence level of STEM graduates and the country's position in the global market continue to receive severe doubts as STEM graduates increasingly work in non-STEM occupations (Preston, 2004). Recent empirical studies have paid considerable attention to the (mis)match between a worker's academic knowledge and job (Robost, 2007), concluding that the mismatch results in significantly diminished wages, lower job satisfaction and productivity, loss of unused skills, higher turnover, feelings of loss in educational return on investment, loss of human capital return on investment, cognitive decline, and inadequate labor force for workforce expansion and growth (Belman & Heywood 1997; Bender & Heywood, 2009; De Grip, Bosma, Willems, & Van Boxtel, 2008; McGoldrick & Robst 1996; Sattinger, 1993, 2012; Sloane, Battu, & Seaman 1996; Tsang 1987). These outcomes intensify the current concerns over the STEM labor market ability of the U.S. to compete in the global market.

One aspect of workforce success is the ability to utilize workers' knowledge and skills gained from the educational investment. Failing to match workers with jobs that present proper intellectual challenge results in underutilization of employees' abilities, posing economic implications for the entire STEM workforce. So far, empirical research on worker-job match has focused on a limited area of the issue, calling for immediate attention yet with different approaches to the current degree-job mismatch. The majority of research on degree-job match has mainly focused on three areas: (1) the consequences of the degree-job mismatch (e.g., Belman & Heywood 1997; Bender & Heywood, 2009; De Grip, Bosma, Willems, & Van Boxtel, 2008), (2) the match between years of schooling and the educational attainment required for the job (e.g., Hartog, 2000; Sloane, 2003), and (3) earning differences between the matched and mismatched workers with regard to returns on investment in education (e.g., Cohn & Kahn, 1995; Groot & Van Den Brink, 2000; Hartog, 2000; Robst, 2006). However, research that measures the consequence of the worker-job mismatch has overlooked the root of the problem; where the mismatch originates from. Further, studies that looked at the relationship between educational attainment required for the job and quantity of schooling have limited themselves to only one way to measure the match between degree and job (Sloane, 2003). To close the gap in the literature, this study took a different approach to addressing degree-job match by looking at what could predict the match during college years. The primary focus of the present study was to understand better the supply side (STEM students) since the demand side has received considerable attention (e.g., Lynn & Salzman, 2006; Manning, Massini & Lewin, 2008; Salzman, 2007; Salzman, Kuehn & Lowell, 2013; Salzman & Lynn, 2010; Sargent Jr., 2010). STEM students are the future generation; they will play a fundamental role in innovation and technological advancement

University officials and policymakers need to understand what can predict STEM students' successful transition into the STEM workforce. Providing STEM graduates with opportunities to choose jobs that match their knowledge and skill level needs to be a shared responsibility between universities, workforce, policymakers, and the graduates themselves. This chapter discusses the shared responsibility concept and presents the implications for policy and practice. Findings from Chapter IV are briefly examined in response to the research questions. Discussion of the theoretical contribution of the degree-job match model is then presented, followed by implications for policy and practice, and finally conclude with recommendations for future research.

Discussion

Building on the Social Cognitive Career Theory (SCCT) and previous empirical research, this study looked at determinants of degree-job match among recent STEM bachelor's degree graduates. Degree-job match in this study refers to the match between degree field, or degree knowledge and skills, to the job. The influence of the mismatch between degree, or degree knowledge and skills, to the job, is substantial. It has been documented by previous research pointing to diminished wages, lower job satisfaction and productivity, higher turnover, feelings of loss in educational return on investment, and improper labor force for workforce' expansion and growth (Belman & Heywood 1997; Bender & Heywood, 2009; McGoldrick & Robst 1996; Sattinger, 1993, 2012; Sloane, Battu, & Seaman 1996; Tsang 1987). The study examined four different sets of predictors that were hypothesized to influence degree-job match; demographic attributes, institutional characteristics, college-related influences and experiences, and career self-efficacy and outcome expectation. Using a nationally representative sample of 1864 recent bachelor STEM graduates from the Education Longitudinal Study of 2002 (ELS:2002), this study addressed the following research questions:

1. How do demographic characteristics of recent STEM graduates influence the match between their degree and their current job?

2. Controlling for demographic characteristics, how do institutional characteristics (i.e., selectivity and control) influence recent STEM graduates' current degree-job match?
3. While controlling for both demographic and institutional characteristics:
    - How do a graduate's major and academic cognitive abilities relate to the match between degree and current job?
    - Does participating in hands-on learning opportunities (e.g., internship and onsite training) during college years increase the odds of match between STEM graduates' degree and current job?
4. Controlling for demographic characteristics, institutional characteristics, and college attributes, to what extent do individuals' career self-efficacy and expectancy predict the odds of match between degree and job for recent STEM graduates?

Descriptive analysis, cross-tabulations and one-way analysis of variance (ANOVA) were performed to analyze the dataset. In the study sample (N = 1864), more than half (53%) of the STEM graduates stated that their jobs are "closely related" to their fields of study; an indication of a good match. By and large, cognitive abilities and career-related experiences during college predict the match to a great extent. On the other hand, institutional characteristics and career self-efficacy were far less important in explaining the degree-job match. The study also used hierarchical multinomial logistic regression as the appropriate statistical analytic method to examine relationships between predictors and the outcome variable (measured by degree-job match).

In answering the first research question, among the demographic characteristics race and socioeconomic status were found to influence the match between degree and job. Asian graduates are less likely to be adequately matched with their jobs as compared to their White counterparts. In fact, White STEM graduates' odds of being appropriately matched with their jobs are nearly 50% higher compared to their Asian peers. Other racial minority groups were not found to have statistically significant results indicating no significant difference in the odds to be matched with jobs between African Americans, Latinos, other minorities (except Asians) and Whites. Furthermore, graduates who come from a low socioeconomic household (as measured by parental education and household income) appear to be mismatched with their jobs at a significantly higher rate compared to their high socioeconomic counterparts. Mismatched workers earn less, as documented in this study, which could translate over time into greater lifetime earning differentials. To break the poverty cycle and climb the social ladder, low-income graduates must make nearly as much as their high-income peers. As evidenced in this study, mismatched workers suffer from a significant wage penalty of about 33% compared to adequately matched workers which further challenges the efforts to ensure equal pay among graduates with different socioeconomic levels and/or race. Neither gender nor graduates' major (in the form of hard or soft STEM) were found to be significant in influencing the degree-job match.

The second research question looked at the impact of institutional characteristics on STEM graduates' degree-job match. Institutional control (public or private) was not found to be a significant predictor of the degree-job match. Although institutional control in this study had a low p-value ($p < .01$), this research used a stringent p-value ($p < .001$) to measure institutional characteristics, and thus this variable was considered insignificant. Similarly, institutional level of selectivity was not found to be a significant predictor of the degree-career match among recent STEM graduates.

The strongest predictor that influenced the degree-job match was cognitive abilities (represented by GPA for all known STEM courses) followed by career-related experiences during college. Academic performance (GPA) during college was found to be a significant predictor of the match; a 0.25 point increase in GPA is associated with a 20% increase in the odds of being matched. This study indicates that the higher the cognitive abilities, the greater odds that graduates be matched with their jobs; controlling for all other factors. Such finding can easily be reconciled with other studies (e.g., De Grip et al., 2008) where mismatched workers, over time, experience decline in their cognitive abilities. This suggests that high cognitive ability is not only associated with a match, but that remaining matched may result in less cognitive decline since matched jobs present more intellectual challenge than mismatched jobs (De Grip et al., 2008).

While the primary focus of this study was not to estimate the rates of return on educational investment, concerns about the cost of being mismatched should not go unnoticed. The lack of fit between degree and job was found to be associated with significantly diminished earnings; a wage penalty of nearly 33% compared to adequately matched workers with similar degrees. This suggests that students should seriously consider finding employment in a job related to their majors, as being mismatched can significantly reduce the returns on educational investment. With that said, students should not consider the earning effects of the mismatch without taking into account the role of prior career-related experiences they gained while in college. In this study, STEM graduates who were better prepared to enter the workforce through participation in hands-on learning experiences, internships, and field training during college were twice as likely to be matched with their jobs. Graduates may settle for mismatched jobs to compensate for their lack of skills and experience when they can avoid making such unfortunate choices by gaining career-related experiences during their college years.

Regarding the relation between career self-efficacy and the proper match between degree and job, career self-efficacy was not a significant predictor of the degree-job match. In sum, race/ethnicity, socioeconomic status, STEM cognitive abilities and career-related college experiences were found to influence significantly how adequately recent STEM graduates are matched with their jobs. On the other hand, gender, major (hard or soft STEM), institutional control and selectivity, and career self-efficacy were all found to be insignificant predictors of the degree-job match models. Such findings should be considered by higher education leaders, scholars in the field, and future STEM students as recommended in the following section.

Theoretical Contribution of the STEM Degree-Job Match Model

The degree-job match model in this study was based on the Social Cognitive Career Theory developed by Lent, Brown and Hackett's (1987). The theory focuses on the relationship between cognitive performance, learning experiences and career self-efficacy, and how the combination of these relationships affect individual’s career choice (Lent, Brown, & Hackett, 2002). The theory also notes the role the environment and personal traits play in influencing the entire process. Drawing upon the theory, the STEM degree-job match model in this study grouped variables as shown in Figure 9. This conceptual framework incorporates individuals' characteristics (race, gender, and socioeconomic level), institutional characteristics (control and selectivity), college attributes (cognitive abilities, major, and career-related experiences), career self-efficacy, and career outcome expectation. These parameters indicate influential factors of STEM degree-job match where intervention regarding policy and practice may take place.

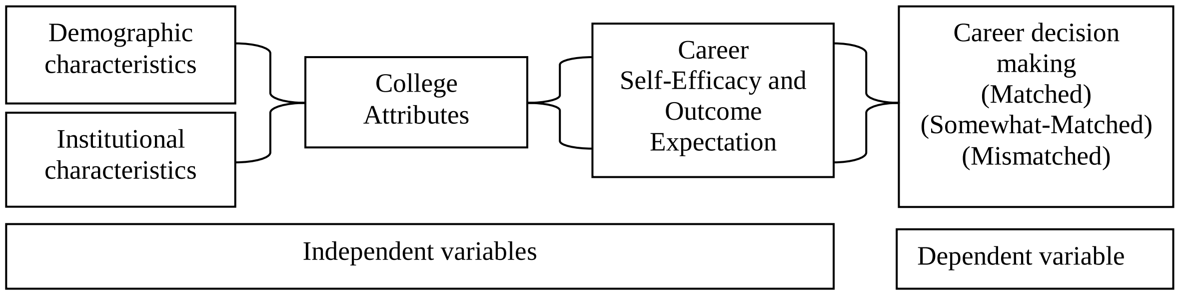


Figure 9. Research Model for Predictors of Degree-Career Match among Recent STEM Graduates

In this model, gender was not found to be a significant predictor of the degree-job match which aligns with findings from previous empirical studies (e.g., Boudarbat & Chernoff, 2010; Garcia-Espejo & Ibanez, 2006; Storen & Arnesen, 2006). However, a few studies (e.g., Robst, 2007; Witte & Kalleberg 1995; Wolbers, 2003) found that female scientists and engineers are more likely to be matched with their careers compared to their male counterparts. On the contrary, Krahn and Bowlby (1999) found that male individuals working in STEM fields have higher chances of being matched with their jobs than females. Mixed results about the role that gender plays in the degree-job match points to the possibility of gender discrimination in STEM job placement. Though findings from this research do not support the possibility of any gender discrimination, the inconclusive conclusions drawn from various related studies merit further investigation.

Past research shows that racial background is considered to be a key predictor of job placements including degree-job match (Boudarbat & Chernoff, 2010). However, this study did not find any significant difference in the degree-job match likelihood between African American and Hispanic STEM graduates as compared to their White counterparts. Interestingly, Asian STEM graduates were found less likely to be adequately matched with their jobs compared to Whites. The National Science Foundation (NSF) also noted similar racial differences; Asians were found to be overrepresented among unemployed scientists and engineers (NSF, 2013). Unemployed individuals may tend to accept jobs where they are overqualified for since other, more suitable, alternatives are not available and the job search process is costly (Sattinger, 1993). Racial discrimination coupled with unemployment should be further examined when investigating the tendency of the mismatch among Asian scientists and engineers. Other factors should be noted as well such as employment location, family constraints, and job conditions.

Among the demographic characteristics, socioeconomic status was documented by various empirical research as critical to college access, persistence, graduation, and even job placement (Carnevale & Strohl, 2010; Perna, 2000; Perna & Titus, 2005). This study found that the socioeconomic status of STEM graduates plays a significant role in the STEM degree-job match model. However, some empirical studies (e.g., Boudarbat, & Chernoff, 2010) found no relationship between socioeconomic levels and degree-job match. In this research, graduates from the low socioeconomic quartile seem to have less chance of a suitable degree-job match as compared to their high socioeconomic quartile counterparts. Lack of appropriate match, as found in this study, results in nearly 33% wage penalty which could translate into greater future earning differentials. Such a consequence has the potential to reduce the capacity for intergenerational investment, thus repeating the cycle of poverty across the generations (Carnevale & Strohl, 2010).

In addition to the demographic attributes, the STEM degree-job match model considers institutional characteristics as a possible influence to the match. Several empirical research noted the characteristics of postsecondary institutions such as sector, control, and selectivity as significant predictors in explaining variations in students' educational outcomes (Astin, 1993; Bandura, 1986; Lent et al., 2002; Tinto, 1975, 1987). However, when applied to the degree-job match model utilized in this research no significant influence either on institutions' control (public or private) or selectivity was found. This study used a stringent p-value ($p < .001$) to measure institutional characteristics considering nesting within variables, thus noting control as insignificant. Little research has attempted to incorporate institutional characteristics into the measurement of degree-job match. This area needs more consideration and attention from scholars in the field.

Researchers have noted variations in the career choice process based on graduates' field of study (Garcia-Espejo & Ibanez, 2006; Grayson 2004; Robst, 2007; Storen & Arnesen, 2006). Graduates from occupation-specific fields are more likely to be matched than fields with general skills (Garcia-Espejo & Ibanez, 2006; Grayson 2004; Heijke, Meng, & Ris, 2003; Krahn & Bowlby, 1999; Robst, 2007; Storen & Arnesen, 2006; Wolbers, 2003). Building on these findings, and using NSF classification, this study categorized STEM graduates' majors into hard-STEM majors (science and engineering), and soft-STEM majors (other STEM-related majors). However, STEM graduates' major was not found to be a significant predictor in the current degree-job match model.

Cognitive abilities, measured by GPA for all known STEM courses, is by far the most powerful predictor of degree-job match found in this research. Empirical evidence from the existing body of research seems to reach a general consensus that academic performance is a strong predictor of desirable outcomes (Boudarbat, & Chernoff, 2010). This study reaffirms that academic abilities are an important predictor of degree-job match (Garcia-Espejo & Ibanez, 2006; Grayson 2004; Storen & Arnesen, 2006).

Several theories (e.g., the Human Capital Theory, the SCCT used in this research) and scholars recognize the importance of skills gained from experiences and training to worker's performance, productivity, and job placement (Allen & De Wert, 2007; Bender & Heywood, 2009; Lynn & Salzman, 2006; Sattinger, 1993). The STEM degree-job match model in this study incorporated similar component; career-related preparedness during college years. Findings from the model corroborate previous research (e.g., Allen & De Wert, 2007; Bender & Heywood, 2009; Lynn & Salzman, 2006; Salzman, 2007) emphasizing the importance of prior experiences and skills not only necessary for better job placement but also for a better match. Qualified individuals with skills that match the workforce's needs are in high demand (Freeman, 2006). Many graduates are unfavorably accepting jobs in which they are mismatched to compensate for their lack of skills (Lynn & Salzman, 2006). The current degree-job match model suggests that such unfavorable outcome can be avoided by increasing the level of career-related preparedness during college years.

The final component of the theoretical STEM degree-job match model utilized by this research suggests career self-efficacy as a possible predictor of suitable match. Career self-efficacy refers to students' perceived confidence in their abilities to plan and execute future careers (Lent et al., 2002; Peterson, 1993). Previous empirical studies linked the ability to identify future career goals with persistence and retention (Lent et al., 2002). This study extends existing literature by linking career planning to degree-job match. The STEM degree-job match model did not find career self-efficacy as a significant predictor of proper match. However, considering the robust line of literature on college retention and persistence that suggests otherwise, future studies should include this component in the model while improving its measurements. This study was challenged by the scarcity of variables that measure self-efficacy, and thus future research is encouraged to keep self-efficacy in the model once better variables are available.

In conclusion, though the STEM degree-job match model derived from the SCCT theory proposed by this research partially worked, it is still useful in understanding predictors of the degree-job match adequacy. The model utilized did not find career self-efficacy to be significant in predicting the adequacy of degree-job match. However, it sheds light on understanding predictors of degree-job match where higher education policymakers, postsecondary institutions, and even current/future students may benefit. As for postsecondary institutions, there is an increasing tendency to evaluate and rank their performance in terms of (1) how their graduates perform in the workforce, and (2) their abilities to transfer workforce needed skills to their students (Bratti, McKnight, Naylor, & Smith, 2004; Krahn & Bowlby, 1999). The suggested degree-job match model provides insight into how and why graduates seek employment related to their education and thereby improving the match between academic degrees and job.

Implications for Policy and Practice

Early recognition and development of adequate policies may resolve and minimize the losses from the degree-job mismatch. Some policy recommendations and initiatives that can enhance appropriate match between STEM graduates' field and their jobs are discussed here.

First, being mismatched is not only costly for individuals, but it may as well be harmful to the workforce. In many studies, the mismatch between workers' qualifications and their jobs has been found to relate negatively to workforce productivity (Rycx, 2012). The improper match between employees and jobs result in lower wages leading to low levels of job satisfaction which eventually correspond to low levels of productivity (Groeneveld & Hartog, 2004; Rycx, 2012). With the broad concern by many workforce officials about the U.S. position in the global market, policymakers should consider approaches that increase the market's productivity. One approach, as suggested by previous research, is a proper match between degree and job. Accurate degree-job match results in higher levels of job satisfaction which translates to higher productivity.

Second, the job search is costly and thus graduates may accept jobs where they are overqualified rather than remaining unemployed. Similarly, employers may hire applicants that do not adequately meet job requirements as leaving the job unfilled is costly. Such situations stem from a lack of information and lack of proper communication between job seekers and the workforce. Initiating an outlet during college years that connect graduates with employers through better communication channels about workforce conditions may help minimize the issue. Additionally, applying policies that reduce unemployment can eventually lessen the mismatch as they provide graduates with some sense of job security, helping them in taking the time to navigate the workforce rather than rushing to accept jobs that they are overqualified for in fear of unemployment.

Third, an appropriate system of career guidance needs to be provided during college years. Postsecondary institutions need to increase their graduates' level of awareness of labor market needs and better prepare their students through job counseling, on-site training, and field experiences. Career-related preparation during college years contributes significantly to graduates' career mobility in the labor market. Many graduates found themselves forced to accept jobs that are lower than their skill level (mismatched) to compensate for their lack of experience. Providing graduates, during college, with experiences and competencies that are transferable across occupations increases their career mobility and ability to navigate the workforce, which in turn increases their chances of proper degree-job match.

Fourth, policymakers and postsecondary institutions should target the specific groups found to be at risk of improper match. Minorities and students with low socioeconomic levels seem to encounter difficulties securing appropriate jobs. Policymakers should ensure an adequate match to all graduates regardless of their race/ethnicity or socioeconomic level. Postsecondary institutions need to create a system that provides support, apprenticeship, and labor programs that targeted such particular groups to increase their chances of an adequate match and better career mobility that can translate to long-term social mobility and intergenerational investment.

Fifth, the STEM field is more sensitive to technological and globalization changes than any other field. Rapid technological changes, offshoring and outsourcing trends and the spread of computerization (elasticity of substitution) alter the degree-job match. The STEM market is evolving at a rapid pace bringing new development, new firms, new customer preference and needs, and new products. The requirements for jobs in the STEM workforce can quickly differ from qualifications students have obtained during their college in preparation for employment. The inability to anticipate changes in the STEM market can substantially contribute to the degree-job mismatch. This issue can be addressed by policies that ensure collaboration between the workforce and universities through networks of trade and technical institute that provide STEM graduates with the anticipated skills needed. Such policies should focus on the future needs of labor, description of such work, and the preparation necessary to match.

Finally, like other empirical research this study notes the crucial importance of math and science preparation in the graduate's persistence and retention in the STEM field. The degree-job match model used in this study concluded that the strongest predictor of the proper match came from cognitive performance in college. Math and science preparation is by large the strongest predictor of a healthy supply of scientists and engineers documented by an extensive line of research (Gonzales, Guzmán, Partelow, Pahlke, Jocelyn, Kastberg, & Williams, 2004; Lowell & Salzman, 2007). However, science instructional time in K-6 is at the lowest number of hours per week (2.3) as a national average since 1988 (Blank, 2012). Science performance is not included in the school accountability annual progress report even with the global emphasis on science proficiency. Policymakers might need to review their school accountability policies and consider a more comprehensive measurement system that covers all vital subjects. Students' math and science performance in K-12 improved over the years (College Board, 2013; Gonzales et al., 2004; Lowell & Salzman, 2007; NCES, 2012). However, internationally their performance does not compare favorably (OECD, 2010). Further, many empirical studies concluded that instructional innovations for STEM college preparation are greatly needed (NSF, 2010). A repeated recommendation is learning through an active and collaborative learning environment inside and outside the classroom. It is recommended that U.S. education officials consider policy implementations that ensure global competitiveness by maintaining a constant focus on improving STEM instructional innovations, and students' math and science performance.

Recommendations for Future Research

The primary intention of this research was to identify predictors of the degree-job match among recent bachelor STEM graduates. Cognitive abilities and work-related experiences gained during college are the strongest predictors of the degree-job match. Asian graduates and graduates from the low socioeconomic quartile have fewer odds to have a suitable match with their jobs. The following is a list of recommendations for future research to consider:

- Though additional quantitative studies should be conducted to help in highlighting attributes to the current degree-job mismatch, it is highly recommended that scholars conduct qualitative research as to why some graduates may voluntarily decide to be mismatched. For example, a qualitative study carried out on unemployed scientists and engineers found that 45% of female Asian scientists and engineers were voluntarily not working due to family responsibilities; highlighting the cultural influence that may affect unemployment. Qualitative studies may help better understand how psychological or cultural attributes influence the current degree-job mismatch. Family and peer influence, along with the surrounding environment are all possible factors influencing the decision to pursue a STEM career.

- The present mismatch between workers and jobs can be influenced by attributes from both the supply and the demand sides. However, little research is available about the workforce recruitment practices. There is a scarcity of information about what firms are looking for in employees during the hiring process. The basis for employers' decisions on hiring a particular worker are largely unknown. Simply matching a job description may not be enough for a candidate to secure a job; it is what employers seek beyond the formal qualifications. Thus, future research should look at the demand side and possibly survey employers to identify what may attribute to the worker-job match beyond formal job descriptions.
- The lack of adequate measurements of self-efficacy and other soft skills in the current national datasets posed a challenge for this type of research. It is recommended that future research include variables that further allow for soft skills assessment. Though this study included a career self-efficacy scale that was built on the SCCT, the scale did not accurately capture the construct of self-efficacy. Thus, this variable may need to be refined in future studies where better measurements of soft skills may substantially advance the area of degree-job mismatch.
- Previous research has identified particular groups for which the degree-job mismatch occur in a significant number. When particular groups suffer greatly than others this will

result on the long run in greater job instability and income inequality. Such groups need to receive greater attention from empirical research, economists, and policy analysis. This study, for example, noted the differences in the degree-job match probability based on a graduate's race and socioeconomic level. Asian STEM graduates in this research seem to be more mismatched than somewhat-matched compared to their White counterparts. It may be that factors such as culture and surrounding environments could be attributed to these significant differences. For example, level of acculturation and family involvement were found to influence Asian students' occupational interests and career placement (Fouad & Smith, 1999). Occupational segregation was as well documented among Asian workers causing low self-confidence and a sense of powerlessness (Fouad & Smith, 1999). Further, graduates from the low socioeconomic quartile are more inadequately matched compared to those with high socioeconomic quartile. Other studies noted similar differences based on gender and field of study (e.g., Robst, 2007; Storen & Arnesen, 2006; Wolbers, 2003). Taken together, particular groups can be more likely to be at risk of being somewhat-matched or mismatched with their jobs rather than being matched. Additional research is warranted to better explain the likelihood of mismatch by race/ethnicity and socioeconomic status.

- More research in the transition from school to work is needed in the STEM field. For example, research can focus on the area of how universities may influence the transition process; how collegiate experiences, for instance, provided by universities influence the decision to pursue a STEM career. Research can focus as well on how graduates' both academic and non-academic qualifications influence the transition from school to work.

- This study examined the degree-job mismatch among STEM bachelor degree recipients. This study can be extended by investigating whether the attributes used in this research can influence other STEM degree recipients including higher degree levels such as master and doctoral. The mismatch between degree and job was documented among STEM higher degree recipients; it was found among scientists and engineers with a Ph.D. degree (Bender & Heywood, 2009). However, the focus was on the consequence of the mismatch, not the attributes. Due to the use of secondary data, the present study could not include differences by degree level as a possible attribute to the degree-job mismatch. Further, this study did not look at students who switched from STEM and non-STEM majors in college. Such students may have different degree-job match patterns that are worth investigating.
- It would be worth investigating whether the probability of a mismatch may influence how students determine whether to avoid certain majors. Studies of college major choice may incorporate this new concept into their research. This study contributes to the body of literature by using the degree-job match as a possible factor influencing the college major choice process. Students base their college major choice decision on many factors including expected earnings and uncertainty (Altonji, 1993; Berger, 1988). When the economic cost to degree-job mismatch results is lower wages, and when degree-job match is uncertain when selecting a college major, how will such factors affect the college major choice process? This research suggests that students should consider the potential match of future employment to the academic major under consideration. Becoming mismatched significantly reduces the educational return on investment, and

thus students should be aware of such outcome before choosing their occupation-specific major.

- An important aspect seems to be overlooked by current literature which may significantly influence the degree-job match. Unemployment behavior can be an important factor in affecting STEM graduates current degree-job match. It is unknown whether the length of unemployment affects the degree-job match or whether the number of times a graduate was unemployed may relate to the decision of accepting a mismatched job. These areas may shed light on the current problem of the mismatch and may help in solving it.
- STEM majors in this research were grouped into hard and soft STEM majors based on NSF classification. Future research is recommended to use a more detailed list of the fields designated as STEM. For example, it may be worth investigating how the adequacy of degree-job match differs by STEM majors such as Engineering, Mathematics, Clinical Science, Psychology and other STEM and STEM-related majors.
- Finally, this research focused on predictors of the degree-job match among the STEM field only. Future research can expand the current study by looking at other fields and majors to explore the degree-job match and mismatch phenomenon.

Conclusion

In an age of accountability, and to meet the high requirements and expectations of the 21st century, postsecondary institutions and policymakers need to be aware of the rapidly changing STEM workforce. Such changes fueled by forces of globalization and internationalization of the STEM market spur new skills, qualifications, and economic challenges that require new ways of preparation and new sets of qualifications. Requirements for jobs in the STEM market can vastly shift from the skills students acquire during their college years. Anticipating the needs of a market that is so vulnerable to global forces and changes will aid future scientists and engineers to transition smoothly to the workforce.

To compete for the world's technological and innovation leading positions, STEM graduates need to be supported and prepared throughout all STEM pathways. Keeping a healthy STEM supply that is responsive to the STEM market's needs will ensure prosperity in all phases and transition paths of the STEM pipeline. Providing a proper match, between workers' field of knowledge and their jobs, results in benefits that go beyond workers and their workplace to reach the entire economy. Concerns should not be focused on the quantity of STEM graduates, but rather on the quality of their preparedness. The U.S. has invested and continues to invest tremendous fiscal support in its STEM education. However, when graduates fail to match their academic degree with their jobs, then the investment needs to be redirected.

This study contributes to the literature on the degree-job match area by accounting for several predictors that have been understudied. The degree-job match model proposed in this study includes a variety of predictors that were proven by many empirical studies to influence persistence, retention/attrition, and job placement. The degree-job match model can be used as a stepping stone to understanding better the current STEM degree-job match problem and can be expanded to include other majors and workforces.

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Appendix A

NSF STEM Classification of Instructional Programs Crosswalk

Listed below is the NSF CIP Code Crosswalk for STEM disciplines.

Agricultural Sciences	
01.09	Animal Sciences
01.10	Food Science and Technology
01.12	Soil Sciences
01.99	Agriculture, Agriculture Operations and Related Sciences, Other
03.0101	Natural Resources/Conservation, General
03.02	Natural Resources Management and Policy
03.03	Fishing and Fisheries Sciences and Management
03.05	Forestry
03.06	Wildlife and Wildlands Science and Management
03.99	Natural Resources and Conservation, Other
Chemistry	
40.05	Chemistry
40.0507	Polymer Chemistry
40.0509	Environmental Chemistry.
40.051	Forensic Chemistry.
40.0511	Theoretical Chemistry.
40.1002	Materials Chemistry.
40.1099	Materials Sciences, Other.
Computer Science	
11.01	Computer and Information Sciences, General
11.0104	Informatics (STEM Only)
11.04	Information Science/Studies
11.07	Computer Science
52.1201	Management Information Systems, General
52.1301	Management Science
Environmental Science	
03.0103	Environmental Studies
03.0104	Environmental Science
Geosciences	
40.06	Geological and Earth Sciences/Geosciences
40.0601	Geology/Earth Science, General
Mathematics	
27.01	Mathematics
27.03	Applied Mathematics
27.0304	Computational and Applied Mathematics.
27.0306	Mathematical Biology.
27.0503	Mathematics and Statistics.
14.3701	Operations Research
27.99	Mathematics and Statistics, Other
30.08	Mathematics and Computer Science
27.05	Statistics
52.1304	Actuarial Science
Physics/Astronomy	
40.02	Astronomy and Astrophysics
26.0507	Immunology
26.0504	Virology
26.0503	Medical Microbiology and Bacteriology
26.1501	Neuroscience
19.05	Foods, Nutrition, and Related Services
30.1901	Nutritional Sciences
26.0910	Pathology/Experimental Pathology
26.1001	Pharmacology
26.1004	Toxicology
26.1104	Computational Biology.
26.131	Ecology and Evolutionary Biology.
26.0707	Animal Physiology. (NEW)
26.0901	Physiology, General. (NEW)
26.09	Physiology, Pathology and Related Sciences
26.07	Zoology/Animal Biology
26.1201	Biotechnology
26.1302	Marine Biology and Biological Oceanography
26.99	Biological and Biomedical Sciences, Other
30.01	Biological and Physical Sciences
30.10	Biopsychology
30.27	Human Biology.
30.3	Computational Science.
30.32	Marine Sciences.
Engineering	
14.02	Aerospace, Aeronautical and Astronautical Engineering
14.03	Agricultural Engineering
14.05	Biomedical/Medical Engineering
03.0509	Wood Science and Wood Products/Pulp and Paper Technology
14.07	Chemical Engineering
14.0702	Chemical and Biomolecular Engineering.
14.0799	Chemical Engineering, Other.
14.1003	Laser and Optical Engineering.
14.1004	Telecommunications Engineering.
14.1099	Electrical, Electronics and Communications Engineering, Other.
14.32	Polymer/Plastics Engineering
14.4	Paper Science and Engineering.
14.41	Electromechanical Engineering.
14.42	Mechatronics, Robotics, and Automation Engineering.
14.43	Biochemical Engineering.
14.44	Engineering Chemistry.
14.45	Biological/Biosystems Engineering.
15.0306	Integrated Circuit Design.
15.1502	Engineering Design.

40.0809	Acoustics	15.16	Nanotechnology.
40.08	Physics	04.02	Architecture
40.0607	Oceanography, Chemical and Physical	14.04	Architectural Engineering
40.0807	Optics/Optical Sciences	14.08	Civil Engineering
40.9999	Physical Sciences, Other	14.0803	Structural Engineering
		14.0805	Water Resources Engineering
Life/Biological Sciences		14.14	Environmental/Environmental Health Engineering
26.0403	Anatomy	14.09	Computer Engineering, General
26.0202	Biochemistry	14.10	Electrical, Electronics and Communi-cations Engineering
26.01	Biology, General	14.12	Engineering Physics
26.1101	Biometry/ Biometrics	14.13	Engineering Science
26.1102	Biostatistics	14.27	Systems Engineering
26.1309	Epidemiology	30.06	Systems Science and Theory
26.0203	Biophysics	14.11	Engineering Mechanics
26.03	Botany/Plant Biology	14.19	Mechanical Engineering
26.0305	Plant Pathology/Phytopathology	14.06	Ceramic Sciences and Engineering
26.0307	Plant Physiology	40.18	Materials Engineering
26.04	Cell/Cellular Biology and Anatomical Sciences	14.20	Metallurgical Engineering
26.0401	Cell/Cellular Biology and Histology	14.28	Textile Sciences and Engineering
26.0204	Molecular Biology	40.10	Materials Science
26.1301	Ecology	14.21	Mining and Mineral Engineering
26.0505	Parasitology	14.23	Nuclear Engineering
26.0702	Entomology	14.25	Petroleum Engineering
26.0801	Genetics, General. (NEW)	14.01	Engineering, General
26.0804	Animal Genetics. (NEW)	14.22	Naval Architecture and Marine Engineering
26.0805	Plant Genetics. (NEW)	14.24	Ocean Engineering
26.1303	Evolutionary Biology	14.99	Engineering, Other
26.0806	Human/Medical Genetics		
26.0508	Microbiology and Immunology.		
26.0807	Genome Sciences/Genomics.		
26.05	Microbiological Sciences and Immunology		

Appendix B

Variables used in the Degree-Job Match Model

Variable Name	Description	ELS Variable Label
Gender	Male = 1 Female = 2	F2SEX
Race	1= American Indian/Alaskan Native, non-Hispanic 2= Asian, non-Hispanic 3= Black or African-American, non-Hispanic 4= Hispanic, no race specified 5= Hispanic race specified 6= more than one race, non-Hispanic 7= Native Hawaii/Pac. Islander, non-Hispanic 8= White, non-Hispanic	F1RACE
Socioeconomic level	Composite variable of mother's education, father's education, family income, mother's occupation, and father's occupation.	F1SES2QU
STEM Cognitive abilities	Grade Point Average for all known STEM courses (using NSF definition of science, engineering, and related fields)	F3TZSTEM2GPA
Postsecondary institution sector	1= Four-year 2= Two-year	F3ILEVEL
Postsecondary institution control	1= Public 2= Private not-for-profit 3= Private for-profit	F3ICNTRL
Postsecondary institution selectivity. Selective here is based on the 2005 Carnegie Classification System which is based on the distribution of entrance examination scores. **Highly** selective institutions are where students' test scores place them in roughly the top fifth. **Moderate** selectivity is where students' test scores place the institutions in the middle two-fifths. **Inclusive** selectivity institutions are those who extend educational opportunity to a wide range of students with respect to academic preparation and achievement.	Selectivity of attended postsecondary institution: 1= Highly selective, 4-yr institution 2= Moderately selective, 4-yr inst 3= Inclusive, 4-yr institution 4= Selectivity not classified, 4yr inst 5= Selectivity not classified, 2yr inst 6= Selectivity not classified, less than 2yr	F3ISELC

Institutions who did not report test score data are not classified.		
On-site training during college	Participation in internship/co-op/field experience/student teaching/clinical assignment during college? 0= No; 1= Yes	F3A14A
Degree level	Credential type: 1= Undergraduate certificate or diploma 2= Associate's Degree 3= Bachelor's Degree 4= Post-baccalaureate certificate 5= Master's Degree 6= Post-Master's certificate 7= Doctoral Degree - research/scholarship 8= Doctoral Degree - professional practice 9= Doctoral Degree - other	F3ICREDTYPE_1
Degree field	Ever earned a postsecondary credential in a STEM field (NSF definition)	F3TZSTEM2CRED
Hard or Soft STEM	Ever earned a postsecondary credential in a science & engineering field	F3TZSCENCRED
Employment status	Working for pay at a full time job 0= No; 1= Yes	F3A01A
Career self-efficacy and outcome expectation	whether the prestige score associated with the respondent's expected age-30 occupation as reported in the third follow-up is higher than, equal to, or less than the prestige score associated with the respondent's expected age-30 occupation as reported in the first follow-up: 1=F3 occupation expectation has higher prestige score than F1 occupation expectation. 2=F3 occupation expectation has same prestige score as F1 occupation expectation. 3=F3 occupation expectation has lower prestige score than F1 occupation expectation.	F3OCC30F1VF3
Relation between field of study and current job	1= closely related; 2= somehow related 3= not related	F3B31
Employment income	2011 employment income: R only	F3ERN2011
Weight	Third follow-up questionnaire respondent weight. A weight for sample members who completed a questionnaire in the third follow-up.	F3QWT

Appendix C

Recoding of variables used in the Degree-Job Match Model

Variable Name	Description	ELS Variable Label
Major is in a STEM field	Variable will be used to separate STEM majors from other majors. Only STEM majors will be kept in the sample, and then divided into hard STEM and soft STEM	Recoded from F3TZSTEM2CRED STEM fields are based on NSF classification as stated in Appendix A.
Major is Hard of Soft STEM	Major is in S&E (Hard) = 1, Other (Soft) = 0	Recoded from F3TZSCENCRED
Income from employment	In U.S. Dollars	Continues F3ERN2011
Gender	Participant's gender, female =1, male = 0	Recoded from F2SEX
Race/ethnicity Hispanic White Asian African American Other races	 Hispanic =1, all other races= 0 White= 1, all other races= 0 Asian= 1, all other races= 0 African American= 1, all other races= 0 American Indian, Alaskan native, Native Hawaii/Pac. Islander more than one race= 1, all other races = 0	Recoded from F1RACE
Socioeconomic status	1= High SES, 0= Other SES 1= Mid SES, 0= Other SES 1= Low SES, 0= Other SES	Recoded from F1SES2QU
STEM Cognitive abilities	GPA for all known STEM courses (using NSF definition)	F3TZSTEM2GPA Continuous
Participation in internship, on-site training during college	0= No; 1= Yes	F3A14A
Postsecondary institution sector	1= Four-year, 0= Two-year	Recoded from F3ILEVEL
Postsecondary institution control	1= Public, 0= Private	Recoded from F3ICNTRL
Postsecondary institution selectivity	Highly selective=1, all other=0 Moderately selective=1, all other= 0	Recoded from F3ISELC

	Inclusive=1, all other= 0 Selectivity not classified=1, all other= 0	
Employment status	Working for pay at a full time job 0= No; 1= Yes Will be used to include only employed graduates	F3A01A
Degree level	Bachelor's Degree=1, all other=0 Will be used to include only Bachelor's degree graduates	Recoded from F3ICREDTYPE_1
Career self-efficacy and outcome expectation	F3 occupation expectation score	F3OCC30F1VF3 Continuous

Appendix D

Literature Review Map