LABOR MARKET OUTCOMES OF RECENT U.S. COLLEGE GRADUATES IN THE STEM DISCIPLINES: IMPACTS OF COLLEGE LOCATION

by

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ABSTRACT

TETIANA LYSENKO. Labor market outcomes of recent U.S. college graduates in the STEM disciplines: Impacts of college location. (Under the direction of DR. QINGFANG WANG)

This research explores the relationship between place and the career experiences of STEM-educated recent college graduates in the U.S. over the 2000-2010 decade. Specifically, it seeks to understand how these graduates' early career outcomes (earnings, odds of unemployment and underemployment) are contingent on the location where they received their degrees, in addition to individual and institutional level characteristics. The findings show that individual factors are the most important factors determining all three outcomes. Women and Blacks are considerably more disadvantaged (compared to male and White counterparts). Higher grades, more experience and spatial mobility are overwhelmingly positively related to higher earnings and lower probability of unemployment and underemployment. Health and engineering are the most lucrative majors in terms all three outcomes. Graduates' outcomes worsened during recent recession, but varied significantly across the geographic areas. Higher education institutional factors, selectivity and college specialization in STEM, are strong predictors of higher earnings, but not other outcomes. Geographic factors, mainly college area's STEM employment concentration and proximity to STEM clusters, are significant in explaining all three outcomes. This study contributes to the scholarship on higher education, labor market, and gender and racial disparity studies from a geographic and comparative perspective. It particularly provides policy implications on higher education policy with regards to STEM disciplines and policies related to racial and gender

disparities in the labor markets. It further calls for investigation of the relationship between higher education institution and regional development, and the integration of the efforts between the two.

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CHAPTER I: INTRODUCTION

STEM (science, technology, engineering, mathematics, and physical sciences) education and research have been promoted since the end of WWII (Rothwell, 2013). However, only recently STEM fields were widely recognized as a crucial driver for modern economies and supported by political leaders, e.g., George W. Bush and Barack Obama (Carnevale, Rose, & Cheah, 2011). The Obama administration committed to produce an additional one million STEM undergraduate students by 2020 (O'Brien, 2014). North Carolina Governor Patrick McCrory and Florida Governor Rick Scott even questioned the value of liberal arts and social science degrees and called for more colleges to offer majors in transportation, agriculture, technology, sciences and finance in their respective states (Anderson, 2011; Arcieri, 2014).

Such heightened interests in STEM aroused from numerous studies that argue that technological innovation is a modern driver of economic progress, which requires an abundance of specialized talent and expertise. Over the several past decades, the decline of manufacturing has been accompanied by the rise of modern technology - biomedical engineering, space exploration, information technology and clean energy sectors. At the same time, while manufacturing relies heavily on the low- and middle-skilled labor, technology firms are largely dependent on college and advanced degree holders (Berman, Bound, & Griliches, 1994; Smith, Collins, & Clark, 2005). Langdon, McKittrick, Beede, Khan, & Doms (2011) predict that most of the fastest growing occupation sectors, which require knowledge and skills in STEM, are expected to grow 1.7 times faster than non-STEM employment in the coming decade. Among these fastest growing sectors are computer, mathematical science, and life sciences; and the largest industries that employ STEM workers are professional and business, manufacturing, information, government, and public education services. It is estimated that 65 percent of new jobs will require either Bachelor or Graduate degrees (Carnevale et al., 2011). Indeed, employers, such as Lockheed Martin, IBM Corporation, Facebook, Boing, and many others, emphasize on the increasing need for new STEM talent and fund various programs that target popularization and advancement of science and technology disciplines (Golod, 2014).

In addition to fulfilling the demand for highly skilled labor, STEM education was also viewed as essential for innovation and scientific advancement. For instance, individuals trained in STEM are most likely to hold a patent (Wai, Lubinski, Benbow, & Steiger, 2010) and produce ideas materialized in innovative entrepreneurial ventures (Moretti, 2012). Innovation is widely recognized as the engine of modern economies, increasing economic competitiveness through growth in productivity and high value-added products and services. Further, the growth generated by innovation creates more jobs and increase wage rates (Cantwell, 2006; Rothwell, 2013). For these reasons, many countries have undertaken major steps in support of STEM education and skill development. For example, in addition to the advanced economies mentioned earlier, both Western and East Asian governments have invested substantially to increase STEM enrollments in higher education and engagement in innovation industrial sectors, in order to improve the technological competence of their economies (Cantwell, 2006).

Remarkably, economic competitive advantage is strongly tied to local and regional clusters of innovation industry and human capital (Moretti, 2012). Economic geographers have long demonstrated that high technology industries are disproportionately concentrated in certain areas due to advantages that companies gain from agglomeration effects, such as knowledge spillovers, venture capital and specialized workforce availability (Acs, Braunerhjelm, Audretsch, & Carlsson, 2008; Audretsch, 1998). The software cluster in Silicon Valley and the biomedical cluster in Boston are well-cited examples of innovative technology agglomerations (Bathelt, 2010). The fight for innovation sectors also happen on sub-national levels, as state governments try to attract industries that facilitate sustained economic growth. In addition to programs in fostering local innovation businesses and subsidizing relocation of existing technology companies (Oh & Masser, 1995), they have also provided STEM research and educational incentives, in forms of grants and scholarships, to universities, research centers, and students to develop innovative infrastructure and human resources locally (Moretti, 2012).

Despite accumulated research on labor market outcomes of college graduates with a focus on individual and institutional characteristics (Abel, Deitz, & Su, 2014; Richards, 1984; Rumberger & Thomas, 1993; Vedder, Denhart, & Robe, 2013), limited research focused on the labor market experiences of STEM graduates. Even less has examined how STEM graduates' labor market outcomes vary across place. Due to the increasing interests in STEM industry and education and their potential contributions to national and regional economies, as discussed earlier, it is urgent to understand the spatial dimension of STEM education and its labor market outcomes. Therefore, the objective of this dissertation project is to explore the relationship between place and the career experiences of STEM-educated college graduates in the U.S. over the past decade, 2000-2010. Specifically, it seeks to understand how STEM-educated college graduates' early career outcomes are contingent on their location where they received their degrees, after controlling for personal level and university level characteristics. The following sets of questions will be addressed:

1) How do STEM graduates perform in labor markets over time and space?
    a. How do their early career experiences vary by race, ethnicity and gender?
    b. How do their early career experiences vary by STEM sub-discipline?
2) How are the STEM graduates' labor market outcomes shaped by individual, institutional, and geographic location characteristics?
    a. What are the factors associated with their early career labor market outcomes?
    b. How do the relationships differ by gender, ethnicity, and STEM sub-disciplines?

Labor market performance and outcomes in this study are measured as job earnings, employment opportunities (employed vs. unemployed) and underemployment (employed full-time vs. involuntary part-time). Underemployment refers to working part time due to full time job unavailability. The first question addresses heterogeneity in job earnings, unemployment rate, probability of underemployment across US metropolitan areas in four distinct STEM graduates cohorts from 2000 to 2010, by gender, race/ethnicity, and sub-disciplines. The second question examines the relationship between the labor market outcomes measured in the above three dimensions across different levels, i.e., individual, institutional, and regional (metropolitan area and (non-)metropolitan area).

Based on the existing literature, it is expected that the early career experiences of STEM college graduates will differ significantly across place. Race, gender, nativity and other socio-economic status are important factors that are associated with their labor market outcomes, in addition to human capital. Further, while everyone holds a college degree in similar disciplines in this study, i.e., STEM, higher education institutional characteristics, such as college prestige, selectivity, and private vs. public institutional control, are expected to play a critical role in labor market experiences and outcomes of college graduates (Black & Smith, 2004; Brand & Halaby, 2006; Brewer, Eide, & Ehrenberg, 1999; Monks, 2000; Pascarella & Terenzini, 2005).

I am particularly interested in testing the relationship between college attributes, college location, and the early career outcomes of recent STEM college graduates. I hypothesize that STEM degree holders vary in early labor market outcomes depending on the local labor market conditions of the location where they attended their college. For instance, graduates from colleges located in high-tech economic activity areas may benefit from proximity to jobs, contingent on their individual or academic background; in contrast, those who attend schools in less economically viable areas, may have more limited labor market information and fewer opportunities to access employment.

Using the National Survey of Recent College Graduates database provided by the National Science Foundation, in combination with data from US Census and Bureau of Labor Statistics, this study is designed to fill the gaps in the scholarship on the geographic understanding of college location and its effects on STEM graduates' career. Examining several distinctive dimensions of labor market outcomes across STEM sub-disciplines, this study provides significant insights on what makes difference in post-graduation success of STEM graduates. It also confirms that individual characteristics are the most important factors determining all three outcomes. Women and Blacks are considerably more disadvantaged (than male and White counterparts), while higher grades, more experience and spatial mobility are overwhelmingly positively related to higher earnings and lower probability of unemployment and underemployment. Per institutional factors, selectivity and college specialization in STEM are strong predictors of higher earnings, but not other outcomes. Geographic controls explain more than 25 percent in between college variance. Contingent on all other factors, including controls for cost of living at current place of residence, both college area STEM employment concentration and proximity to STEM clusters significantly increases graduates' earnings, while unemployment rate and share of manufacturing has an opposite effect.

The rest of this dissertation is structured as following: Chapter II provides a review of the current knowledge relevant to this study. Chapter III describes data and methods used in this research. Chapters IV to VI describe the findings from descriptive analysis of individual, institutional and geographical factors. Then, the regression analyses base on the total STEM sample are presented in Chapter VII, and the regression results by sub-disciplines in Chapter VIII. Finally, Chapter IX summarizes the findings, implications, limitation, and future research agenda.

CHAPTER II: LITERATURE REVIEW

1. Human capital, social capital, cultural capital, and occupational attainment

The neoclassic economic perspective argues that labor market outcomes are a function of human capital, which consists of ability, education, training, and skills of an individual (Becker, 1964, 1985; Mincer & Polachek, 1974). According to this perspective, individuals, through investments in education and training, accumulate human capital in form of skills and knowledge that are usually associated with better job attainment and career success. Thus, holding other conditions constant, a higher level of human capital should result in increased level of personal gains. Accordingly, providing equal access to investment in human capital would achieve greater income equality and equity in other labor market outcomes among different racial, ethnic, social and gender groups (Schultz, 1997).

Paglin and Rufolo (1990) extend this theory to account for variability of demand for certain skills and knowledge which referred as heterogeneous human capital theory. They argue that human capital changes with the choices that a person makes during life, resulting in heterogeneous set of skills, knowledge, and experience that influence options that are available for further investment. Therefore, individual's innate ability dictates her choice of college major, which in turn is an important determinant of occupational choices. They state that math ability is one of the scarce abilities that differentiate college major wages. Those majors that require high-levels of math ability tend to lead to high-paying jobs. In other words, graduates who work in areas requiring a greater degree of mathematical ability achieve a higher rate of return to their investment in human capital than students who generate a type of human capital that makes less use of mathematical ability.

Similar to human capital, social and cultural capital also are resources to enhance individual productivity (Putnam, 1995) and profitability (Bourdieu & Passeron, 1977), foster social network for job placement (Putnam, 1995), increase productivity (Coleman, 1988), and facilitate socioeconomic upward mobility (DiMaggio & Mohr, 1984; Lamont & Lareau, 1988). Social capital takes the form of instrumental, productive relationships or information-sharing networks (Coleman, 1988; Stanton-Salazar, 1997). Granovetter (1973) and Burt (1997) claimed that individuals, who are able to connect and communicate with potential employers and have the opportunity to speak directly with decision makers, have better career prospects. Indeed, extensive evidence suggests that personal contacts provides an indisputable advantage in securing employment. For example, through interpersonal networks, individuals gain exposure to a wider set of opportunities when they maintain contacts with others (Mau & Kopischke, 2001).

Cultural capital, on the other hand, is the system of linguistic and cultural competencies that includes beliefs, tastes, and preferences obtained from family, peers and other authorities. These attributes ultimately define an individual's class status (Bourdieu & Passeron, 1977; McDonough, 1997; Stanton-Salazar, 1997). One way cultural capital may influence one's economic and labor market outcomes is through the provision of knowledge and information about college, jobs, and career options (Bourdieu & Passeron, 1977; McDonough, 1997). Cultural capital may also refer to one's values and preferences for education, such as values about obtaining a college degree (DiMaggio & Mohr, 1984; McDonough, 1997).

While all these concepts may be true in perfect labor markets, many other theories challenge this view. These perspectives indicate other forces that cannot be completely eliminated by market processes outlined by human capital theory. For instance, persisting income gaps between different demographic groups, even when education is accounted for, cannot be explained by productivity differentials. Thus, job competition theorists argue that labor productivity is determined by job attributes and not necessarily by worker characteristics (Thurow, 1975). In other words, higher education credentials serve as a signal to employers, helping them to sort out individuals with the highest potential productivity. In a sense, a degree works as proxy for immeasurable attributes, such as ability, adaptiveness or motivation, for which an employer was willing to pay more (Sobel, 1982; Spence, 1973).

Sorting of individuals into internal (primary) and external (secondary) markets is often not based on differences in human capital attainment, but rather on employer characteristics and preferences (Doeringer & Piore, 1971). In Thurow's (1975) view, potential workers are assigned to queues based on social and institutional factors, while employers determine whom to hire based on perceived ability of an individual. Therefore, workers are paid in accordance to the job they hold, while the jobs are assigned to wages defined by normative regulations. These approaches are drastically different from human capital theory as they consider that individual characteristics, such as level of education, have no effect on career beyond entry level job assignment (Rosenbaum, 1984).

Gender, race, ethnicity, nativity, immigration status as well as intersections of such factors often determine the likelihood of finding adequate employment, occupational status, salary and benefits, as well as job satisfaction (Borjas, 1987; Browne & Misra, 2003; Raijman & Semyonov, 1997; Reich, Gordon, & Edwards, 1973). For instance, gaps in earnings between males and females, and between whites and minorities on average have decreased during the past 50 years (Farley, 1984; Goldin & Katz, 2007), however, the gaps are considerably wider in certain professional occupations and industries (Grodsky & Pager, 2001; Petersen & Morgan, 1995). According to Corbett and Hill (2012), one year after graduation from college, women who work in the same occupation, hours, and industry earn 7% less than their male counterpart in the identical situation. Although many disadvantages in labor market among females and minorities are attributed to differences in access to human and social capital (Autor, 2011; Bobbitt-Zeher, 2007), numerous studies suggest that prejudice and discrimination on the job market play a crucial role in labor market experiences (Arrow, 1973; Cain, 1987; Carneiro & Heckman, 2003). For instance, Reskin & Roos (2009) theorize that employers have preferences for individuals with certain background which put them in the front of the so called hiring queue. Hence, the less desired candidates only get hired after the preferable prospective employees leave such queues. Another perspective suggested by Bielby and Baron (1986) and extended by Altonji & Pierret (2001) states that employers "rationally" discriminate against certain socio-demographic groups based on the stereotypes about such individuals. Due to limited information availability about prospective workers, employers assess their fit and productivity based on previous interactions with, or simply a perception of, members of given gender, race or ethnicity groups (Bertrand, Chugh, & Mullainathan, 2005).

2. The role of higher education institutions in labor market outcomes

There are more than 4000 colleges and universities in the United States that constitute a diverse network of higher education providers. They vary in type, quality, prestige, size, and numerous other indicators, such as institutional mission, reputational rating, academic expenditures per student, average SAT score of freshman class, faculty-student ratio, and level of tuition (Fitzgerald, 2000; Pascarella & Terenzini, 2005). The effects of individual characteristics (such as human capital and social capital) and field of discipline on career outcomes may vary depending on school quality, usually measured by student body selectivity.

The overwhelming evidence suggests that attending a highly prestigious college leads to increased rewards in the labor market. Graduates of elite institutions are more likely to have higher occupational status, salary and career mobility (Black & Smith, 2004; Brand & Halaby, 2006). Indeed, most research finds that attending a highly selective college is positively related to individual's earnings and job security (Fitzgerald, 2000; Loury & Garman, 1995). One explanation is that elite institutions tend to enroll students with higher occupational aspirations, which in turn results in better chances for career success (Pascarella & Terenzini, 2005). Additionally, students enhance their future earnings by surrounding themselves with high-quality fellow students. Such student quality is usually measured by average SAT score of freshman class, which was found to have a significant positive effect on graduate earnings (Solomon, 1973). Further, institutional impact may come from peer group effect as career choice of graduates is largely impacted by most common major at their college (Pascarella & Terenzini, 2005; Rosenbaum, 1984).

At the same time, researchers find that elite institutions may help students to develop better social capital. According to Cornwell and Cornwell (2008), social contacts with experts provide access to scarce knowledge and opportunities not available to general public. Similarly, elite campuses provide frequent and easier access to experts and resources that may not be available elsewhere, which impacts students' career aspirations and further employment opportunities. For example, Waters and Leung (2013) state that efficient alumni networks affect graduates' employment opportunities and social mobility. Lee and Brinton (1996) argue that graduates from South Korean prestige universities are significantly more likely to find a job in large firms due to a higher quality of social capital attained in elite institution in comparison to lower-ranked colleges. Furthermore, Waters (2005, 2006, 2007) demonstrates that middle-class families in Hong Kong send their children to Canada for the 'overseas education' which was subsequently rewarded in the labor market. (Hall, 2011) demonstrates that the MBA graduates from leading business schools in the USA and the UK actively utilize their alumni networks and educational ties in London's financial services district as effective social and cultural capital for their career advancement.

As for different types of higher education institutions, researchers compared the graduates from public and private universities. Some argue that graduates who attended private colleges have only marginal increase in earnings over people who attended public universities (Brewer et al., 1999; James, Alsalam, Conaty, & To, 1989). Fitzgerald (2000) demonstrates that male graduates who attended private research universities tend to earn less than those who study elsewhere. On the other hand, females who went to private liberal arts colleges earn ⅓ more than those who attended other types of schools. To understand the differences between public and private institution effects, Astin (1992) finds that graduates of private colleges tend to choose more lucrative careers than those of public schools. However, there is substantial variability within public universities. For instance, Hoekstra (2009) compares earnings of graduates who attended flagship state universities to those who were barely rejected the admission. The study finds that white male who attended selective public college graduates earn on average 20 percent more than those who were almost admitted there.

Other factors such as Carnegie classification shows little impact on graduates' labor market outcomes, while a larger size of college appears to have a positive effect on both occupational status and income (Pascarella & Terenzini, 2005). Both higher faculty salary (Behrman, Rosenzweig, & Taubman, 1996; Solomon, 1973) and lower student/faculty ratio (Liang Zhang, 2008) is associated with increased earnings. Expenditures per student as a separate measure of quality has a modest influence on graduates' earnings (Dale & Krueger, 2014; Solomon, 1973). Further, some of the institutional effects vary for different demographic groups. For example, women tend to benefit from going to larger schools more than men did; and further, the amount of college expenditures per student had a slight effect on male, but not female earnings (Fitzgerald, 2000).

Researchers have also looked at the effects of attending historically black college or university (HBCU) or a single-sex schools on career outcomes, especially of African Americans and women. Fitzgerald (2000) and Strayhorn (2008) find a significant negative effect of graduating from HBCU on post-graduation earnings. On the other hand, Brown and Davis (2001) discuss the importance of social capital gained by African

Americans at HBCUs which provide significant advantages in the post-graduation labor market. Furthermore, graduates of women's colleges are more likely to be overrepresented in high-status male-dominated occupations, such as medicine, research, and engineering. However, this finding is attributed to college student recruitment practices, rather than socialization that occurred on campus (Stoecker & Pascarella, 1991).

Overall, the existing literature suggests that the specific environment and conditions at the HEI institutional level could interact with individual characteristics, such as class, race, and gender, to shape college graduates' major choice, human, social and cultural capital formation, and, further, labor market experiences and outcomes. More importantly relevant to the current study, institutional effects may highly depend on disciplines. For example, James et al. (1989) and Black, Kolesnikova, and Taylor (2009) argue that college major has a greater effect on both earnings and employability when college selectivity and major are considered simultaneously. In a study of MBA graduates' earnings, Grove and Hussey (2011) suggest that graduating from elite institutions increases earnings, but, not as much as majoring in finance and information systems. In other words, lucrative majors have a more prominent positive effect on earnings than institution elite status. When focusing only on STEM graduates, research suggests that starting salaries of engineering majors are relatively uniform across institutions, while heterogeneous for other non-science majors (Fitzgerald, 2000).

3. College location, regional labor market, and college graduate occupational attainment

Although the geographic location of college is a crucial factor in college choice for prospective students, the effects of college location on graduates' post-graduation experiences have been largely overlooked (Chapman, 1981). Hanson and Pratt (1991) reflected on a role of place in knowledge production, in terms of relationships between employees and employers within metropolitan areas. They argue that economic and social dimensions of labor force act unitedly and varied depending on spatial context. For instance, access to job opportunities may be spatially constrained for many groups of workers, due to economic and social constructs, such as journey to work, place-based social networking, and strong ties to a particular area for both employers and employees. Along the same lines, others have argued that place, particularly the socioeconomic local labor market contexts, have a significant impact on individual labor market experiences and outcomes (Fernandez & Su, 2004; Hanson & Pratt, 1991; Sorenson, 2003). Although these studies are not focused on college students in particular, the theoretical framework is useful for the current study. Specifically, human capital, social capital, and other individual characteristics and the institutional level features at the university level are all embedded within their local and regional contexts. Their geographic location does not only provide a spatial container, but more importantly, they interact with individual and the higher education institution to shape college graduates' labor market outcomes.

Purcell, Elias, Ellison, and Atfield (2008) argue that when choosing college, future students are guided either by a strong preference for certain institution characteristics or the location where they want to study. The preference for certain locations is often a function of proximity to home, job availability, local amenities, and attractiveness of an area (Kinzie et al., 2004; Paulsen & St. John, 2002; Perez & McDonough, 2008; Wajeeh & Micceri, 1997). According to Mattern and Wyatt (2008), more than 50 percent of all undergraduate college students in the US attend colleges less than 100 miles from home. One line of explanation stems from economic factors, such as cost reduction through attending college in-state or/and living at or close to home (Patiniotis & Holdsworth, 2005). Others may want to maintain close social ties with friends and family[1]. Wajeeh and Micceri (1997) find that students who decide to attend an urban university put a greater emphasis on the ability to combine study and work. Indeed, Price, Matzdorf, Smith, and Agahi (2003) finds that students who attended colleges in large cities were more likely to enjoy part-time job opportunities. Further, internships and career-related work experience, especially in specialized fields, like business, engineering and computer science, significantly increased their chances of post-graduation employment (Callanan & Benzing, 2004; Knouse, Tanner, & Harris, 1999; Sagen, Dallam, & Laverty, 2000). Therefore, for the students who go to colleges in the metropolitan areas with thick, abundant job opportunities, labor markets may have a positive earning premium due to relevant work experiences they received during their studies (Suhonen, Pehkonen, & Tervo, 2010).

The structure of local labor markets are largely defined by industrial composition. According to Jacobs (1969), the local diversity of industries creates a competitive environment, which facilitates economic growth and innovative activity. Jacobs argues

[1] On the other hand, students who attend college further from home may form a more extensive network of personal contacts, as they are "forced to make new friends" at unfamiliar locations (Regan and Dillon, 2015).

that knowledge spillovers happen between different industries and diverse businesses, transferring inventions from one sector to another. Another view on economic performance of regions is argued by Glaeser, Kallal, Scheinkman, & Shleifer (1992). They state that geographic specialization of industries is crucial for knowledge diffusion. Businesses within same industry benefit from proximity to each other, which reduces costs of transportation and information exchange. Additionally, industry specialization creates more efficient labor markets. For instance, in areas with high concentration of businesses within the same industry workers can find new employment more easily. Such flows of labor between firms also contributes to information exchange. Indeed, Freedman (2008) finds that workers in software publishing clusters are more likely to switch jobs that those who work in isolated firms. Moreover, they tend to earn more and receive salary increases more often than workers outside of the industry clusters.

In an international study of higher education effects on graduates' performance in labor market, García-Aracil (2014) reports that close interaction with employers and availability of proper internships increase graduates' career success. Such close interaction between college and employers is defined as social proximity (Rosenbaum, 1984). It may be comprised of college activities in the local community, information exchange and consulting relationship they have with companies. Therefore, graduates from universities that are socially close to local employers, may benefit from employer's enhanced recruiting efforts at these colleges (Rosenbaum, 1984). The author also notes that college's geographical proximity to employers, although not a perfect substitute for social proximity, showed a significant impact on earnings and promotions of college graduates, even when controlling for selectivity. In other words, having such connections to communities outside of campus provided more rounded learning experiences to college students and their post-graduation outcomes (Dugdale, 2008).

On the employer side, proximity to universities provides firms with a better access to human capital resources. Studies suggest that for high-tech industries, proximity to universities is crucial due to their reliance on knowledge exchange through personal interaction, which may be possible only within relatively short distances (Fallah, Partridge, & Rickman, 2013). Consequently, many universities across the US, that are located in rural and suburban settings, have recently invested in development of college branches in cities or larger localities. College administrators argue that such moves were crucial, due to increased importance of securing links between industry and university (Selingo, 2014). Historically, college career services establish such links with employers and assisted students with job placement services. Recently, such services became even more important due to increasing popularity of internship programs as means to attaining full-time employment. For instance, large companies like Facebook, Enterprise Rent-a-Car and Ebay hired 70-80% of new employees through such programs, while other employers' interest in intern hires is also on a rise (Selingo, 2014). According to McGrath (2002), colleges that partner with multiple employers may even experience competition for its students and graduates, especially at times of high demand in engineering and computer science specialists.

Even though the college-educated are the most mobile socioeconomically, only 30 percent of graduates work outside their home state (Moretti, 2012). In the study of college-to-work migration, Gottlieb and Joseph (2006) find that a large number of STEM graduates prefer staying in the place where they went to college. This effect is especially strong for those who went to college in their home state. According to Schwartz (1973), there are certain psychological and informational barriers that may prevent an individual from moving, even though migration may lead to economic gains. Environmental psychologists argue that among the anchors that were preventing people from moving are social and community factors that form place attachment (T Beckley, 2003; Regan & Dillon, 2015). This limited labor mobility may benefit graduates who went to college in an area with higher economic activity, as they are more likely to reside in the same or nearby area after graduation. On the other hand, graduates who stay in cities with lower economic activity, may be willing to accept lower wages with higher risk of unemployment or underemployment (Suhonen et al., 2010). For instance, Büchel (2002) finds that over-education rates are lower in areas with plenty of jobs and higher spatial mobility. In other words, people who have a car are less likely to be overeducated, while individuals who need to travel longer to a large agglomeration of employment opportunities are more likely to be occupationally mismatched.

On the labor market demand side, increasing evidence suggests that employment growth is stronger near the regions in a close proximity to urban areas, and the remote areas are likely to be economically disadvantaged (Partridge, Rickman, Kamar, & Rose, 2008). To add to that, Glendon and Vigdor (2003) argue that areas that experience local labor demand shocks in export-sector employment tend to negatively affect neighboring local labor markets up to 600 miles in diameter. From the economist's perspective, such local market conditions will result in out-migration of workforce (Borjas, Freeman, & Katz, 1997). In other words, job seekers need to be more spatially mobile and willing to search for a job at a greater distance. However, Bound, Groen, Kézdi, & Turner (2004) find that in the states with a large number of college graduates per capita, bachelor degree holders earn only slightly more than high school graduates, which indicates that the college-educated were imperfectly mobile across states. Moreover, unemployment, underemployment and over-education rates are also uneven across places, which is commonly explained by either skill or spatial mismatch (Büchel, 2002; Moretti, 2012; Wang & Lysenko, 2013). Phelps (1970) argues that migration from one labor market to another is costly and this cost increases with distance, which in turn inhibits workers from moving, especially to remote areas. Van Ham, Mulder, & Hooimeijer (2001) also state that individuals who attained sector-specific human capital may have to be more spatially flexible, as jobs in that sector may be available only in few locations. Therefore, place attachment and spatial inflexibility potentially restrict graduates' job opportunities, while better access to such opportunities may increase their wages and employment probabilities (Fallah et al., 2013; Regan & Dillon, 2015).

College location does not only influence students, it also affects university faculty hiring. For instance, Solomon (1973) argues that some institutional factors, like faculty salary, is not a perfect indicator of quality, as colleges located in undesirable areas have to pay higher salaries only to compensate for their spatial "unattractiveness." He claims that high quality faculty is willing to accept lower wages at colleges with attractive surroundings and better labor market opportunities. Indeed, in the study of community college faculty hiring, Cejda (2010) finds that rural campuses are struggling to find and retain qualified faculty. As size and quality of faculty has a direct impact on higher institution and its students, college location can then indirectly affect students' attainment of knowledge, abilities, skills, and social/cultural capital formation which further impacts their labor market experiences.

In sum, college location and the regional labor market can have significant impacts on college students through human and social capital formation, intern and employment opportunity provision, local community engagement, and other mechanisms. In addition to the influences on students and faculty, the location is crucial to students also because of the spatial and institutional relationship between university and employers, near or far. Furthermore, as a majority of graduates stay close to where their colleges are, the regional labor market conditions, economic structure, robustness of local economy, and institutional environment at the college location can shape these graduates' labor market experiences and outcomes.

4. STEM disciplines and college graduates' labor market experiences

It is widely perceived that college major is an important determinant of future earnings and overall occupational experiences. In some studies, college major is found to be a better predictor of person's earning than demographic variables. For instance, (Gerhart, 1990) finds that choice of major explains differences in earnings better than gender. Selection of majors depends upon many different facts, such as perceived or observed monetary returns to various abilities, preferences in the workplace, and personal interests. STEM has been marketed to individuals as a lucrative field of study in college, as graduates who major in disciplines such as engineering and computer science, on average earned more annually and over a lifetime than those who specialize in any other fields (Arcidiacono, 2004). Moreover, STEM degree holders earn 11 percent more than their non-STEM counterparts, even if they are employed in a non-STEM job (Carnevale et al., 2011; Langdon et al., 2011). In fact, more than 50 percent of STEM graduates diverge to non-STEM occupations at their midcareer (Xu, 2012), which is explained by widespread need for science, math and technology skills and the broader reach of innovation in other professional sectors.

Given the current demand for technological skills, STEM graduates also experience lower levels of unemployment and underemployment, as well as higher wage growth opportunities (Carnevale et al., 2011). For example, even during the recent economic downturn the unemployment rate for STEM workers (5.3 percent) was half that of their non-STEM counterparts (10 percent) (Langdon et al., 2011). Researchers argue that higher than average pay and lower unemployment indicate a relative shortage of STEM workforce. Apart from better career outcomes, some STEM workers also enjoy greater nonmonetary benefits, such as job satisfaction. Research shows that STEM workers are more satisfied with job security and have better work conditions (Carnevale et al., 2011; Xu, 2012).

Whereas STEM education is commonly viewed as economically beneficial to individuals and a society, others maintain that returns on STEM education may vary when additional factors are taken to account such as age, gender and ethnicity, which may have an effect on STEM graduates' career (Beede et al., 2011; Chen, 2009; Graham & Smith, 2005). For instance, women in STEM tend to earn significantly less than men. Moreover, the gender gap in STEM surpasses the income disparity in non-STEM occupational sectors by the time workers reach 50 years old. According to Hunt (2015), around 24 percent of both men and women work outside of their field of training and there is no significant difference between gender in science and engineering. However, women are 3.2 percent more likely than men to exit engineering fields. Although the exit rate is relatively small compared to the female shortfall in entry to engineering, it may negatively affect women's perception of STEM employment. Similar to the gender disparities, the earnings of African-Americans and Latinos are also relatively lower than that of white non-Hispanic and Asian STEM workers, although the gap between these groups is narrower than in the non-STEM occupations (Broyles & Fenner, 2010).

There are also differences within STEM occupations, with engineers earning the most and life and physical science workers the least. For STEM graduates working outside of traditional STEM occupations, they are paid the highest wages in managerial and professional sectors (Carnevale et al., 2011). In addition, men with majors in engineering, architecture and engineering technology earn about 12 percent more than those in business majors, while mathematics, computer and physical science majors earn as much as those with business majors. For women, majoring in engineering does not translate into higher earnings; however, mathematics and computer science graduates are on average paid more (Fitzgerald, 2000). Same demographic factors also affect graduates' unemployment and underemployment rates disproportionately.

Geographically, STEM employment is unevenly distributed across the US. It is well documented that high-tech, innovative industries tended to agglomerate in localized clusters (Cortright & Mayer, 2001; Moretti, 2012). Software development, clean energy and biomedical research are the examples of industries that were historically concentrated in California, Washington and Massachusetts, respectively. One of the reasons to such clustering is strong ties to local universities and research facilities. For instance, Stanford University was a birthplace of Google, which continues to maintain strong research, financial and graduate job placement relationship with the university. Such established relationships, combined with college prestige are likely to enhance STEM college graduates' post-graduation career opportunities. That said, high-tech companies do not exclusively hire from elite universities. LinkedIn university profile data further suggest that although a large share of workers at Apple and Google come from Stanford and Berkley, the rest are from other local colleges, such as San Jose State and UCLA (Pearlstein, 2014). Similarly, Microsoft which is headquartered in Seattle, Washington hired its workers mostly from the local universities, such as the University of Washington and Washington State. This may indicate both employers' preference to hire locally, as well as individuals' intent to find local employment. Therefore, we can expect that colleges in areas with high concentration of STEM employment would produce similar early labor market outcomes, while controlling for other college characteristics.

As discussed in earlier sections, there are significant gender and race effects on occupational attainment at both individual, institution, and regional level, respectively. However, the intersection of STEM, gender, location, and labor market outcomes have not been very well understood. In one of the studies that looks at spatial distribution of gender wage disparities, McCall (2001) finds that although wages are higher in labor markets with clustering of high-technology and service industries, such premiums are much higher for college educated men, compared to their female counterparts. Moreover, wage gap among college graduates is the widest in such regions. Olitsky (2013) also finds that, although STEM majors earn on average 25 percent more than their non-STEM counterparts, STEM wage premium constituted 18 percent for women and 28 percent for men. As for race effects, Cohen (1998) finds that higher concentration of African-

American population in a metropolitan area is associated with increased earnings of Whites and depressed earnings of Blacks. Another study on spatial inequality confirms that concentration of single racial or ethnic population in a metropolitan area brings wages down for a given group. Conversely, in labor markets with considerable racial and ethnic mix, all demographic groups tend to benefit from higher earnings (Wang & Pandit, 2007). However, again, we still do not know much about the particular experiences of STEM college graduates.

Overall, with the persistent underrepresentation of women and ethnic or racial minorities in the STEM disciplines and STEM occupations, I expect that the labor market experiences and outcomes for STEM college graduates are highly contingent on their individual characteristics, institutional environment, and the interaction with local and regional labor market; furthermore, such contingency may differ by their social identity such as gender and race. Therefore, this study will answer these questions: 1) How do STEM graduates perform in the labor market over time and space? 2) How are college graduate career outcomes shaped by individual, institutional and geographic locational characteristics? The first question addresses the heterogeneity in unemployment, underemployment and job earnings across US (non)-metropolitan areas in four distinct cohorts of STEM graduates, from 2000 to 2010, across gender, race/ethnicity, and sub-disciplines. Second question examines the relationship between the labor market outcomes and the characteristics at different levels, individual, institutional, and college-location.

CHAPTER III: DATA AND MODELING

1. Data

The data come from four sources: the student-level data from the National Survey of Recent College Graduates (NSRCG), the institutional-level data from the Integrated Postsecondary Education Data System (IPEDS), and the area-level data from the US Census and the Bureau of Labor Statistics.

The first dataset, NSRCG, is administered by the National Science Foundation (NSF) every two years to a nationally representative sample of baccalaureate graduates. The NSRCG survey utilizes a multistage sample design with institutions as the first stage unit and graduates from schools as the second stage unit. The NSRCG is the most comprehensive source of data on recent college graduates in the US and four samples combined contain 52,673 respondents. This dataset focuses on science and engineering degrees, classified into seven macro categories: computer science, mathematics, life sciences, physical sciences, social sciences, health and engineering. The sample of graduates used in this analysis is limited to respondents of NSRCG 2003 - 2010 panels with eligible institution code and the highest and the most recent degree at the bachelor level. Individuals who were enrolled or taking classes during survey week are removed from the sample. Additionally, the analysis is restricted to Bachelor's degree holders under age of 30, which is a commonly used threshold for young college educated workforce (Stone, Van Horn, & Zukin, 2012; Weinberger, 1998).

The NSRCG dataset includes an abundant set of measures regarding the respondent's academic history, family background, and recent educational involvement. In particular, the NSRCG reports undergraduate school, major, year of graduation, salary, occupation, current labor market status, as well as age, gender, race and other demographic variables. When linked with institutional and geographical variables over time, these datasets are particularly valuable for assessing individuals' local labor market outcomes.

In order to increase sample size, this study uses four of the latest NSRCG samples that include individuals who received a bachelor's degree during the period between 2000 and 2010. Thus, the data will be comprised of the following samples: NSRCG 2003 (classes of 2000, 2001 and 2003), NSRCG 2006 (classes of 2002, 2003, 2004 and 2005), NSRCG 2008 (classes of 2005, 2006 and 2007) and NSRCG 2010 (classes of 2007, 2008 and 2009). When combined, the final dataset represented the four cohorts of recent college graduates of the first decade after year 2000. The final dataset contains 19,149 unweighted cases.

The second dataset, Integrated Postsecondary Education Data System (IPEDS), supplies the institutional level data. IPEDS is managed by U.S. Department of Education, National Center for Education Statistics (NCES), which collects by law the most comprehensive data on postsecondary institutions on annual basis. It contains information on higher education institution attributes such as college control type (private vs. public), the student body demographics, degrees conferred, students enrolled, tuition, and other institutional features. In this study, the NSRCG respondent's graduation institution is matched to its corresponding IPEDS institutional characteristics. Because institutional code and myriad of other crucial indicators are not available in public datasets, restricted NSRCG data files were obtained to merge the variables relevant to the study with IPEDS. In order to fully merge individual-level data with the IPEDS datasets, the cases that have missing institutional codes were omitted from the NSRCG data.

The third dataset, The Integrated Public Use Microdata Series (IPUMS) contains nationally representative microdata from American Community Surveys for all the years since 2000 (Ruggles et al., 2010). This dataset provided a variety of individual and household characteristics, including race, ethnicity, gender, age, occupation, industry and many others. Most important is that IPUMS provides geographical location indicator, which allows one to aggregate data to different geographic scales (e.g., (non)-metropolitan areas). In addition, the Occupational Employment Statistics (OES) program from the Bureau of Labor statistics provides employment and wage estimates for more than 800 occupations by metropolitan and nonmetropolitan area on an annual basis. The IPUMS data and Occupational Employment Statistics (OES) are merged together and further matched to each respondent from the NSRCG by their university geolocation. In this way, the final dataset has variables at three different levels: Individual graduate respondent (from NSRCG), university (from IPEDS), and geographic location (from IPUMS and OES).

2. Dependent Variables

For the dependent variables, I examined three dimensions of labor market outcomes: unemployment, underemployment, and job earnings.

a. Unemployment

The first dimension of labor market outcome unemployment. It is a dichotomous outcome coded to reflect whether graduate was employed (0), versus unemployed (1) during survey reference week.

b. Underemployment

Underemployment is measured in different ways in the existing literature (Jensen & Slack, 2003). In this study, it is defined by working hours. The survey asks a question: "During a typical week on your principal job, how many hours did you work?" Those who work below 35 hours due to the work unavailability are coded as underemployed (=1), if employed or working part-time voluntarily, 0.

c. Job Earnings

The third indicator is job earnings. Natural logarithm of yearly salary is used to adjust for positive skewness in the distribution. Considering the time span of the data, earnings are adjusted for inflation to represent a consistent compensation values of year 2010.

3. Independent variables

a. Individual level factors

Individual-level independent variables considered for this study measure graduates' 1) demographic, 2) human capital, 3) social capital, and 4) cultural capital attributes at the individual (and family) level. The demographic attributes include age, gender, race/ethnicity, nativity, marital status and having children or not. Prior research has shown that expanded econometric models that include measures of human, social, and cultural capital are improved over traditional economic models when explaining college student decisions and outcomes (Mullen, Goyette, & Soares, 2003; Perna, 2007). In this study, human capital includes GPA, field of study, and work experiences. The NSRCG dataset includes limited information on individual's social capital. However, recent studies have shown that, recent graduates whose parents have higher level of education have higher career aspirations and tend to rely heavily on parents' professional networks when looking for a job (Gardner, 2010; Try, 2005). Therefore, parental educational attainment serves as a control for both social and cultural capital. In addition, graduation cohort, cost of living, and history of migration are included as control variables. The detailed measurement for each variable is provided in Table 1.

TABLE 1: Description of individual variables

Variable	Measurement	Justification/Literature
Age	Continuous number between 19 and 29	Older individuals usually have more established careers, which leads to better labor market experiences.
Gender	Female=1; Male=0	It is well established that women are disadvantaged in the job market (Pascarella & Terenzini, 2005; Weinberger, 1998)
Race/Ethnicity /Nativity	1=Asian; 0=otherwise 1=Black; 0=otherwise 1=Hispanic;0=otherwise 1=Other race; 0=otherwise 1=Foreign born; 0=native born;	As discussed earlier, labor market outcomes significantly differ by race and ethnicity (Melguizo & Wolniak, 2011; Lei Zhang, 2008). To add to that, foreign born indicator was added to control for immigrant status.
Marital status	1=Married; 0=otherwise.	Structural theorists suggest that marriage may be a signal to hiring departments of responsibility and stability for men, and of lack of work commitment for women. Hence, married men are expected to have better labor market outcomes than single men, whereas the relationship is expected to be reversed for women (Glauber, 2008; Pollmann-Schult, 2011).
Children	1=Have children; 0=otherwise.	Having children, especially younger ones, is expected to influence labor market experiences and outcomes differently for men and women (Correll, Benard, & Paik, 2007).
GPA	Coded as an ordinal variable where undergraduates grade-point average was aggregated into five categories – 1) 1.75-2.24; 2) 2.25-2.74; 3) 2.75-3.24; 4) 3.25-3.74; 5) 3.75-4.00.	Many researches argue that higher grades tend to lead to better career experiences, because they are likely to signal about greater human capital or used as a screening tool (Gemus, 2010; Jones & Jackson, 1990). This variable serves as a crude proxy for ability.

TABLE 1, continued.

Experience	Defined as time after graduation that was calculated in months between graduation year and month and survey reference year and month. Because there is no information when graduate started working, I assume that they enter labor force upon graduation from college.	Experience, as part of human capital, also expected to improve individual's career outcomes (Mincer & Polachek, 1974).
Major	Dummy controls for six broad STEM disciplines - 1) Biological, agricultural, and environmental life sciences, 2) Computer and information sciences, 3) Mathematics and statistics, 4) Physical and related sciences, 5) Engineering 6) Social sciences. Health sciences major will serve as a reference group (List of sub-disciplines within these majors is provided in Appendix 1)[2]	College major is believed to be one of the most important factors in graduate's post-graduation success (Eide, Hilmer, & Showalter, 2015). More so, some researchers conclude that major choice, to a large extend, is a reason why earning gaps exist (Eide, 1994; Loury, 1997).
Parental education	1=Mother has a BA degree; 0=otherwise 1=Father has a BA degree; 0=otherwise	Having parents with higher level of education is positively associated with better labor market outcomes (Coleman, 1988; DiMaggio & Mohr, 1984; Lamont & Lareau, 1988).
Cohort	The combined NSRCG dataset consists of 4 distinct cohorts of recent graduates. Dummy variables for three last cohorts.	Used to control for time. Considering that the last cohort overlaps with recent economic depression, it also allows for comparing STEM graduates' early careers in different economic climates.
Working full-year	1 – working 50+ week a year; 0 – otherwise.	Controls for part-time employment (earnings models only).
Working full-week	1 – working 35+ hours a week; 0 – otherwise.	
Cost of living	Regional price parities (RPP) index	Control for variation in economic conditions at place of residence. Considering that this dataset does not include information on graduate's area of residence, controlling for state of residence variables helps to account for current residence location effects.
Migration	Dummy control for whether graduate moved out-of-state (1) or stayed (0) in-state after graduation.	

[2] The NSF definition and classification of STEM, which includes social and health sciences, is used in this study. According to Brecker (2007), excluding social and behavioral sciences from such classifications "marginalizes them and deprives from resources". Moreover, disregarding this disciplines as sciences leads to poor understanding of what science is. That said, because treating these disciplines as part of STEM is unconventional, results of this research may differ from conclusions of prior studies on outcomes of STEM education. With this said, this study still provides the analyses of disaggregated sub-disciplines within STEM which will differentiate social sciences from other STEM majors.

b. Institutional level factors

The sample size of colleges and universities used in the study is 303. The institutional-level variables extracted from the IPEDS include the following (Table 2 provides the specific measurement for each variable):

Quality. The institutional reputation, usually measured by college ranking or selectivity, is found to affect graduates' labor market outcomes (Loury & Garman, 1995; Pascarella & Terenzini, 2005). In addition to these, researchers often use average standardized test scores of freshmen class (SAT or ACT), as measure of institutional quality. Average test scores are not available for all colleges in my sample; plus, common college rankings do not cover all universities in the US. Therefore, this study uses applicants' acceptance rate to control for college quality. At the same time, it controls for institution types to differentiate institutions with doctoral degree granting.

Diversity. As discussed earlier, racial diversity of intuitions is associated with positive learning outcomes (Antonio et al., 2004; Chang, 1999) and higher wages for certain groups (Daniel, Black, & Smith, 2001). This study includes the diversity index of student population to reflect the probability of students' interactions across race and ethnicity. Additionally, shares of Black and Hispanic student population variables were added to the model to control for minority concentration.

STEM specialization. Prior research suggests that college graduates tend to follow major and career choices that correspond to the most dominant major at institution that they attended (Pascarella & Terenzini, 2005). Astin (1970) theorize that it is due "progressive conformity", which is a student's tendency to strive for challenging and demanding majors and careers in competitive environments. This is especially relevant for minorities. For example, Tusin and Pascarella (1985) argue that women are less likely to major in education in colleges with abundance of programs that lead to higher professional status careers than school teaching. This is likely because in highly intellectual and competitive environments there is a larger presence of female role models who aspire to more lucrative and traditionally male-dominated professions.

It is possible that college specialization in STEM disciplines may influence career outcomes of its disciplines. Thus, the location quotient of institution specialization in STEM disciplines is included at the institutional level.

TABLE 2: Description of institutional variables

Variable	Measurement	Justification/Literature
Control	Private institution dummy variable	Institution control has mixed influence on graduates. Researchers find that it affects different groups disproportionately (Astin, 1992; Brewer et al., 1999; Fitzgerald, 2000).
Quality	Acceptance rate, calculated as a ratio of accepted applicants to a total number of applications.	The institutional reputation, usually measured by college ranking or selectivity, is found to affect graduates' labor market outcomes (Loury & Garman, 1995; Pascarella & Terenzini, 2005).
Type	Dummy control for research and doctoral degree granting institution	Controls for institution type, such as Carnegie classification categories, is commonly used as institution level variables in previous research. Although, their effects on student’s and graduate’s outcomes are highly inconsistent (Pascarella & Terenzini, 2005).
Diversity	Institutional diversity scores range from 0 to 1, with 0 representing absolute homogeneity and 1 representing absolute heterogeneity. Dummy controls for Black and Hispanic shares.	Racial diversity within institutions makes difference (Daniel et al., 2001).
Size	In this study, college size is measured by institutional annual enrollment	Some researchers argue that institution size affect labor market outcomes of certain populations (Pascarella & Terenzini, 2005).
Specialization	The location quotient of institution specialization in STEM disciplines.	Prior research suggest that college graduates tend to be employed in the jobs and industries that correspond to the most common major at institution that they attended (Pascarella & Terenzini, 2005).

c. Locational Characteristics

Characteristics of metropolitan or non-metropolitan areas where the higher education institution is located is used to measure the spatial effects.[3] The location characteristics include size, racial diversity, industrial structure, STEM concentration, and unemployment rate. These factors have been found significantly related to labor market outcomes in previous research, as discussed in the literature review. In addition, in order to capture economic effects of remoteness in the urban hierarchy, this study includes a measure of geographic proximity to other metropolitan and non-metropolitan areas with high-STEM employment. For example, opportunities are fewer for more remote places (Lindsay, McCracken, & McQuaid, 2003). They argues that unemployed workers in remote areas are being cut-off from professional social networks that are invaluable for securing employment. On the other hand, many non-urban areas have a high demand for certain professionals, such as health workers (Lehmann, Dieleman, & Martineau, 2008). Thus, it may be easier to find employment following graduation and receive higher compensation in such regions, due to shortage of labor with specialized skills (Corcoran, Faggian, & McCann, 2010). Table 3 provides detailed information on each variable.

TABLE 3: Description of locational variables

Variable	Measurement	Justification/Literature
Size	Total population aggregated by metropolitan and non-metropolitan areas, obtained from the U.S. Census.	Population size is commonly associated with the employment opportunity structure of the given area. For example, Fallah et al. (2013) find that employment growth in high-technology sectors has a positive association with city population size

[3] The discussion of how college location may affect graduates are provided in Chapter II, Section 1.

TABLE 3, continued.

Racial/Ethnic diversity	Herfindahl index of racial diversity, where 0 denotes full homogeneity and 1 – full homogeneity. Herfindahl index of diversity, as calculated using $H = \sum_{i=1}^{N} s_i^2$, where s_i is the share of race/ethnicity population *i* in an area, and N is the total population	Previous research finds racial diversity is significantly related to labor market outcomes (Ottaviano & Peri, 2006; Wilson, 2003).
Share of STEM employees	Ratio of individuals employed in STEM occupations to total employed population.	Areas with specialization in high-tech tend to employ more STEM graduates (Fallah et al., 2013).
Manufacturing	Ratio of individuals employed in manufacturing industry to total employed population.	Early career industry and occupation is shown to influence not just worker's early career experiences, but also their wages in the long run (Bosley, 2004). Share of manufacturing is included in the models to capture the effects of area industrial composition.
Unemployment rate	Ratio of unemployed individuals to total number of individuals in labor force.	I included the unemployment rate to control for variance in local economy conditions.
Proximity index	Ranges from 0 to 100, where 0 is absolute isolation and 100 - absolute proximity to metropolitan and non-metropolitan areas with high STEM employment. Potential values of proximity to STEM employment markets, as calculated using $P_i = \sum_j D_j * f(C_{ij}\beta)$, where P_i is a potential value of college location i, D_j – attraction value for destination labor market j, β – the distance decay parameter, C_{ij} – distance between college location *i* and STEM labor market *j*.	Specialized jobs are scarce in many non-metropolitan areas (Lindsay et al., 2003), while moving elsewhere to get a job has its costs, both monetary and psychological (Beckley, 2003; Regan & Dillon, 2015). Conversely, salaries may be higher for certain occupations in more remote areas to facilitate stable recruitment and retention (Corcoran et al., 2010).

4. Methodology

a. How do STEM graduates perform in the labor market over time and space?

The objective is to explore the spatial and temporal patterns in STEM graduates' early career outcomes. Descriptive statistics is performed on the three indicators of labor market performance by the demographic and educational background of survey respondents. It has both temporal and spatial dimensions.

First, considering that the data consist of four distinct cohorts of college graduates, I compare these sub-samples in terms of socio-demographic and educational characteristics, as well as the changes of key outcomes over four time periods represented by the cohorts. In particular, a comparison is conducted before and during/after the great economic recession around 2008.

Second, the variability of all three dimensions of labor market outcome is summarized based on their spatial distribution. This step examines the spatial patterns of post-graduate career experiences across places. Considering that the vast majority of graduates chose not to relocate immediately after obtaining a degree, labor market conditions in metropolitan area of college location may determine their early career experiences

In addition, gender, racial and ethnic groups are compared at the location level as well. Therefore, the differences in career outcomes may reflect the variability in labor market conditions across the country, as well as demonstrate how these conditions affect certain demographic groups over distinct time periods. Following this, the results of this phase are mapped to demonstrate the spatial and temporal distribution of key characteristics.

b. How are the labor market outcomes associated with individual, institutional and geographic locational characteristics?

Earnings model

In research of how college affects people, the most commonly used technique is OLS regression:

$$Y = \alpha + \beta X + \varepsilon$$

where Y is a dependent variable; α – intercept; β – slope; X – independent variable; and ε – error term. This approach was widely used since the 1960s in multi-campus studies (Astin & Denson, 2009). The hierarchical nature of multi-level data raises concerns when estimating the effects of aggregated variables. For instance, disaggregation of institutional and location variables to the individual graduate level violates the OLS assumption of independence. Therefore, a multi-level regression modeling (MLM) technique is employed to resolve the aggregation bias that occurs in OLS models when analyzing hierarchal data. Specifically, in HLM models, the variance-covariance components are separated into separate within- and between-institution/location components (Astin & Denson, 2009; Raudenbush & Bryk, 2002). For the current study, the decision to use MLM is driven by a few factors. Firstly, the NSRCG data has a nested structure. The NSF used two-step sampling framework - in the first step they sampled colleges and universities, and then sampled graduates within those institutions. Therefore, MLM analysis has a good fit for the sampling framework used to collect this data, because it accounts for interdependence of observations within institutions. Moreover, MLM allows to assess the relative importance of factors on level-2 over what was contributed by level-1 variables. Because the research interest of this study lies in the geographical factors, this MLM approach permits to analyze to what extent these factors at different levels explain the career outcomes.

An unconditional model is first estimated to explore whether there was a significant variance of intercepts between institutions. Then, grand-centered independent variables are added to the model in the stepwise manner. This way, the gradual addition of variables helps to explore how aggregated controls mediate the effects of individual predictors. In other words, the addition of location variables to the model presents not only their relative predicting power of graduate's earnings, but also showed how they are mediated by the effects of individual and institutional variables.

Then, three 2-level hierarchical regression models are conducted on three dependent variables - unemployment, underemployment and earnings. The independent variables are categorized into three groups that represent two levels of regression models. The first level is at the individual level that includes demographic, field of study, social and cultural capital variables; the second level represents a block of institution variables and location attributes. I conduct the MLM by adding each level into the regression modeling. Stepwise regression modeling helps to examine how addition of new sets of variables changes the effects of predictors on selected career outcomes (Table 4).

TABLE 4: Stepwise HLM regression structure

Dependent Variable	Model 1	Model 2	Model 3
Earnings	Level-1: Individual factors only	Individual factors	Individual factors
		Level-2: HEI Institutional factors	HEI Institutional factors Locational factors

The first level of hierarchical model is presented as following:

$$Y_{ij} = \beta_{0j} + \sum_{q=1}^{Q} \beta_{qk} IND_{qij} + e_{ij}$$

for graduate i ($i = 1, \ldots, n_j$), in institution-location j ($j = 1, \ldots, J$). The Y_{ij} is the value of a given dependent variable, while β_{0j} are estimates of an average level of job earnings for each individual i in institution-location j, after adjusting for covariates in the model. β_{qj} represent the level-1 coefficients for individual-level variables IND_{qij}. e_{ij} is variance. The individual-level variables IND_{qij} are those shown earlier in Table 1.

On the second level, β_{qj} coefficients are the function of the institution and location characteristics:

$$\beta_{qj} = \theta_{q0} + \sum_{s=1}^{S} \theta_{qs}(College\ and\ LOC_{sj)} + \mu_{qj}$$

where θ_{q0} is a measure of average salary indicator of each institution-location, θ_{qs} – is second level coefficient, after taking to account of individual characteristics, while $(Collge\ and\ LOC_k$ represent institution and college-location characteristics (Table 2 and Table 3). The earning outcome was logarithmically transformed to achieve a relative normality of distribution, which makes it a log-level model. In log-level models, coefficients are interpreted as percentage change in outcome with one unit change in dependent variable.

Underemployment and unemployment model

For underemployment and unemployment dependent variables, because the dependent variable is a binary variable taking on a value of either zero or one, which is known as the Bernoulli distribution, a hierarchical generalized linear model is conducted (HGLM). The first level of the model follows:

$$Prob\left(DEP_{ij} = 1 \middle| \beta_j\right) = \varphi_{ij}$$

$$\log[\varphi_{ij}/(1 - \varphi_{ij)}] = \beta_{0j} + \sum_{q=1}^{Q} \beta_{qk} IND_{qij} + e_{ij}$$

where i = 1, … , n_j denotes individuals within college-location and j = 1, … , J denotes college-locations. At level 1, DEP_{ij} is conditionally distributed as Bernoulli, taking on a value of 1 with probability φ_{ij}, β_{qj} represent the level-1 coefficients for individual-level variables IND_{qij}. and e_{ij} is variance.

Level-2 formula is specified in a following way:

$$\beta_{qj} = \theta_{q0} + \sum_{s=1}^{S} \theta_{qs}(College\ and\ LOC_{sj)} + \mu_{qj}$$

where θ_{q0} is a measure of average odds of underemployment or unemployment indicator of each college-location, θ_{qs} – is second level coefficient, after taking to account of the individual characteristics, while $College\ and\ LOC_k$ represent institution and college-location level predictors. Similar to the earnings model, independent variables are centered by the grand mean. In the logit models, the coefficients are commonly interpreted as odds-ratio. Therefore, I could assess the influence of individual, locational and institutional variables on the odds of unemployment and underemployment. All analyses are conducted using restricted maximum likelihood estimation.

CHAPTER IV: FINDINGS FROM DESCRIPTIVE ANALYSES

This section examines the descriptive data of the sample over the cohorts: 2003, 2006, 2008 and 2010 by selected characteristics. The descriptive analyses answer the first set of research question: How do STEM graduates perform in the labor markets over time and space? The differences in labor market outcomes across race, ethnicity, gender, and different disciplines were tested for significance using Chi-square and T-test statistics.

The data sample is comprised of four cohorts of STEM graduates in 2000s: The first cohort shares 19 percent of the sample, the second shares 33 percent, the third shares 24 percent, and the fourth shares 23 percent of total sample. Of the entire sample, over half of the sample (54.3 percent) are female. The racial composition of STEM graduates is highly uneven, with only 5.9 percent Black, 8.5 percent Hispanic, 12.0 percent Asian, 69.1 percent White and 4.4 percent other. Foreign born make up a significant portion of STEM graduates with 11.9 percent. 47.1 percent of college graduates' mothers have a bachelor degree, while 53.8 percent of fathers have a bachelor degree or higher. The average age in this sample is 24.7, with only 20.7 percent married and 10.1 percent having children. Mean, standard deviation, minimum and maximum values of each variable are presented in the following table (Table 5).

TABLE 5: Description of location variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Individual:				
Female	0.54327	0.49812	0	1
Asian	0.12042	0.32545	0	1
Black	0.0598	0.23711	0	1
Hispanic	0.08504	0.27894	0	1
White	0.69103	0.46207	0	1
Other	0.04372	0.20447	0	1
Foreign Born	0.11944	0.32431	0	1
Married	0.20762	0.4056	0	1
Has children	0.10099	0.30131	0	1
Age	24.7318	1.61555	19	29
Mother has a Bachelor degree	0.47039	0.49912	0	1
Father has a Bachelor degree	0.53819	0.49854	0	1
GPA	3.55123	0.90951	1	5
Months since graduation	24.0125	8.24105	10	45
Moved out-of-state	0.32424	0.46809	0	1
Regional Price Parities (state of residence)	102.004	9.5573	86.7	118.2
Major:				
Computer science	0.05823	0.23418	0	1
Life science	0.10716	0.30932	0	1
Physical science	0.08904	0.28481	0	1
Social science	0.30033	0.45841	0	1
Engineering	0.33239	0.47108	0	1
Health science	0.06261	0.24227	0	1
Math science	0.05024	0.21844	0	1
Cohorts:				
2003	0.19232	0.39412	0	1
2006	0.33073	0.47048	0	1
2008	0.24356	0.42923	0	1
2010	0.23339	0.42299	0	1
University:				
Enrollment	19241.8	22440.2	185	79470
College diversity index	0.51659	0.20831	0.0642	1
Share of Blacks	.0804482	.1359636	0	.9635812
Share of Hispanics	.0773584	.1337443	0	0.998564
STEM specialization	1.19847	0.43819	0	2.872878

TABLE 5, continued.

Acceptance rate	0.63084	0.19397	0.07652	0.998564
Private institution	0.34577	0.47562	0	1
Research/Doctoral degree granting institution	0.52846	0.49919	0	1
Area:				
Area diversity index	0.57646	0.18036	0.27162	0.946727
Share of STEM workers	0.01032	0.01436	0	0.094475
Proximity index	35.7496	21.6245	1	100
Population	318, 2539	500, 4402	59, 106	19,500,000
Unemployment	5.44504	1.77544	0.01746	0.174115
Manufacturing	0.04445	0.01334	0.0163	0.099841

In terms of GPA, the majority have higher than average grades. 38.5 percent have a GPA between 3.25 and 3.74, 35.3 percent are between 2.75 and 3.24, 14.8 percent are higher than 3.75. Only 10 percent have GPA between 2.25 and 2.74, while under 2 percent have GPA lower than 2.24. Women tend to have a higher average GPA than men across all majors. Whites and Asian had higher GPA than their Black and Hispanic counterparts.

On average, college graduates have two years of labor market experience, as measured by months since graduation. Moreover, there are no graduates with less than ten months of experience in this sample. In terms of post-graduation migration, only 32.4 percent of graduates in this sample moved to another state after graduation. The likelihood of migration also varies by college major. For instance, engineering (38.4 percent), physical (39.9 percent) and math (36.1 percent) science majors are more likely to move across the state border. Women (68.1 percent) are slightly less mobile and more likely to stay in the state where they went to college than men (67.0 percent). Hispanics (78.9 percent) and Asians (73.3 percent) also tend to stay in a college state, compared to Blacks (67.5 percent) and Whites (65.1 percent). This indicates that women and ethnic minorities tend to stay at home state for their higher education when compared to men and Whites. Graduates who moved after graduation are more likely to have higher salary and less likely to be unemployed or underemployed. 69.8 percent of employed graduates worked for private employer, while the rest work for government (30.2 percent).

1. Gender composition by major over time

The most popular major field is social science (43.3 percent), followed by health (14.9 percent), engineering (13.8 percent), life sciences (12.7 percent), computer science (9.5 percent), physical sciences (2.8 percent) and math (2.9 percent). The choice of major and its labor market outcomes vary drastically by cohort, demographics and location.

Figure 1 illustrates the differences among major choice by cohort and gender. The largest three majors for males are social sciences (36.8 percent), engineering (24.7 percent), and computer sciences (16.7 percent). In contrast, around 5 percent of females choose to major in engineering in the first two cohorts, and the number drops to 3 percent in the last cohort. Only 3.3 percent of females major in computer sciences. Possibly due to economic recession, computer sciences became much less popular in the second half of the study period for both genders (7.2 percent decrease for males and 2.7 percent - for females). Social sciences are significantly more prevalent among females (10 percent higher than males), with the third cohort being the lowest for males (35.6 percent) and the highest for females (52.2 percent). Health sciences are the second largest major for female (24.5 percent) in comparison of only 3.4 percent of males. However, health majors have become more popular among both genders with average of 4 percent for males (1 percent increase) and 25 percent for females (8.3 increase)[4]. The third largest major for females is life sciences (14.2 percent for females and 11.2 percent for males). Both mathematical (3.4 percent) and physical (3.5 percent) science majors are more common among men than women (2.3 and 2.4 percent, respectively).

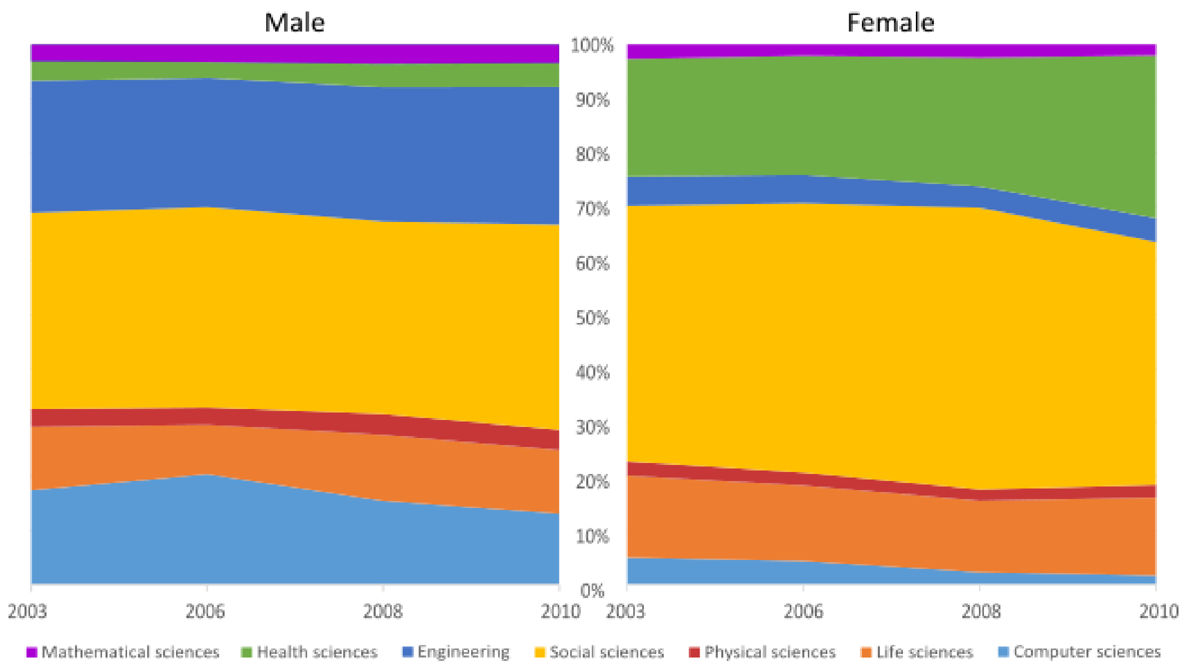

FIGURE 1: Distribution of graduates by gender, major and cohort

2. Racial composition by major over time

The distribution of academic major by race and cohort is presented in Figure 2. On average, 18.1 percent of Asians major in computer science, however their share drops considerably in the last two cohorts with only 11.3 and 6.6 percent of Asians graduating in 2008 and 2010 cohorts with computer science degrees, respectively. Statistically equal number of Asians and Whites graduate with life science degrees - 13.4 and 13.2 percent. Although, the popularity of life sciences has increased among Asians throughout four

4 It reflects the increasing demand of health industry in the labor market. At the same time, NSF changed their sampling approach to health majors in later cohorts. This could have impacts as well.

cohorts and stayed relatively stable for all other groups. Only 2.3 percent of Asian graduates in this sample major in physical sciences, which makes it the least popular major for this group. Like all other groups, the largest share of Asians major (36.1 percent) in social sciences. That said, the share of social scientists among Asians is the smallest compared to any other group, though its popularity slightly grew in the second part of the decade. Health majors (7.3 percent) is not particularly popular among Asian graduates compared to all other groups. Asians are also the most likely to graduate with an engineering (18.7 percent) and math (3.2 percent) degree, compared to other majors.

Almost two thirds of Black graduates have a degree in social (49.4 percent) or health (18.7 percent) sciences. Moreover, Blacks are more likely to major in health sciences than any other group. Among Blacks, Hispanics and Whites, 8 percent major in computer science on average; there is a slight increase in the second cohort for Blacks and Hispanics, with 13.0 and 10.1 percent, respectively. The number of Black (10.7 percent) and Hispanic (11.2 percent) life science majors is slightly smaller than their White and Asian counterparts

Physical science is the least popular degree among Asians (2.4 percent), Blacks (1.7 percent) and Hispanics (1.9 percent), while only slightly more prevalent among Whites (3.2 percent) over mathematical sciences (2.9 percent). Mathematical sciences is the second least popular for all other groups with average of 3 percent of graduates. These two majors consistently attracted the lowest numbers of students across all groups and cohorts.

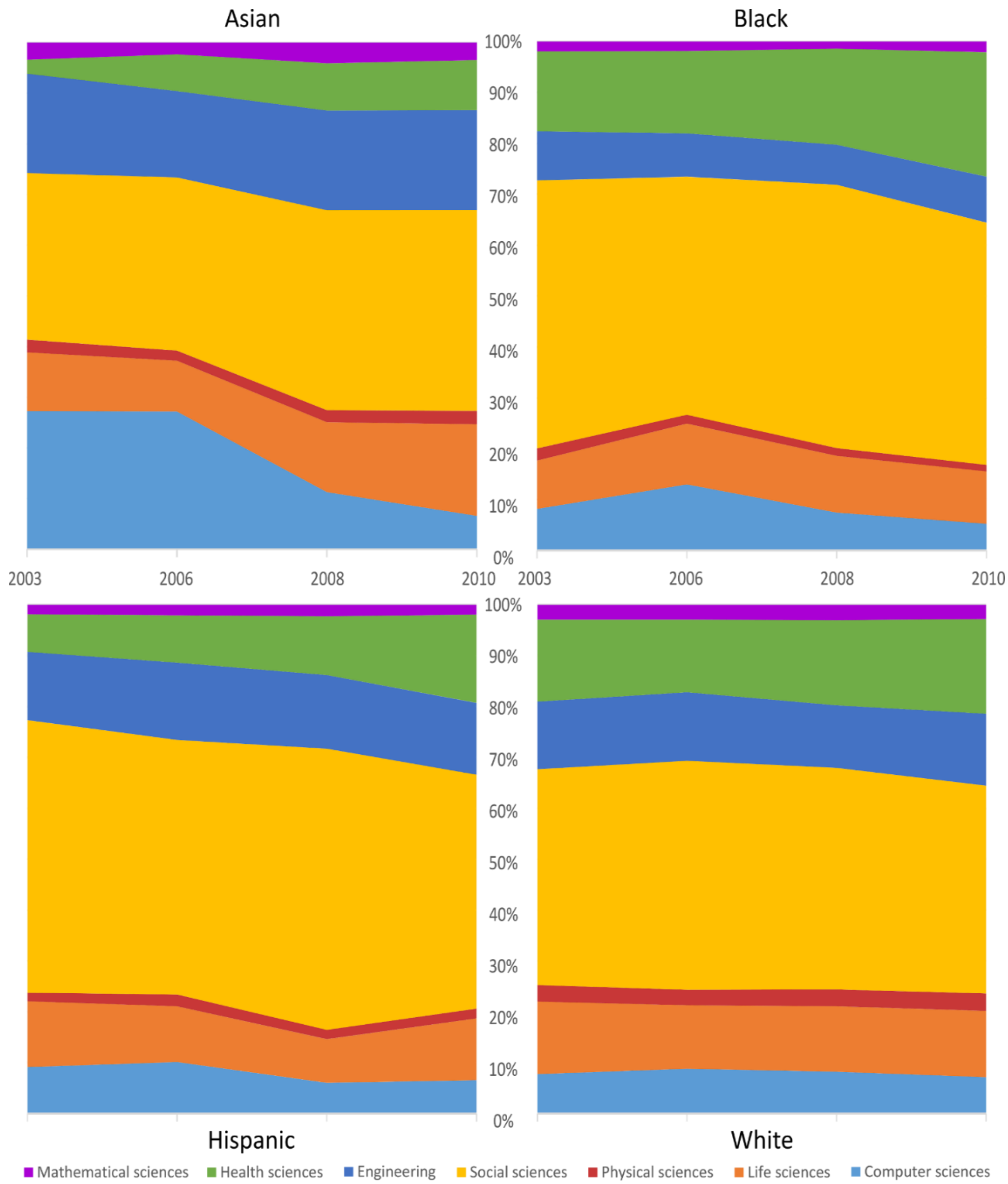

FIGURE 2: Distribution of graduates by race/ethnicity, major and cohort

The majority of Hispanics (51.2 percent) graduate with a social science degree. This number is slightly lower for Whites (43.0 percent) and Asians (36.5 percent). However, the percentage for Hispanics and Whites have decreased in the last two decades. Hispanics (14.3 percent) are also more likely to major in engineering than any other group except for Asian (19.0 percent). The popularity of engineering degrees remained stable over four cohorts among all groups. Similar to Blacks, health (16.4 percent) is the second and life sciences (13.0 percent) is the third most common STEM majors among White graduates.

3. Job earnings by gender and major over time

Figure 3 shows the temporal changes in average salaries by gender and major. Female STEM graduates earn less than males across all the disciplines, except engineering and health sciences. Engineering is the highest paying major. Although women are underrepresented in engineering occupations, female engineers earn slightly more than male engineers (0.7 percent higher) and their salaries dropped less during recession (3.0 percent) compared to males (4.4 percent). Computer sciences is the second highest paid major. On average, female computer scientists earn approximately 2 thousand less annually than their male counterparts, $49,815 and $47,889 respectively. However, female health majors earn 5.9 percent more than males and their salary was cut by only 6.1 percent, compared with 12.3 percent for males during recession.

Although a large number of female graduates major in life sciences, they earn 8.9 percent less than their male counterparts. But, similar to computer science majors, female life scientists experience a lesser salary decrease (6.9 percent) than males (11.4 percent) over the years. In physical sciences, female graduates earn 9 percent less than males, while both genders experience an approximately 12 percent salary reduction in the last cohort. Female mathematicians also earn 9 percent less than their male counterparts; however, during recession their salary decrease by only 19.5 percent compared to 26.8 percent drop in male salaries. Social science degree holders are second to last in terms of average salary, following life scientists. Female social scientists earn 11.9 percent less than males. In the last cohort, the annual salary of social scientists decreases by 9.3 percent for females and 14.7 for males.

Generally, women are likely to dominate low-paying majors – social and life science disciplines, with one exception, health sciences, where salaries are relatively high. Moreover, women with health and engineering degrees on average have higher salaries than their male counterparts. In terms of temporal change, salaries drop considerably for both genders after economic recession, but to a different magnitude - 23.3 percent decrease for males and 16.7 percent - for females, in the last cohort.

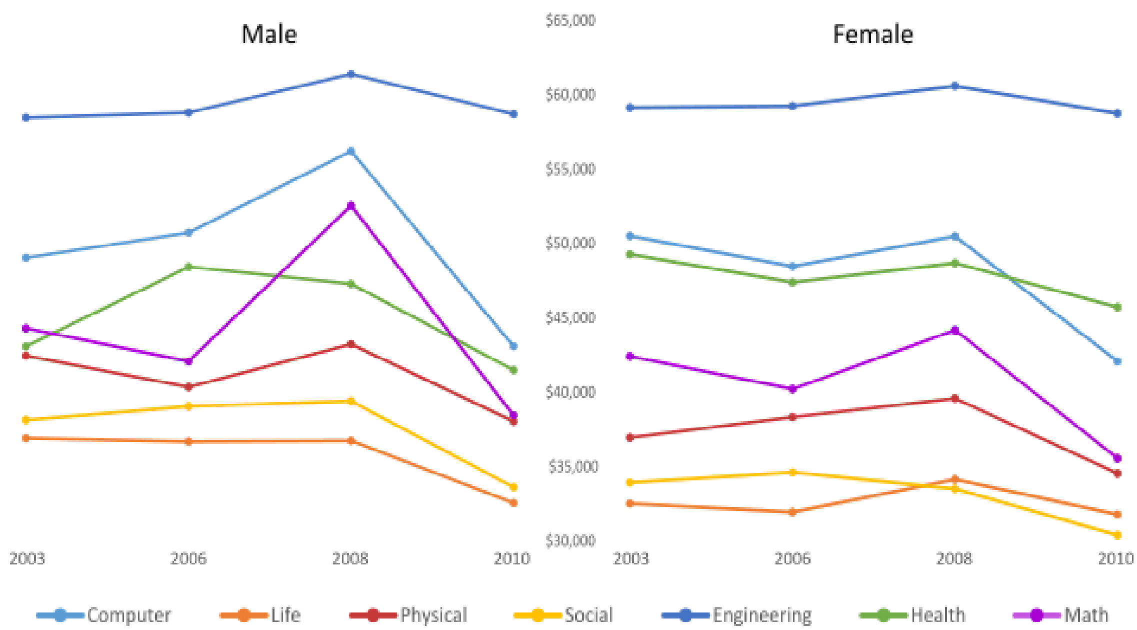

FIGURE 3: Average salary by cohort, major and gender (constant 2010 US dollars).

4. Job earnings by race and major over time

Annual earnings vary drastically across majors (Figure 4). All racial groups benefit financially the most from majoring in engineering. But the second most lucrative major varies by racial group. For instance, Asians with degrees in math, Blacks and Hispanics with health degrees and Whites with computer science degrees are the second highest paid groups in the sample. Moreover, there is a considerable difference among racial groups even within the same major. For instance, Asian and White computer science graduates, on average, earn 33.5 and 23.2 percent more than Blacks, and 20.2 and 8.0 percent more than Hispanics, respectively. Additionally, Asian computer scientists is the only group that has a salary increase in the last cohort (1.6 percent), while all other groups experience a significant decrease (around 25 percent) during the economic recession. Similar to computer sciences, Asian and White life science graduates are the highest earners, with $38,817 and $34,233 average salary, respectively. Blacks and Hispanics on average earn a statistically equal salary - around $32 thousands per year.

Asians with physical and mathematical science degrees earn the most, with Blacks the least, compared to other race/ethnic groups with the same major. The difference between the highest and the lowest paid group is 9.7 percent in physical and 37.3 percent in mathematical sciences. Whites and Hispanics with such degrees earn around $40 thousands per year, which is 6.1 percent less than Asians in physical sciences and 30.8 percent less in math sciences. Almost every group experience salary drops during recession, with exception of Asians with math degrees (5.5 percent increase). While the largest change is for Black and Hispanic math graduates with 22.2 and 45.5 percent decrease respectively. This drastic change is likely due to increase in underemployment and occupational mismatch rates for these groups in the last cohort. Like other majors, Asians with social science degrees earn 21.4 percent more than Blacks, 11.3 percent more than Hispanics, and 15.9 percent more than Whites with the same major. During recession, median salary of social science degree holders drops for all groups on average by 16.3 percent.

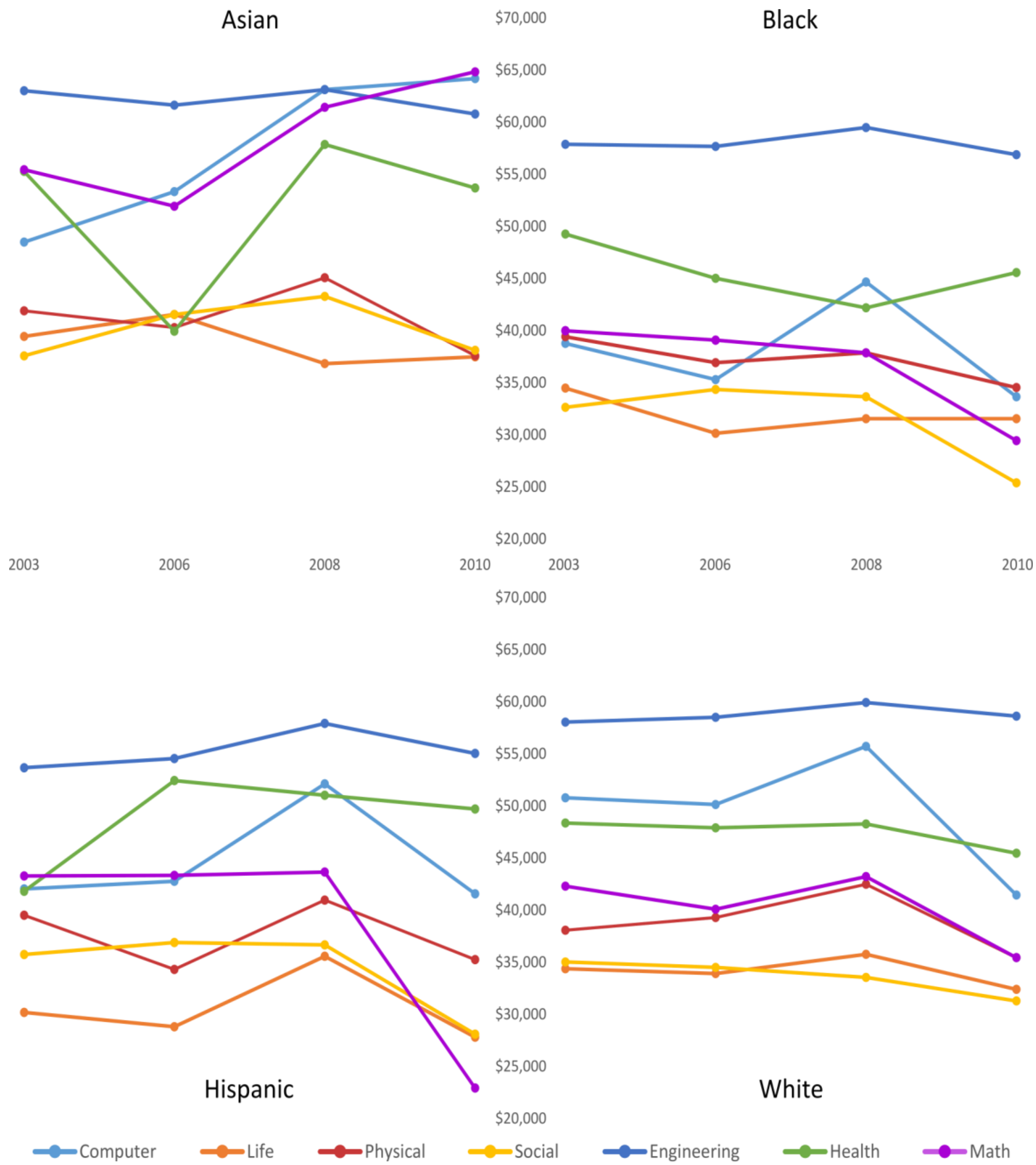

FIGURE 4: Average salary by cohort, major and race/ethnicity (constant 2010 US dollars).

On average, Asian STEM graduates have the highest average annual earnings in this sample ($49,951), followed by Whites ($43,349), Hispanics ($42,450) and Blacks ($39,842). Over time, Asians have a slight increase (1.8 percent) in pay during recession, Blacks earn statistically the same as previous cohort, while Hispanics and Whites experience 20.7 percent and 9.4 wage reduction in the end of 2000s, respectively. There is the lowest salary variation between racial/ethnic groups with engineering degrees. Although Asians have a salary premium, they earn only 6.6 percent more than Blacks, 9.6 percent more than Hispanics and 5.2 percent more than Whites. Asians and Hispanics have a higher annual salary than their White and Black counterparts with health major. Moreover, for Blacks and Hispanics, obtaining a degree in health on average leads to a greater salary than majoring in computer science, with 16.3 and 8.1 percent pay advantage, respectively.

5. Unemployment rate by gender and major over time

Generally, women (4.9 percent) with STEM degrees have a lower unemployment rate than men (5.2 percent). Both numbers are lower than average unemployment rate for US labor force in the first decade of 2000s. Across majors, the highest unemployment is among graduates with life (7.4 percent for women and 6.3 percent for men) and social (6.3 percent for women and 6.9 percent for men) science degrees, and the lowest unemployment rates are among health majors (1.8 percent for women and 2.0 percent for men). Due to economic recession, the unemployment rate increases considerably in almost every group, except for physical science degrees and women with computer science degrees (Figure 5).

The average unemployment rates for computer scientists is the same for men and women - 4.6 percent. However, they vary considerably over time. For instance, for males the unemployment rate is slightly below 6 percent in the first part of the decade, then drops to under one percent in the third cohort, and then, rises up to 8 percent in the recession cohort. For females, unemployment rate is under 3 percent in early 2000s and increases up to 7 percent in the later years of the decade. Life science graduates have the highest average unemployment rate compared to all other STEM majors. Their unemployment rate doubles for both genders from the first (around 5 percent) to the last cohort (around 10 percent), however, the average rate for all cohorts is 1.1 percent lower for males.

Unlike computer and life science majors, unemployment rate for physical scientists decreases in the recession cohort for both genders, while the average unemployment rate being lower among females (5.5 percent) than males (6.0 percent). Math majors, regardless of gender, have one of the lowest unemployment rates in the first part of 2000s (under 3 percent). However, unemployment triples for males and increases five times for females during the study period and reaches over 10 percent during recession cohort for both genders. Social science degree holders have the second highest unemployment rate in the 2000s, with 6.9 percent among males and 6.3 - among females. It decreases considerably in 2006 cohort (under 4 percent) and more than doubles in the next two cohorts for both genders (over 9 percent). Overall, unemployment rate was lower during and after the recession for most graduates with STEM degrees compared to US labor force in general (9.6 percent). The only majors that had higher than labor force average unemployment are math, life and social science graduates.

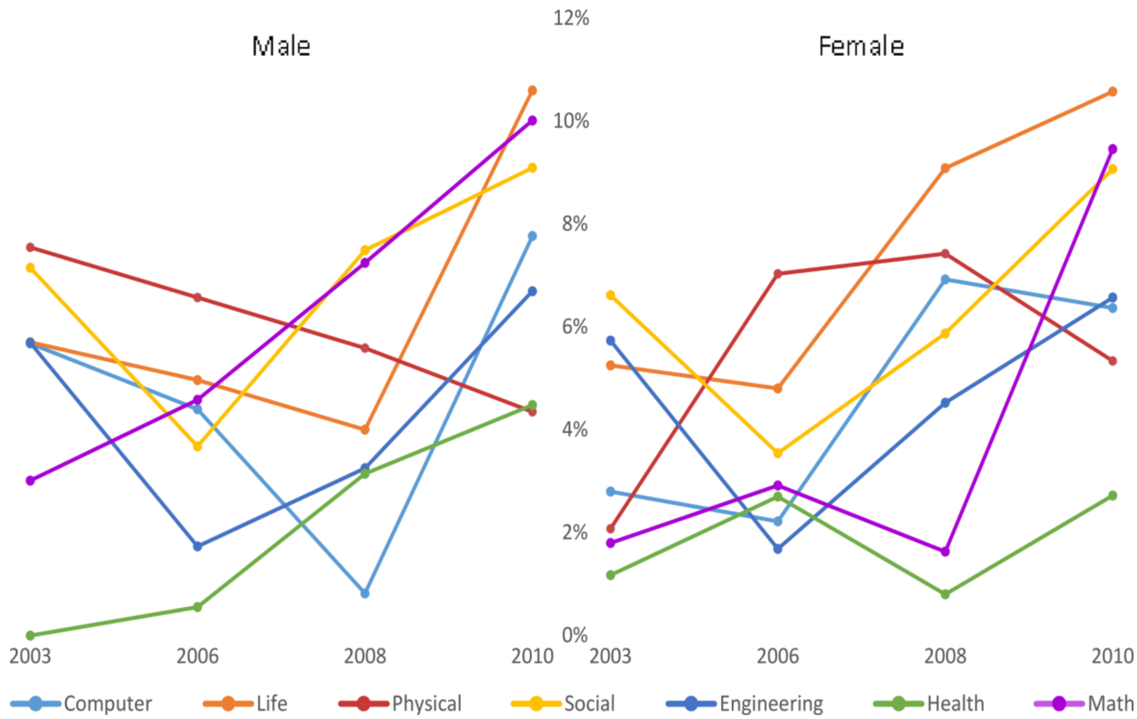

FIGURE 5: Average unemployment by cohort, major and gender.

Unemployment among engineering graduates follows the similar pattern across time, however it is significantly lower on average (under 5 percent) and reaches its highest in the last cohort - 6.7 for males and 6.6 for females. Health graduates experience the lowest rates of unemployment compared to other majors in this sample (2 percent for both genders). The time trend is different for males and females, where the former experience a steady growth in unemployment, while the latter are more likely to be unemployed in 2006 (2.9 percent) and 2010 (9.5 percent) cohorts.

Overall, the increasing trend of unemployment rate reflects the impacts of economic recession. Engineering and health major have the most stable and strong labor market demand, while life and social science are hit the worst. As women are highly concentrated in life sciences and social sciences, they obviously suffer more from economic recession.

6. Unemployment rate by race/ethnicity and major over time

Asians and Hispanics have the largest increase in unemployment, as Whites have the lowest change in unemployment over the time (Figure 6). Furthermore, as the unemployment rate of health majors remains low and stable for Hispanics and Whites, it is volatile and increases significantly for Asians and Blacks. Overall, despite Asians being the highest paid graduates in this sample, they are also the most likely to be unemployed (8.1 percent), followed by Blacks (7.2 percent), Hispanics (6.4 percent) and Whites (4.3 percent). Of all the majors, Asians (12.7 percent), Hispanics (10.4 percent) and Whites (6.0 percent) with life science degrees and Blacks (10.4 percent) with computer science are the most likely to be unemployed.

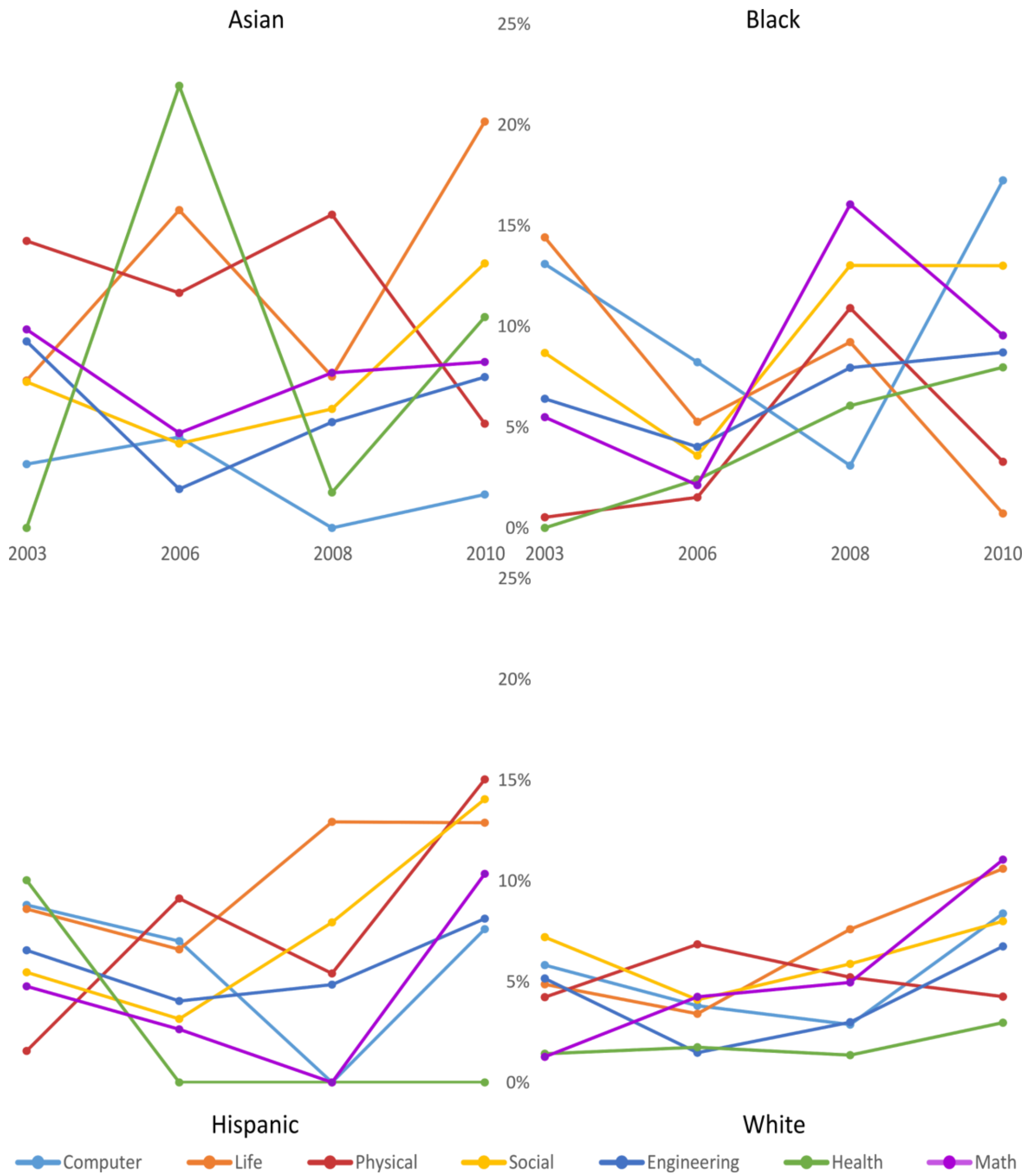

FIGURE 6: Average unemployment by cohort, major and race/ethnicity.

Asians with computer (2.3 percent), social (7.6 percent) and mathematical (7.6 percent) science degrees are the least likely to be jobless compared to their co-ethnic peers with other majors. Moreover, this is the lowest unemployment rate among graduates with computer science degrees. Cohort-wise, Asians with life and social science degrees experience the largest rise in unemployment during the last cohort, while

2006 cohort health science graduates have a spike of unemployment (22 percent) in this sample.

Among Blacks, the average unemployment is the lowest among physical (4.1 percent), health (4.1 percent) and engineering (6.8 percent) science degree holders. Furthermore, Black physical science graduates have the lowest unemployment compared to other groups with the same major. Interestingly, unemployment does not rise significantly for majority of Black graduates during the recession, with exception of computer science majors, where it increases by 14 percent compared to previous cohort.

Health (2.5 percent), math (4.5 percent) and computer (5.9 percent) science majors experience the lowest average unemployment among Hispanics compared to graduates with other degrees. The unemployment rate for math graduates also is the lowest compared to other groups with the same major. Recession affects Hispanics the most as they are more likely to be jobless in 2010 than in previous years in every discipline, with only one exception – health sciences. Furthermore, in this sample, all Hispanics who graduated with health degree had a job in three last cohorts.

Whites with degrees in health (1.2 percent), engineering (3.4 percent) and physical (4.5 percent) sciences are more likely to be employed than their counterparts with other degrees. Moreover, Whites with life, social, engineering and health degrees have the lowest unemployment compared to other racial groups with same degrees. Although unemployment grows in the last cohort for Whites with all kinds of STEM degrees, this rise is considerably smaller than for other groups.

Overall, the most substantial differences in unemployment in all majors and cohorts is between Whites and the rest, which is evident in Figure 6. Furthermore, recession negatively affects all groups, but to a different extent, with Blacks being the only group for whom unemployment decreased in most disciplines in the last cohort.

7. Underemployment by gender and major over time

Gender differences in unemployment rates by major are illustrated in Figure 7. Like unemployment, underemployment rate also increases for almost all majors in the recession cohort. The only exception is computer sciences for women (3.6 percent decrease) and life sciences for men (4.3 percent decrease). Specifically, the underemployment rates among computer science graduates differs by gender, where females (1.7 percent) have a rate only a half of males (3.4 percent). Women also fare much better in the last cohort with almost no underemployment, compared to 4.7 percent for males.

Engineering majors have the lowest underemployment compared to other majors (under 2 percent). However, it increases dramatically for female engineers during recession years (from 0.5 to 4.6 percent), while it only marginally rises for men (from 1.4 to 1.7 percent). Similarly, underemployment rate for health majors is also low (under 5 percent), however it significantly increases by the end of decade, especially among men (8.1 percent).

Overall, like unemployment, female (4.3 percent) graduates are more likely to be underemployed than their male (3.3 percent) counterparts. Moreover, underemployment is considerably higher among female-dominated majors, such as social and life sciences.

When both male and female STEM majors are hit by economic recession, female suffer more as indicated by the rate of underemployment.

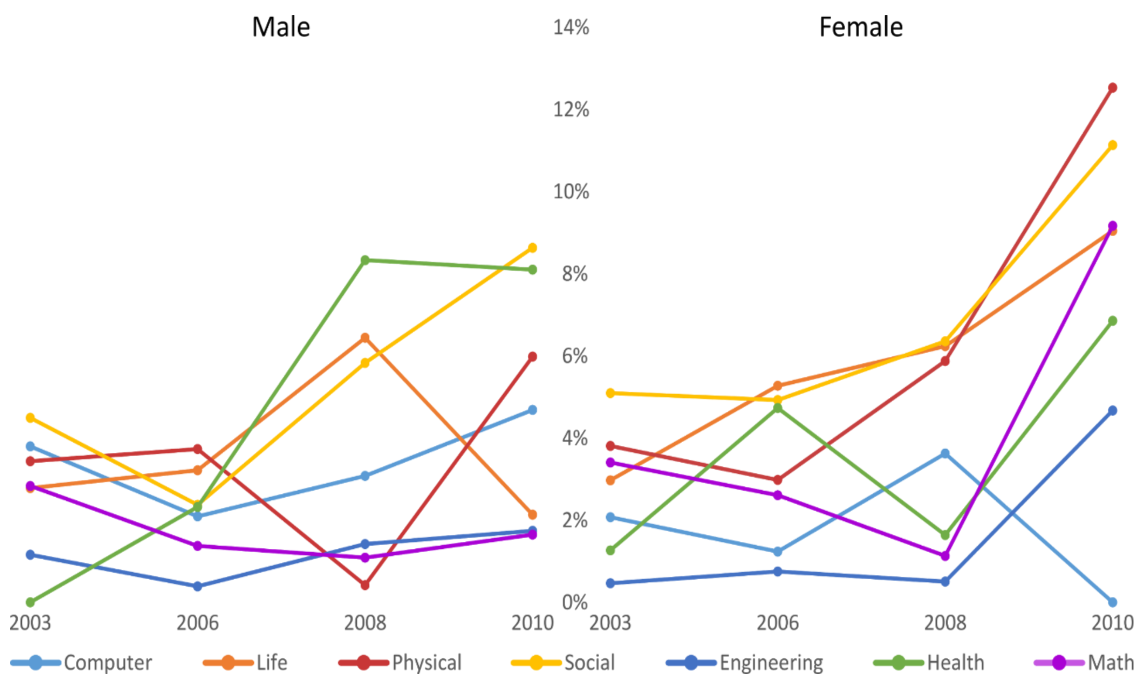

FIGURE 7: Average underemployment by cohort, major and gender.

8. Underemployment by race/ethnicity and major over time

Figure 8 illustrates the differences in underemployment rates across majors, cohorts and race/ethnicity groups. Underemployment among STEM graduates in 2000, differs considerably between race/ethnicity groups. White graduates on average experience the lowest underemployment (3.3 percent), followed by Asians (3.8 percent), Hispanics (5.5 percent) and Blacks (6.5 percent). The rate differs significantly across majors as well.

Asians and Hispanics with computer science degrees have similar rate of underemployment, 4.6 and 4.4 percent, respectively. Black computer scientists have the highest rate of underemployment in 2000s, 9.7 percent, much higher than Whites, 2.5 percent. Generally, underemployment for computer scientists decreases over the decade, with exception of Asians, 10.4 percent of whom are working part time in the last cohort.

The life science is the most volatile for Black and Hispanic graduates, who experience the sharpest increase in underemployment in later cohorts.

Underemployment among life scientists is more even across race/ethnicity groups, as only 4.8 percent of Asians, 4.3 percent of Hispanics and 4.5 percent of Whites with life science degrees are underemployed. However, underemployment is more prevalent among Blacks - 7.2 percent on average during four cohorts.

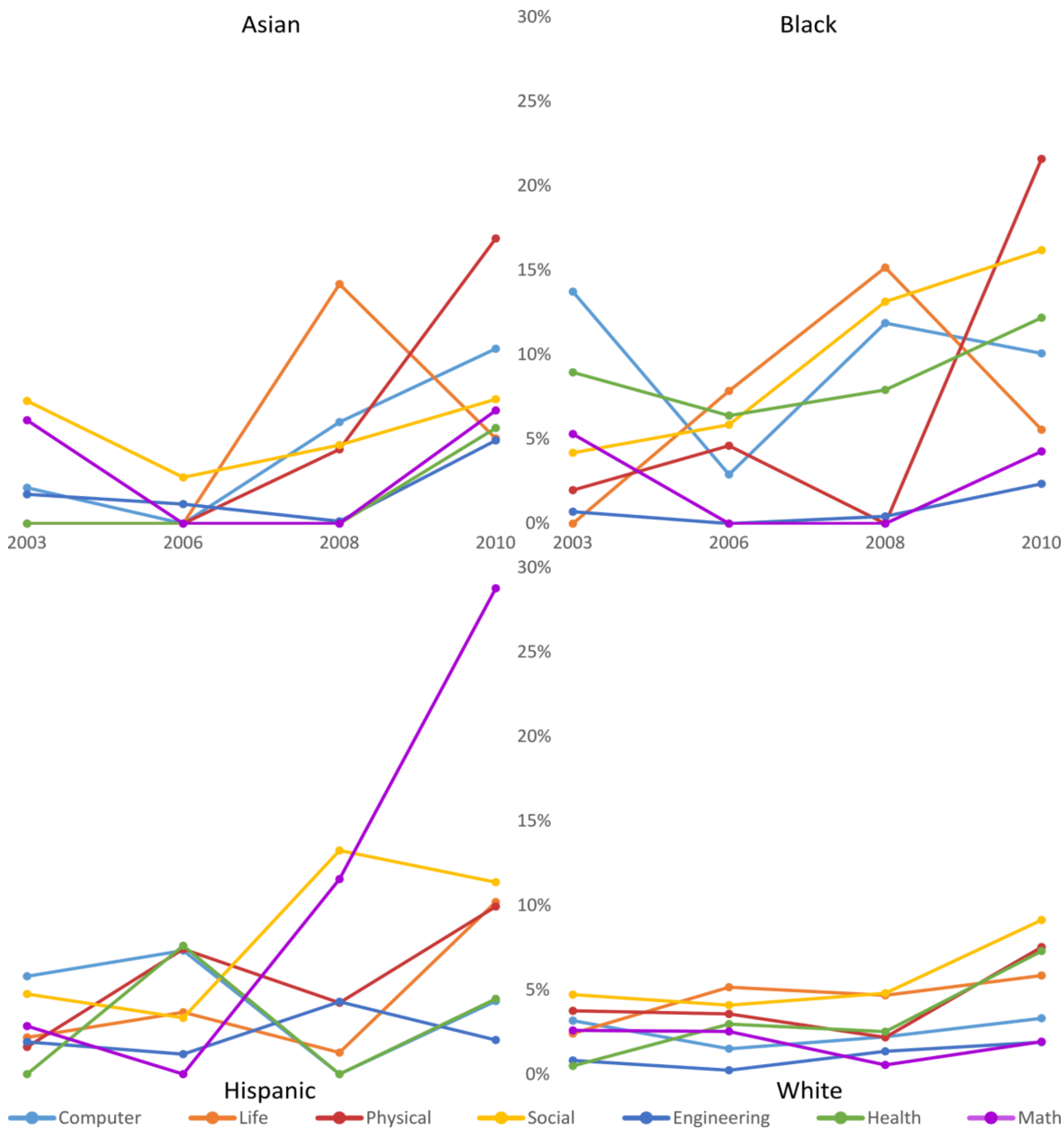

FIGURE 8: Average rate of underemployment by cohort, major and race/ethnicity.

Similar to computer and life science majors, Blacks in physical sciences have the highest underemployment, 7.1 percent. Asians, Blacks and Whites, who majored in math science experience a relatively low underemployment, less than 4 percent, while Hispanics are twice more likely to be underemployed (10.8 percent). Additionally, last cohort of Hispanic math science graduates are considerably more likely to be underemployed than their counterparts in previous cohorts. In social sciences, Asian (5.5 percent), Black (9.9 percent) and White (5.7 percent) have the highest underemployment compared to their peers with other STEM degrees. Moreover, their likelihood of being underemployed increases dramatically by the end of decade. On the other hand, engineering majors are the least likely to be underemployed.

9. Summary

In sum, over the decade of 2000s, the choice of major remains relatively steady with exception of computer sciences (decreases) and health sciences (increases), while the gender divide remains across all the STEM majors in this sample. In terms of salary, men fare better in all of the majors except health and engineering. All majors experience a considerable decrease in yearly salaries during recession years. However, women' salaries decrease significantly less than men's during recession. Therefore, the gender pay gap, actually, narrows for graduates in the recession cohort. In terms of racial differences, Asians earn more than every other race/ethnicity group across all STEM majors, followed by Whites, Hispanics and Blacks. The differences in job earnings are especially drastic in computer and math sciences.

The average unemployment rate for all majors and across all cohorts is under 7 percent. However, there is a significant variation across majors, cohorts and genders. Health, physical sciences and math majors have the lowest unemployment rate during the study period, while life, social, physical and math have the highest rise in unemployment in the last cohort. The underemployment rates generally follow the pattern of unemployment both across majors and genders. The only exception is engineering majors who have a lower underemployment rate than those with health science degrees. This suggests that variations in unemployment and underemployment are affected similarly by shocks in the labor market.

Overall, women are severely disadvantaged across all three outcomes compared to men, with exception of the post-recession cohort where women are negatively affected to the lesser extent than men. In terms of racial differences, Asians and White have a largest advantage in the labor market, on average. Asians have the highest average salaries, while Whites have the lowest average unemployment and underemployment. The differences between Whites and other groups are especially striking in unemployment and underemployment outcomes. Health and engineering majors provide the most lucrative and stable employment for most groups. Late 2000s are associated with diminished labor market outcomes for all groups and most majors, but to the different extent.

CHAPTER V: DESCRIPTIVE ANALYSES OF HEI CHARACTERISTICS

This chapter provides the descriptive statistics of selected college characteristics in relation to college graduate early career outcomes. Average college size increases by 14 percent over the study period. STEM degree holders graduate from universities of various sizes. The largest share, 57.5 percent, have attended a college or university that enrolled less than 20,000 students. More male than female students graduate from larger schools. Among the racial groups, Asian graduates are more likely to hold degrees from schools that enroll more than 20,000 students, than any other group. Similarly, foreign born respondents tend to graduate from schools with larger enrollment. Graduates from large universities on average have the lowest undergraduate GPA and are less likely to move out of state after graduation. Large universities tend to graduate more engineers, math and physical science majors, while smaller schools are likely to produce more social and health science graduates.

There is a positive correlation between earnings and college size, $r(17613)=0.16$, $p<0.01$ (Figure 9). Graduates from colleges that enroll less than 2500 students, on average, earn $4,390 less than those who have attended colleges with more than 50,000 enrolled students. Similarly, underemployed graduates are significantly more likely to have attended smaller sized institutions (M = 18483, SD = 600.17), than those who are employed full-time, $t(17549) = 2.27$, $p = .023$. Unemployment is also associated with graduation from college with smaller enrollment (M = 18652, SD = 504.73), $t(17538) = 2.25$, $p = .024$.

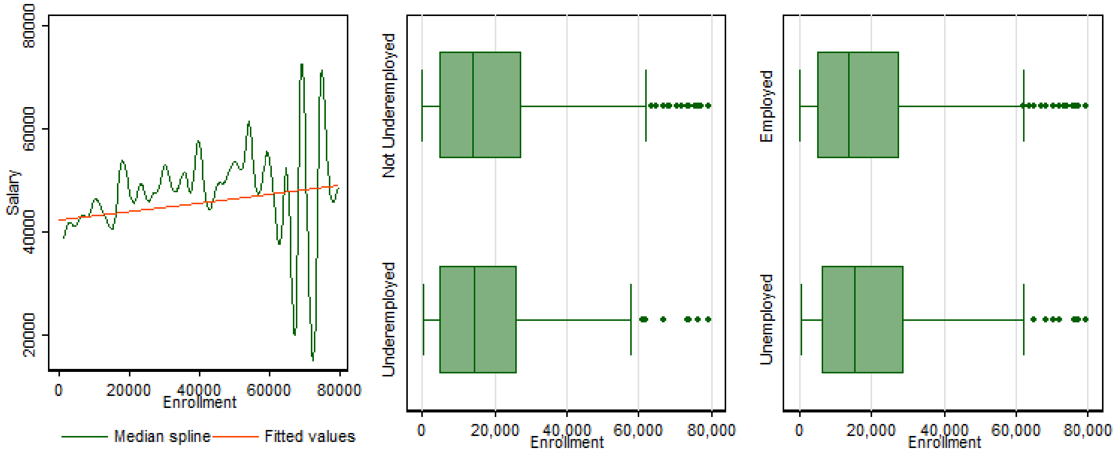

FIGURE 9: Enrollment and labor market outcomes (constant 2010 US dollars).

Graduates from colleges with higher racial diversity are likely to earn more as well, *r*(17613)=0.12, *p*<0.01 (Figure 10). However, college racial diversity appears to have slightly negative, but statistically significant, relation with underemployment, *t*(17547) = -1.83, *p* = .033. The relationship between unemployment and college diversity is not significant, *t*(17536) = -1.32, *p* = .188. Figure 10 illustrates the distribution between racial diversity and the three labor market outcome indicators.

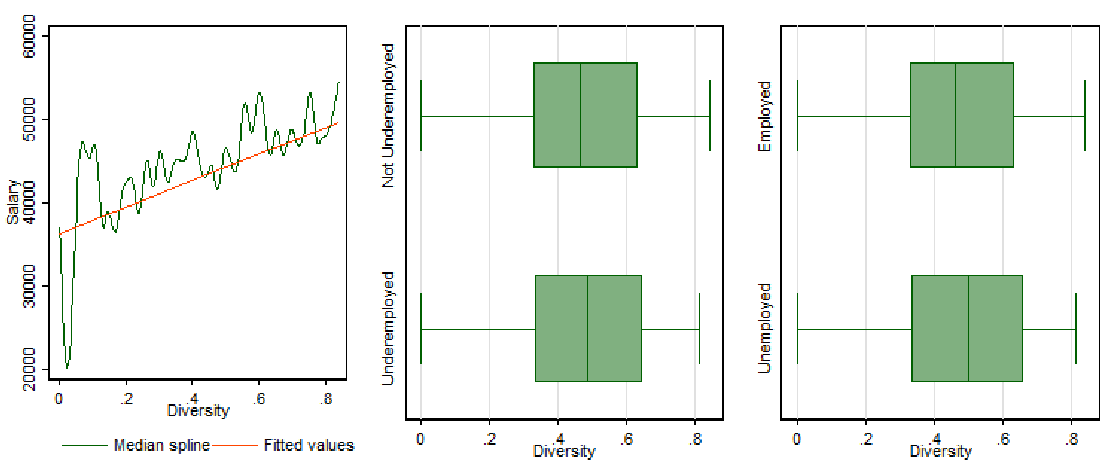

FIGURE 10: Racial diversity and labor market outcomes (constant 2010 US dollars).

Although racial mix appears to have a positive relation with earnings, larger Black enrollment is negatively correlated with annual salary, $r(17613) = -0.03$, $p<0.01$. Similarly, predominantly White colleges tend to produce graduates with lower pay, $r(17613) = -0.05$, $p<0.01$. However, colleges that enroll larger populations of international students are likely to have a higher level of salary, $r(17613) = 0.20$, $p<0.01$. Underemployed graduates are more likely to graduate from colleges with larger shares of Asians (M = 0.09, SD = 0.005), $t(17447) = -1.63$, $p = .001$, and Hispanics (M = 0.10, SD = 0.006), $t(17447) = -2.33$, $p = .019$.

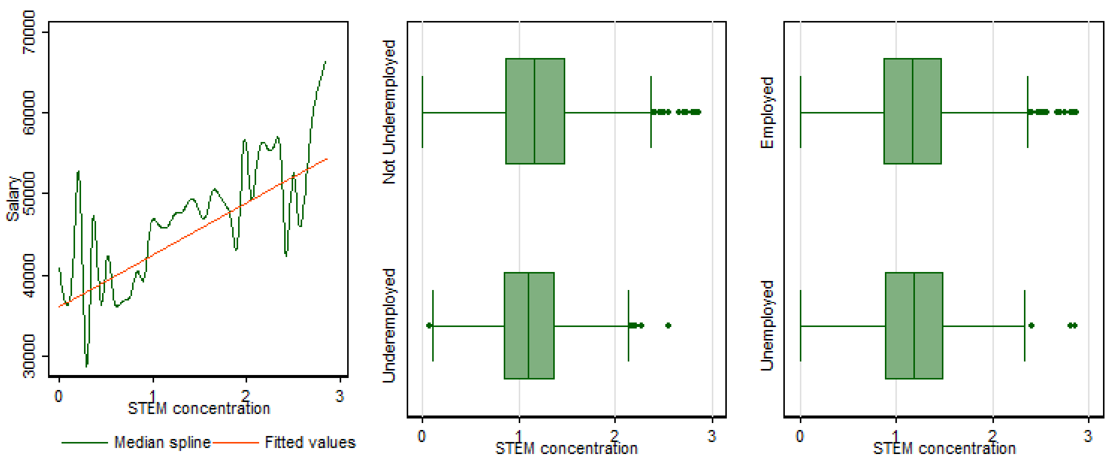

FIGURE 11: STEM concentration and labor market outcomes (constant 2010 US dollars).

Higher-paid graduates are more likely to graduate from colleges and universities that specialize in STEM, $r(17614) = 0.17$, $p<0.01$ (Figure 11). Full-time employment (M = 1.26, SD = 0.003) is also significantly associated with college STEM concentration, $t(17548) = 4.81$, $p<0.001$. Unemployment status (M = 1.26, SD = 0.003) has an insignificant relationship with college STEM concentration, $t(18537) = 0.42$, $p=0.669$.

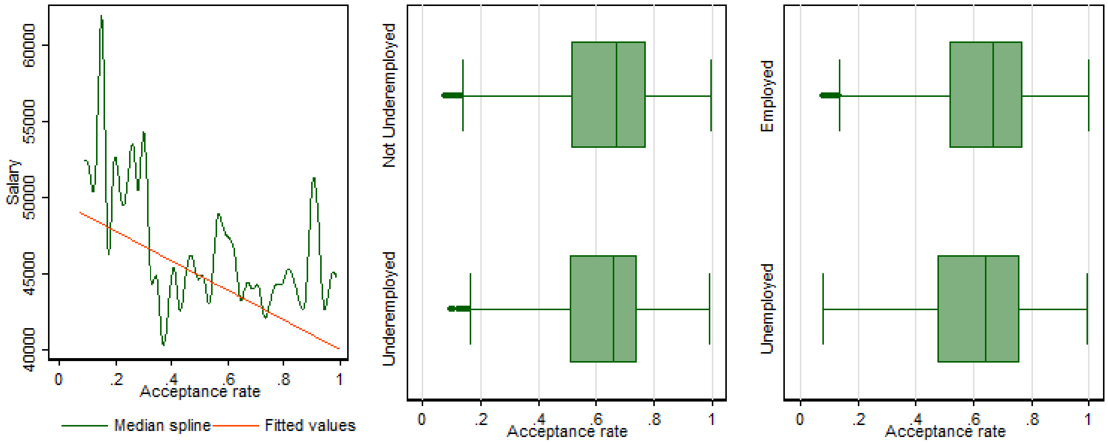

FIGURE 12: Acceptance rate and labor market outcomes (constant 2010 US dollars).

Employees with higher salaries tend to graduate from more selective institutions (colleges with lower acceptance rates), *r*(17457)= -0.05, *p*<0.01. Employment (M = 0.62, SD = 0.001) is also positively associated with college selectivity, *t*(18377) = 3.70, *p*<0.001. Though, acceptance rate does not any significant relationship with underemployment.

College control (i.e., public versus private) is only marginally related to career outcomes (Tables 6-7). While graduates from public colleges receive a slightly, though not significantly, higher salary, private colleges tend to have slightly lower numbers of unemployed and underemployed graduates. College type, on the other hand, is a significant factor in graduates' salary. On average, graduates from research and doctoral degree granting institutions earn $7,311 more than their counterparts with degrees from other colleges. However, relationship between college type and employment status is mixed. Students from the research and doctoral granting institutions are less likely to be underemployed but more likely to be unemployed.

TABLE 6: Average salaries by college control and type

		Job earnings (constant 2010 dollars)		
		M	*SD*	*t*
Control	Public	47,114	242.287	0.7141
	Private	46,759	506.480	
Type	Other	42,701	317.469	-15.9548**
	Research/doctoral	50,012	312.063	

**p<0.001

TABLE 7: Distribution of underemployment and unemployment across college control and type

Outcome		Control			Type		
		Public	Private	X^2	Other	Research/ Doctoral	X^2
Underemployed	No	95.51%	95.63%	18.336**	95.43%	95.67%	315.825**
	Yes	4.49%	4.37%		4.57%	4.33%	
Unemployed	No	94.71%	95.23%	317.026**	95.37%	94.46%	860.067**
	Yes	5.29%	4.77%		4.63%	5.54%	

**p<0.001

In sum, graduates from the institutions that are larger, more racially diverse, more selective, research and doctoral degree granting, and with higher STEM concentration are positively associated with higher earnings. Larger college size, private status, higher STEM concentration, and lower Asian and Hispanic enrollment are associated with decreased underemployment. At the same time, unemployment is associated with graduation from the smaller, less selective and public colleges.

Generally, these results align with existing literature on between-college differences in labor market experiences. For instance, attending a highly selective institution is predominantly associated with better post-graduation outcomes (Black, Haviland, Sanders, & Taylor, 2006; Eide et al., 2015; Fitzgerald, 2000; Loury & Garman, 1995), so as graduation from larger colleges (Pascarella & Terenzini, 2005). However, the effects of college racial diversity on career outcomes are mixed, with results suggesting no effect (Hinrichs, 2011), positive (Daniel et al., 2001) and negative (Arcidiacono & Vigdor, 2010) influence on labor market experiences. Unlike prior research (Brewer et al., 1999), in this study sample there are no significant correlation between attending private universities and higher salaries. The descriptive statistics also suggest a relationship between research and doctoral degree granting and higher unemployment rate which is not clear in previous research (Pascarella & Terenzini, 2005).

Pascarella and Terenzini (2005) suggest that graduates tend to pursue careers that correspond to the most dominant major in the college they attend. However, there are no specific studies that have explored the STEM concentration effects. The descriptive analyses from the national data in this study suggest that attending colleges that produce higher number of STEM graduates is related to better opportunities for higher earnings. While these patterns are interesting, they are only based on a bivariate relationship between selected college characteristics and the outcomes of interest. Further regression analyses are provided in Chapters VII and VIII.

CHAPTER VI: FINDINGS FROM DESCRIPTIVE ANALYSES OF GEOGRAPHIC FACTORS

1. Characteristics of college locations

Almost 90 percent of respondents went to college in areas with less than 10 million population. Generally, those who graduated from colleges in large urban areas are more likely to earn more *r*(17169)= 0.03, *p*<0.01) than graduates from smaller college towns. However, attending college in regions with higher population is negatively associated with graduates' employment prospects, i.e., higher unemployment and underemployment (Figure 13).

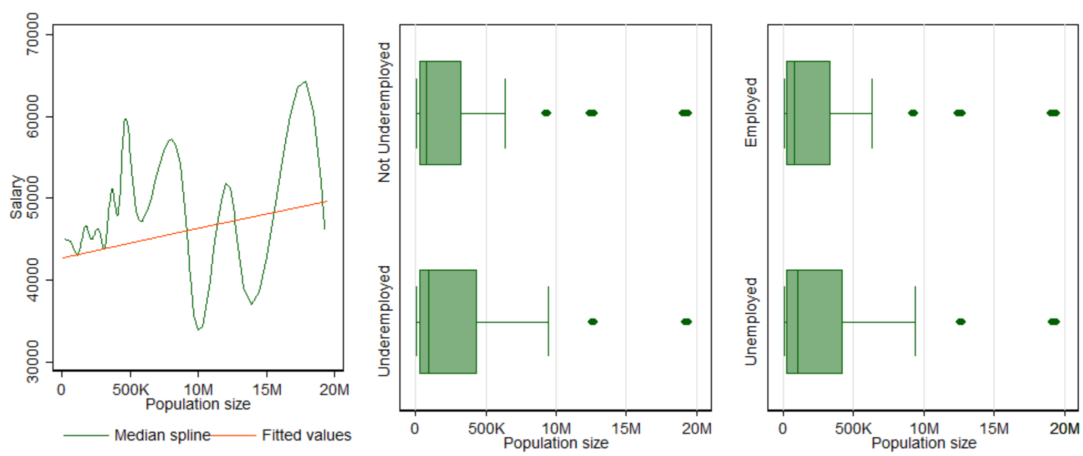

FIGURE 13: Population size and labor market outcomes (constant 2010 US dollars).

Most colleges and universities in this sample (55.9 percent) are in moderately racially diverse areas, 33.1 percent in relatively homogeneous, and 10.9 percent in very diverse regions. Generally, more diverse areas are slightly more correlated with higher earnings than the racially homogeneous areas, *r*(17169)= -0.05, *p*<0.01 (Figure 14). Other outcomes have the opposite relationship with racial diversity, however. Underemployment (M = 0.44, SD = 0.007), *t*(17106) = -2.51, *p*=0.01 and unemployment (M = 0.45, SD = 0.006), *t*(18051) = -3.65, *p*<0.001 are more prevalent among those graduates who received their schooling in more diverse areas. Therefore, the relationship between region's racial diversity and labor market experiences is not straightforward which has not been examined in previous studies.

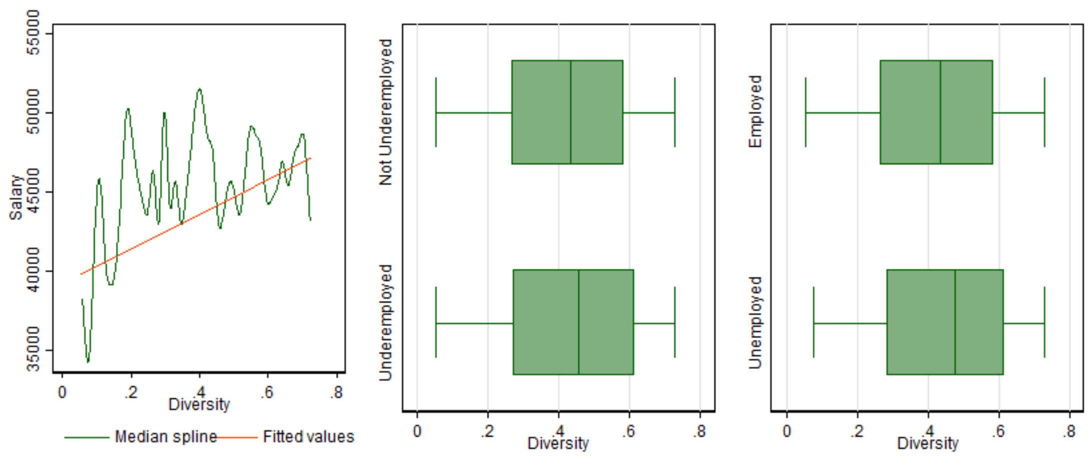

FIGURE 14: Area diversity and labor market outcomes (constant 2010 US dollars).

STEM workforce clusters are disproportionally distributed across the country. More than 90 percent of colleges, in this sample, are located in areas where STEM employment constitutes less than 3.5 percent of local labor force. Higher STEM employment concentration in a college region is associated with higher earnings, $r(17137)= 0.41$, $p<0.01$. Moreover, underemployment (M = 0.007, SD = 0.0004) , $t(17372) = 7.89$, and unemployment (M = 0.084, SD = 0.0003) , $t(18351) = 6.52$, are more likely associated with college areas with smaller STEM labor force (Figure 15). Overall, STEM employment concentration in a college location indicates better labor market outcomes.

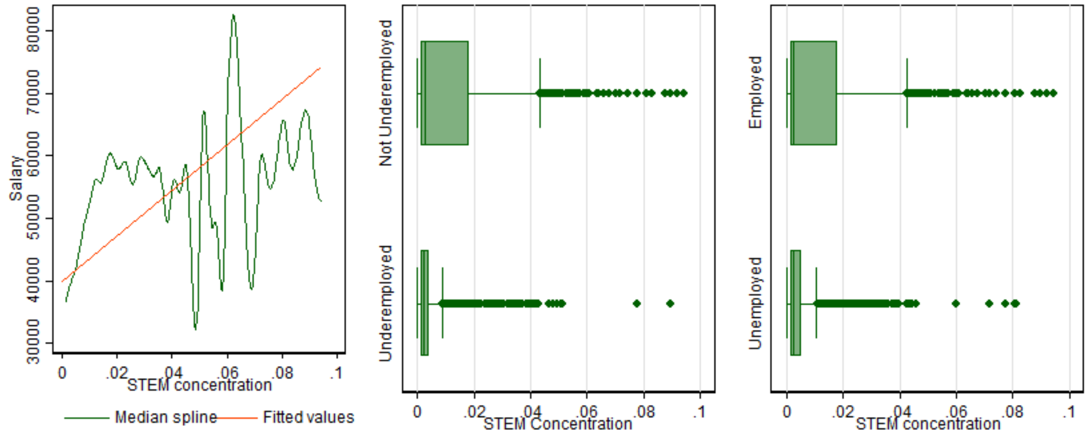

FIGURE 15: STEM concentration and labor market outcomes (constant 2010 US dollars).

Similarly, college proximity to regions with higher STEM employment have a slightly positive relationship to the post-graduation pay, *r*(17615)= 0.06, *p*<0.01. However, closeness to potential job markets is not significantly correlated with either unemployment or underemployment (Figure 16).

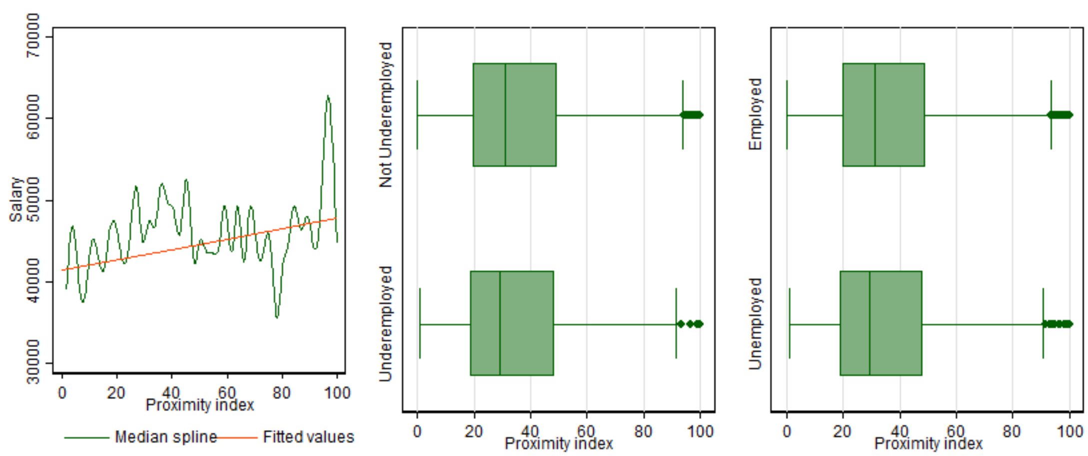

FIGURE 16: Proximity index and labor market outcomes (constant 2010 US dollars).

Almost half of colleges in this sample are in areas with relatively low unemployment rates, under 5 percent. Lower unemployment in college location is positively related to higher salaries, *r*(17169)= 0.03, *p*<0.01. At the same time, colleges located in areas with higher unemployment are correlated with higher underemployment (M = 0.06, SD =

0.0008), $t(17549) = -6.7373$, and unemployment (M = 0.06, SD = 0.0008) , $t(18538) = -7.5994$. Figure 17 illustrates the patterns.

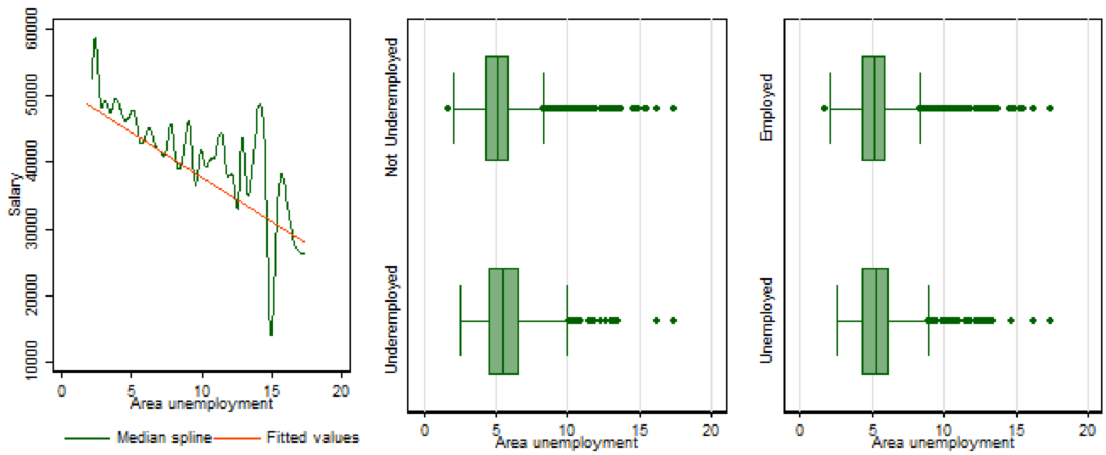

FIGURE 17: Unemployment rate and labor market outcomes (constant 2010 US dollars).

Generally, college area industrial composition is a significant factor related to post-graduation career experiences. For instance, colleges located in areas that specialize in manufacturing industries ($r(17053)= -0.02$, $p<0.01$) have lower-paid graduates. Moreover, the likelihood of underemployment increases significantly in college locations with larger shares of manufacturing (M = 0.04, SD = 0.0005). Figure 18 illustrates such patterns.

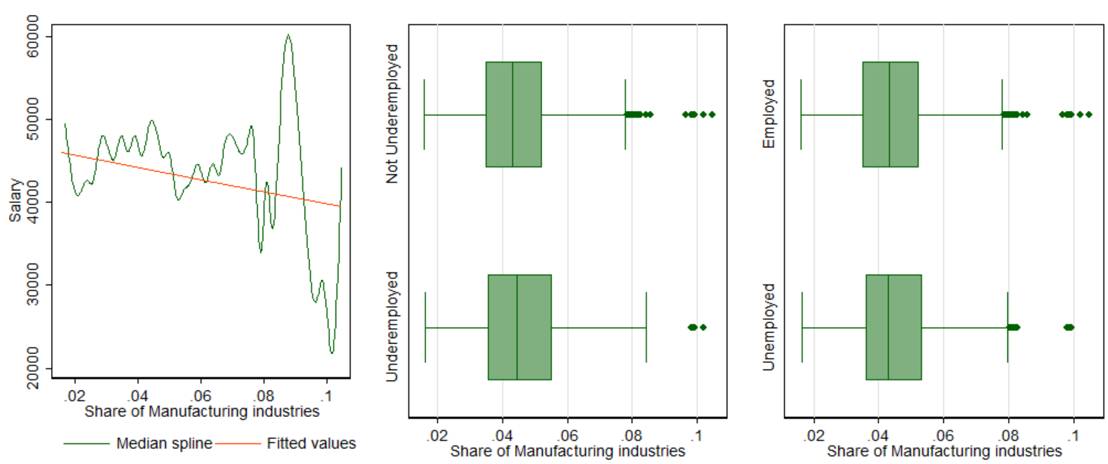

FIGURE 18: Share of manufacturing industries and labor market outcomes (constant 2010 US dollars).

In sum, STEM college graduate labor market experiences vary drastically by college location. On average, areas with larger population size, higher racial diversity, lower unemployment rate, higher STEM employment and closer to STEM clusters, are related to higher job earnings after graduation. But, higher shares of manufacturing in the college area were negatively associated with salary.

The relationship between the geographical factors and college graduates' early career experiences is not consistent across the three measures of labor market outcomes. On average, underemployment and unemployment tend to be more prevalent among those who went to college in large and diverse areas, with higher unemployment rate, manufacturing share and smaller STEM workforce. Again, these relationships are only based on a binary correlation. To further explore their net effects, a hierarchical linear regression is presented in Chapters VII and VIII.

2. Geographic distribution

All the college graduates in the sample are from 182 US metropolitan and nonmetropolitan areas (full list of areas provided in Appendix 2) . The largest MSAs, such as New York (5.6 percent), Los Angeles (4.7 percent), Chicago (3.2 percent), San Francisco (2.3 percent), Boston (2.1 percent) and Washington, DC (1.5 percent), have the largest number of college graduates in this sample. The rest of recent bachelor's recipients are evenly dispersed across the rest of geographical areas in the US (under 2 percent each).

a. Job earnings

The national average salary of all STEM college graduates is $40,524. However, it varies considerably between different college locations (Figure 19). Across all the majors and cohorts represented in this sample, the highest median salaries are in San Luis CA, Cleveland OH, Central Missouri nonmetropolitan area, El Paso TX, Ithaca NY, Trenton NJ, Corvallis OR, Lubbock TX, Baltimore MD and Augusta GA. Graduates in these areas earn on average over than $50,000 per year. Among the areas from where college graduates earn the least are Eastern and Southern Colorado metropolitan areas, Portland OR, Bellingham WA, San Angelo TX, Lynchburg VA, Northern Indiana nonmetropolitan area, Honolulu HI, Santa Cruz CA, San Juan PR and Daytona Beach FL. College graduates from these areas earn a median yearly wage lower than $30,000.

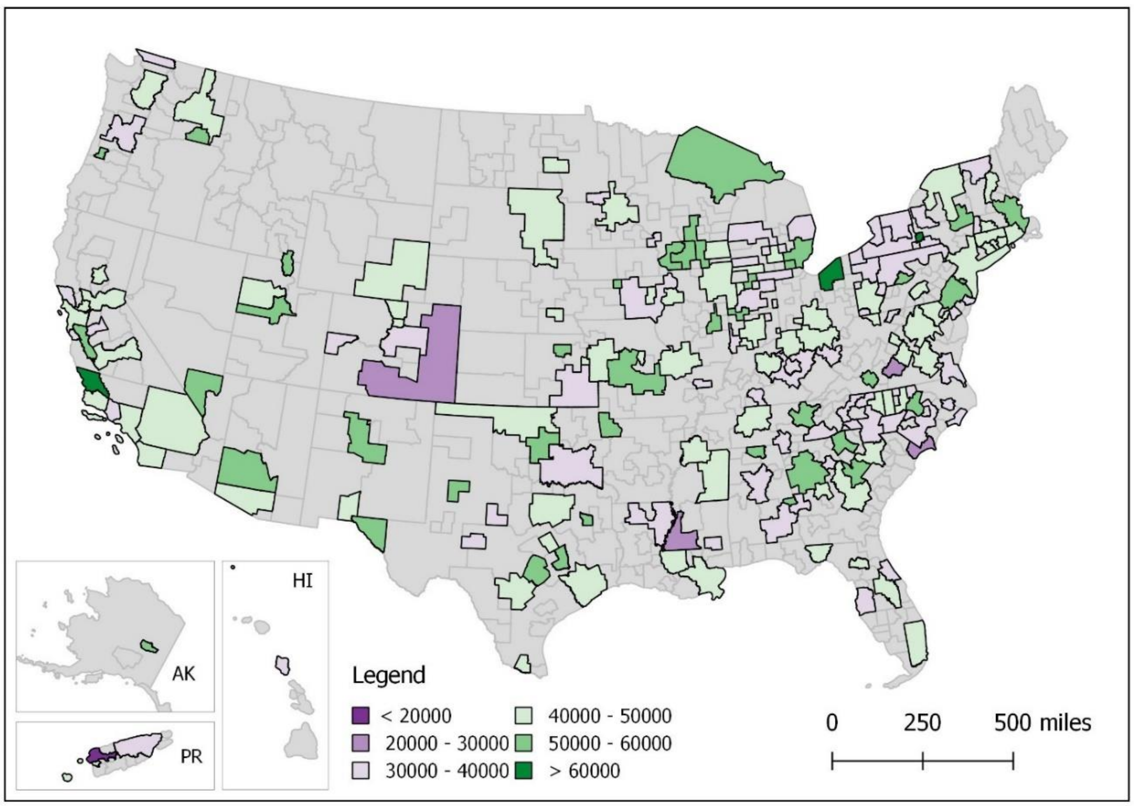

FIGURE 19: Median salary by college location

The distribution of earnings across geographical areas also vary by cohorts. To simplify comparison over-time, cohort-variant median salaries in each area are normalized by grand mean and presented in Figure 20. In the first half of the decade, there is significantly less deviation from grand average and lower variance between geographical areas. This suggests that during this period, average earnings are higher and more evenly distributed across the country.

The average salary varies significantly more among college areas in the last cohort, compared to the previous three. Overall, the average STEM salary decreased significantly and disproportionally across locations in the second half of the 2000s. Most areas that experience the largest drop in average earning during recession are in the Southeast, Rocky Mountain and western New England, Greensboro, NC; San Angelo, TX; South Bend, IN; Grand Junction, CT; Carbondale, IL; Santa Maria, CA; Columbia, SC; Dover, DE; as well as Northeast Mississippi and Northeast Louisiana non-MSA areas

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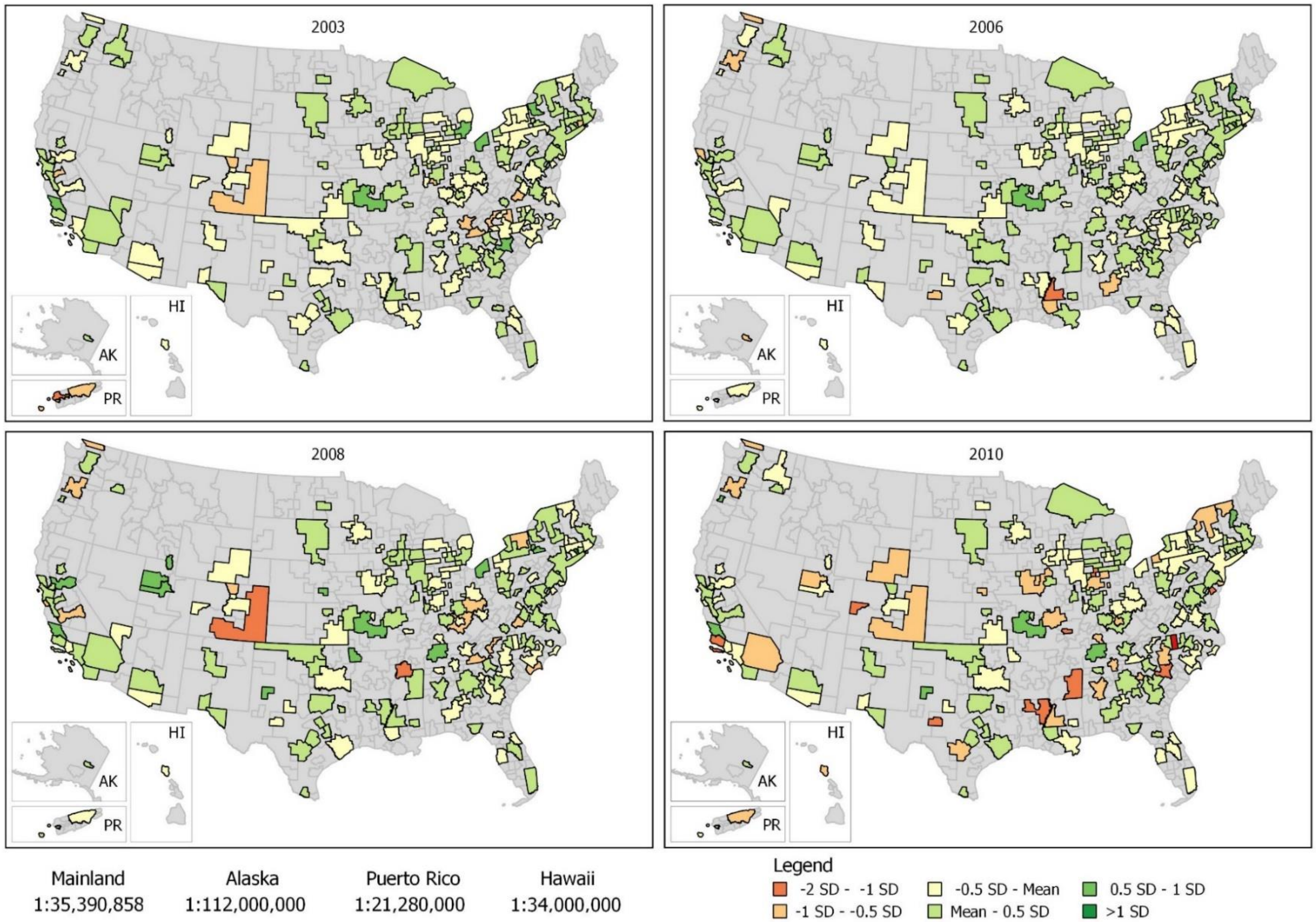

FIGURE 20: Median salary, by area and cohort

The spatial differences in STEM earnings vary by major (Figure 21). Computer science graduates from majority of college locations earn more than the STEM average. The few outliers are Southwest Mississippi and Mayaguez PR, where graduates’ salaries are significantly lower. Life science graduates, on the other hand, have much lower salaries almost in every college location. Only 16 percent of areas average with higher life science salaries than the STEM median pay. Moreover, graduates who earn their life science degree in El Paso, TX and Hattiesburg, MS earn considerably lower salary than graduates from other areas and compared to other majors. Graduates with physical science degrees have a relatively higher than STEM average salary in 40 percent of areas, that are mainly located in the Mideast, New England and California. Physical scientists with degrees from Northeast Louisiana have the lowest salaries compared to other areas and majors.

Social science, on average, is one of the lowest paid STEM majors. However, some college locations average with higher social science salary than STEM median wage. Those areas include New Haven CT, Ithaca NY, San Jose CA, Nashville TN, as well as West Central New Hampshire, Southwest Massachusetts and Southeast Coastal North Carolina non-MSAs. Overall, these geographic differences may reflect different costs of living.

Engineering majors outperform all other majors in terms of earnings. Only three college locations, Dover, DE; Huntington, WV; and San Juan, PR; have graduates with lower salary than STEM median. Health science is the second most lucrative major after engineering. More than 65 percent of areas have graduates with higher than the STEM median salary. The areas below the median are mostly clustered in the Great Lakes, the

Rocky Mountain and the Carolinas regions. The geographical distribution of math science graduates' earnings generally follows the patterns of physical science majors, with exception of some areas in Midwest and Mississippi, where the former earns relatively more.

In sum, life and social science graduates have the largest pay disadvantage, with only a couple of college locations where their outcomes are more favorable. Engineering graduates perform well regardless of where they went to college, while computer scientists fare worse in the South and the Midwest; math and physical science graduates from the Coastal areas are paid relatively more than in other areas; and health science graduates benefit from degree from California, the Southwest and New England.

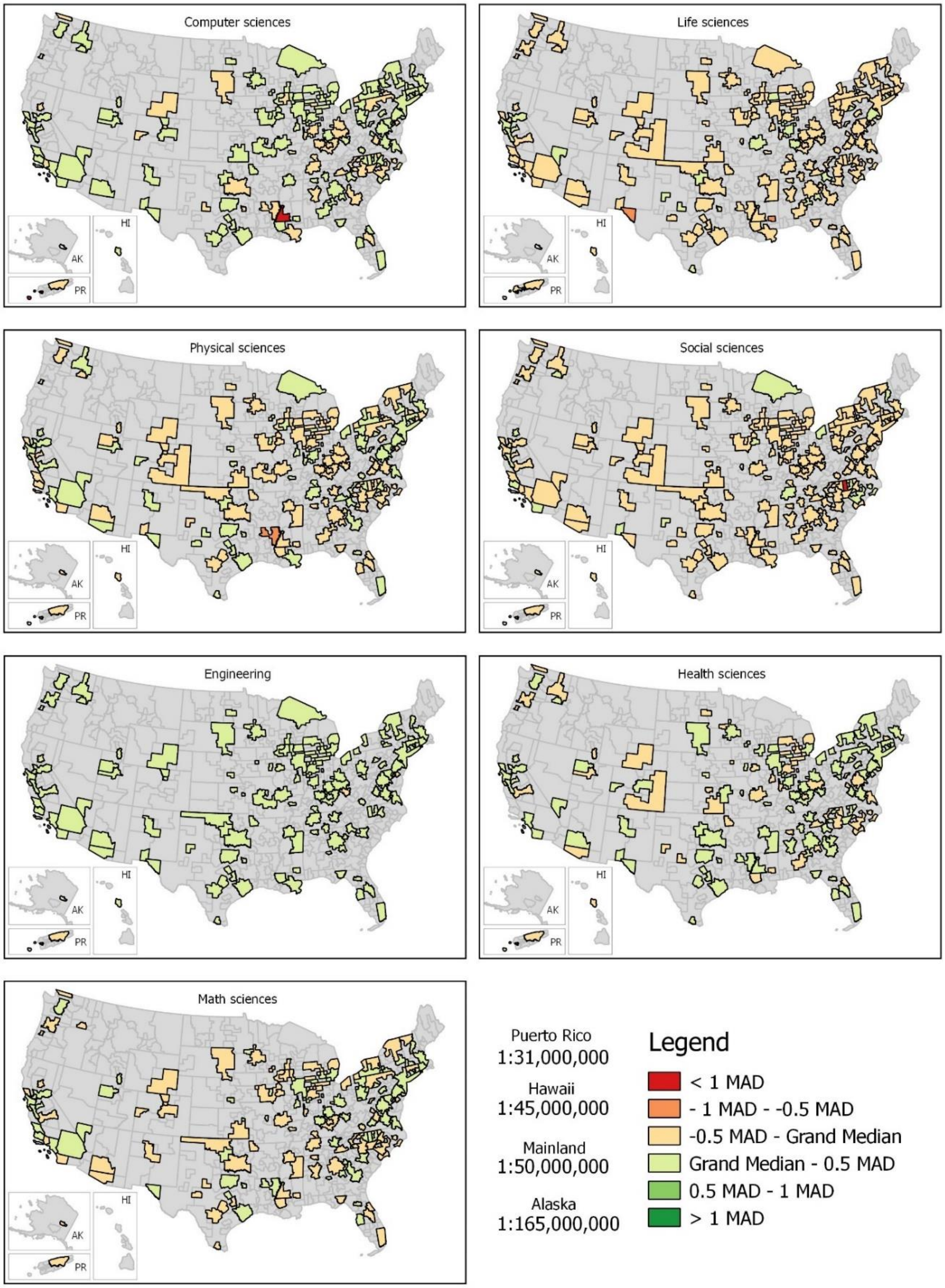

FIGURE 21: Median salary by college location and major

b. Underemployment

The national average underemployment rate in this sample is 4.4 percent. As shown in Figure 22, graduates from some college location are more associated with higher unemployment rate than others, such as Sacramento, CA (16.5 percent); Greensboro, NC (19 percent); Honolulu, HI (14.2 percent); Riverside, CA (11.5 percent); Winston-Salem, NC, (17.3 percent); New Bedford, MA (11.6 percent); Northern Mississippi (13.1 percent) and Northern Vermont (16.4 percent) non-metropolitan areas. Areas with underemployment under 1 percent include Pittsburgh, PA; Provo, UT; Tyler, TX; Kansas City, MO; Abilene, TX and Northwest Massachusetts nonmetropolitan area.

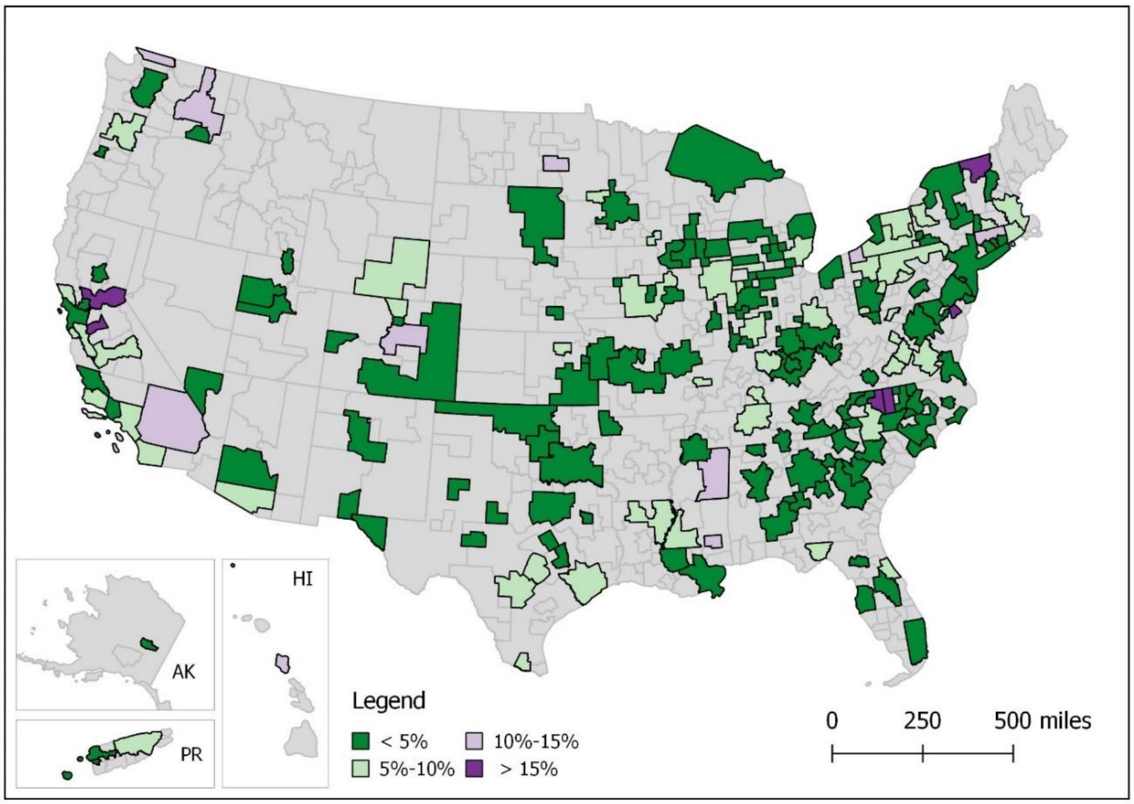

FIGURE 22: Average underemployment rate by college location

The illustration of temporal and spatial distribution of underemployment rate is provided in Figure 23. Generally, fewer graduates are underemployed in the first part of the 2000s. Moreover, underemployment is more evenly dispersed across college locations, with few outliers. For instance, in 2003 cohort, Modesto, CA; San Antonio, TX; Terre Haute, IN; Hattiesburg, MS; Fort Collins, CO; Winston Salem, NC; Albuquerque, NM; Morgantown, WV and Bowling Green, KY have a considerably higher share of underemployed graduates than the sample average. In the next cohort, the highest concentration of underemployed is mostly in the Mideast and the South, including Athens, GA; Charlotte, NC; McAllen, TX; Kalamazoo, MI; Southern Mississippi and Northern Vermont non-MSAs.

In the second half of the decade, underemployment is significantly higher across the country. During the recession, 32 percent of locations have higher underemployment rates than in prior cohorts. Among them are areas in Pacific Northwest, Southern California, Northeast Louisiana, Central Kentucky, Southeast Alabama and large parts of Midwest. Similar to geographical distribution of STEM salary reduction in the last cohort, rise in underemployment is not uniform across the country, but rather clustered in certain regions.

The geographical distribution of underemployment differs drastically between majors (Figure 24). Although computer scientists are among the least likely to be underemployed, those who went to college in Bellingham, WA; Erie, PA; Bridgeport, CT; Southwest Mississippi; Northeast Louisiana; Southeast Alabama and Southern Ohio non-metropolitan areas have a relatively higher chance of being underemployed. Interestingly, computer science majors are considerably less likely to be underemployed if graduated in areas west of Mississippi river. Larger shares of underemployed life science graduates are from colleges in Dover DE, Springfield OH, Hattiesburg MS, Providence RI, Fort Collins CO and Central-Southeast Wyoming. Underemployment in physical sciences is higher in the Great Lakes and Mideast regions, which includes Bridgeport CT, Lansing MI and Northern Pennsylvania. Orlando FL, Honolulu HI, Waco TX, Salt Lake City UT and Southwest Mississippi are also among the areas with disproportionally high underemployment rate among their physical science graduates.

As discussed in earlier chapters, social science degree holders are the most likely to be underemployed on average. In particular, social science graduates who went to colleges in California, Mideast, Honolulu HI, Greensboro NC, Winston Salem, NC, Northeast Mississippi and Northern Vermont have the highest rate of underemployment. In contrast, engineering graduates experience the lowest underemployment than any other major. Only graduates who received their engineering degree in Pittsfield MA, Indianapolis IN and Milwaukee WI are more likely to be underemployed than the average STEM graduates. Similar to the engineering major, health sciences and math are among the least likely to be underemployed; however, their underemployment is highly uneven across the country. For health science graduates, those from Lubbock TX, Bellingham WA, Daytona Beach FL, Winston Salem NC, Houston TX, Tucson AZ, Lawrence KS, Kalamazoo MI and East Washington non-MSA are the most likely to be underemployed. For math science graduates, the underemployed disproportionally graduated from the Great Lakes area and Washington DC.

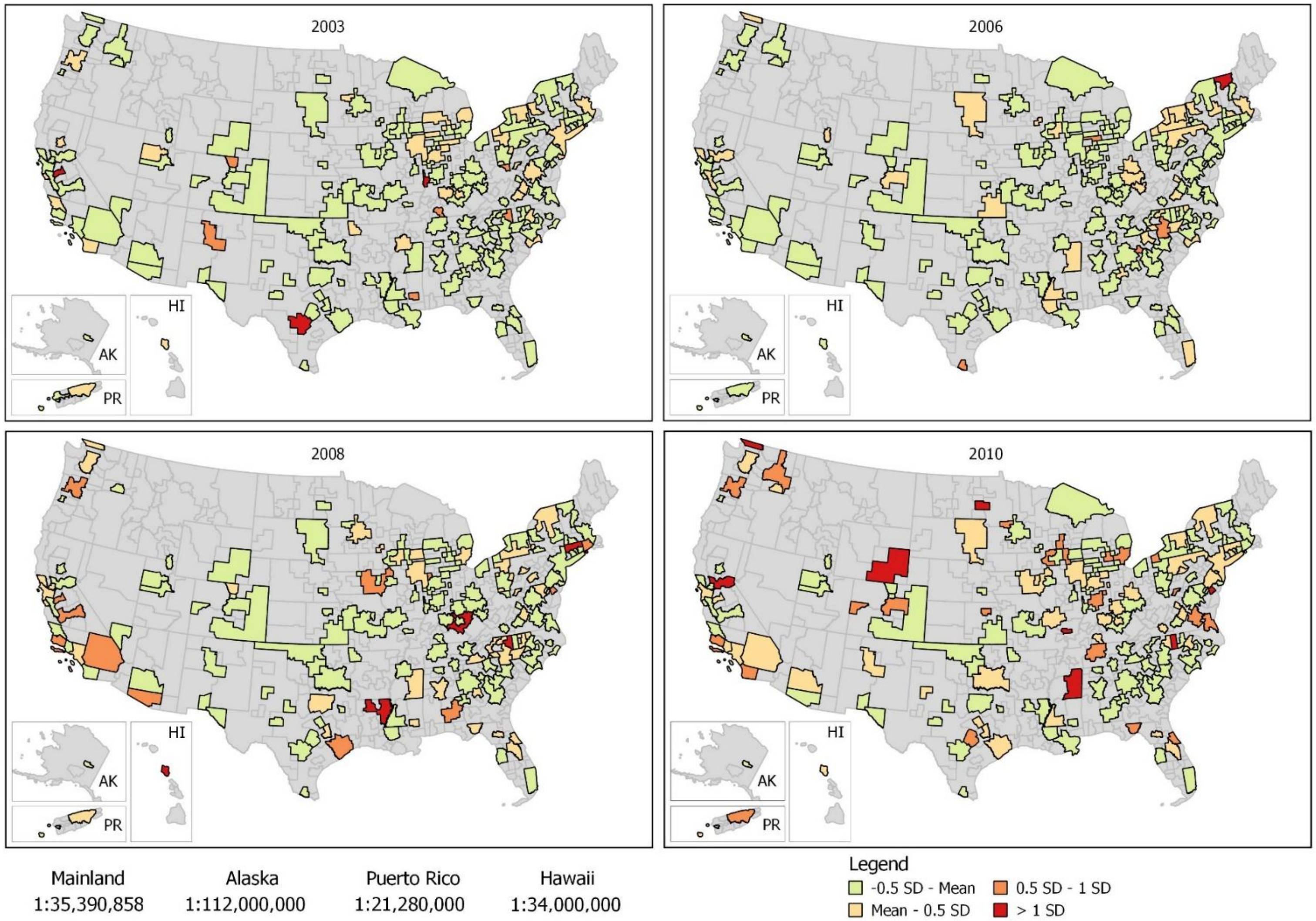

FIGURE 23: Average underemployment rate by college location and cohort.

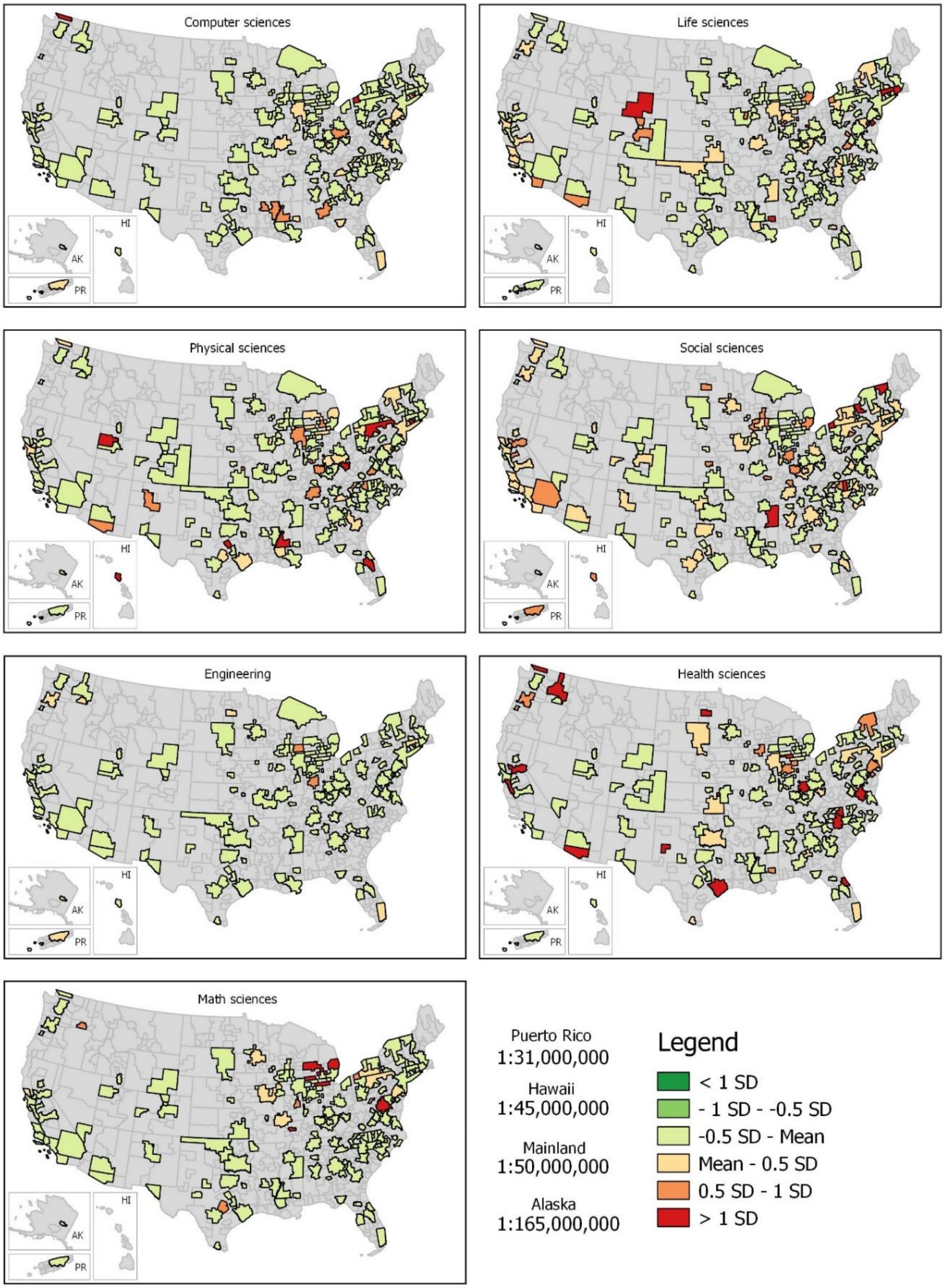

FIGURE 24: Average underemployment rate by college location and major.

c. Unemployment

The average unemployment rate for all majors across four cohorts is 5.2 percent. However, unemployment rate of college graduates is highly uneven across the college geographic areas (Figure 25). New Orleans, LA (20.7 percent); Virginia Beach, VA (18.3 percent); Binghamton, NY (18.2 percent); Providence, RI (14.5 percent); Tampa, FL (13,7 percent); Vallejo, CA (13 percent); Fort Collins, CO (13 percent); Southwest Mississippi (19.4 percent) and Northeast Louisiana nonmetropolitan (15.7 percent) areas have the highest unemployment among bachelor recipients in this sample. Compared to US labor force, unemployment rates in these areas are much higher in this sample than reported unemployment rates by US Census. Augusta, GA; Las Vegas, NV; Kansas City, MO; New Bedford, MA; Milwaukee, WI; Abilene, TX; Columbus, GA; Southeast Coastal North Carolina and Northern Pennsylvania nonmetropolitan areas have the lowest unemployment rates among its college graduates (all under 1 percent).

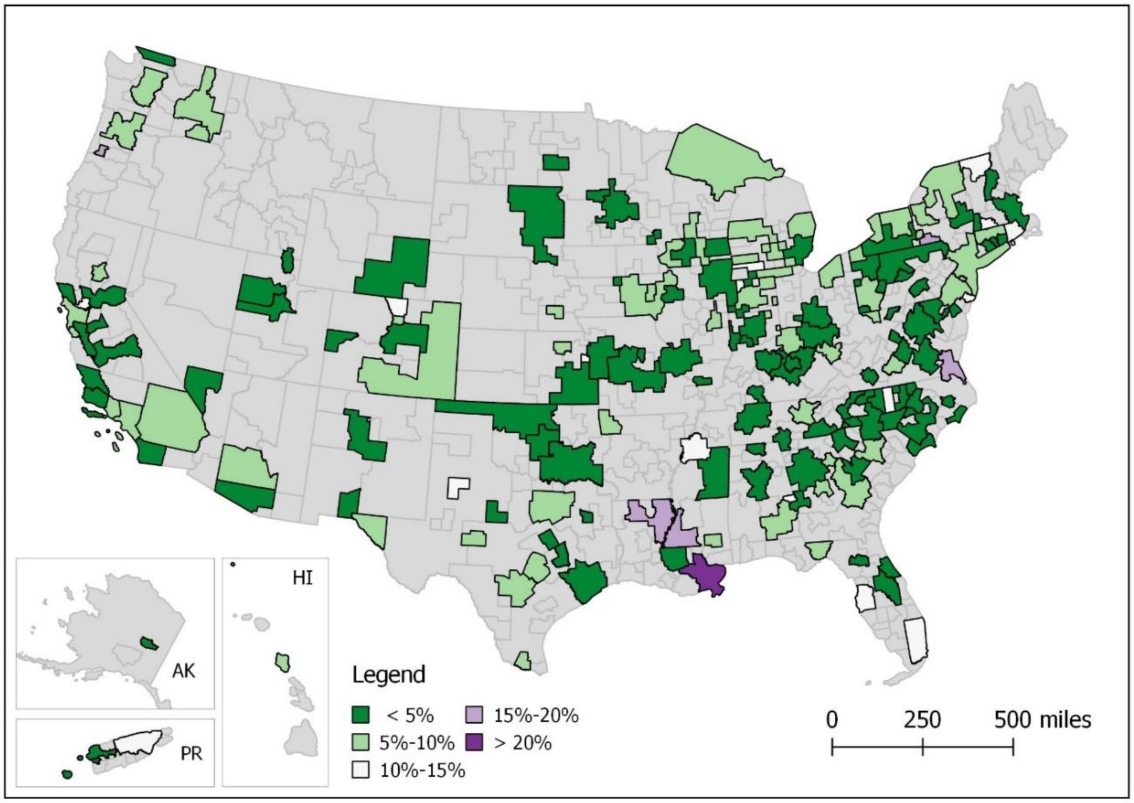

FIGURE 25: Average unemployment rate by college location

The distribution of unemployment over time and space is provided by Figure 26. On average, graduates are more likely to be unemployed in the beginning and the end of the study period, while mid-decade cohorts average with relatively low unemployment. In the 2003 cohort, there are few clusters of unemployment in Louisiana, Mississippi and the Great Lakes region. In 2006-2008 cohorts, unemployment decreases considerably across the most regions of the country, with exception of Southeast Mississippi, where the unemployment rate remains relatively high, and Corvallis, OR; where the rate increases significantly. The last cohort of graduates has the highest rate of unemployment that concentrated in Great Lakes, eastern New England, Louisiana and eastern Colorado regions.

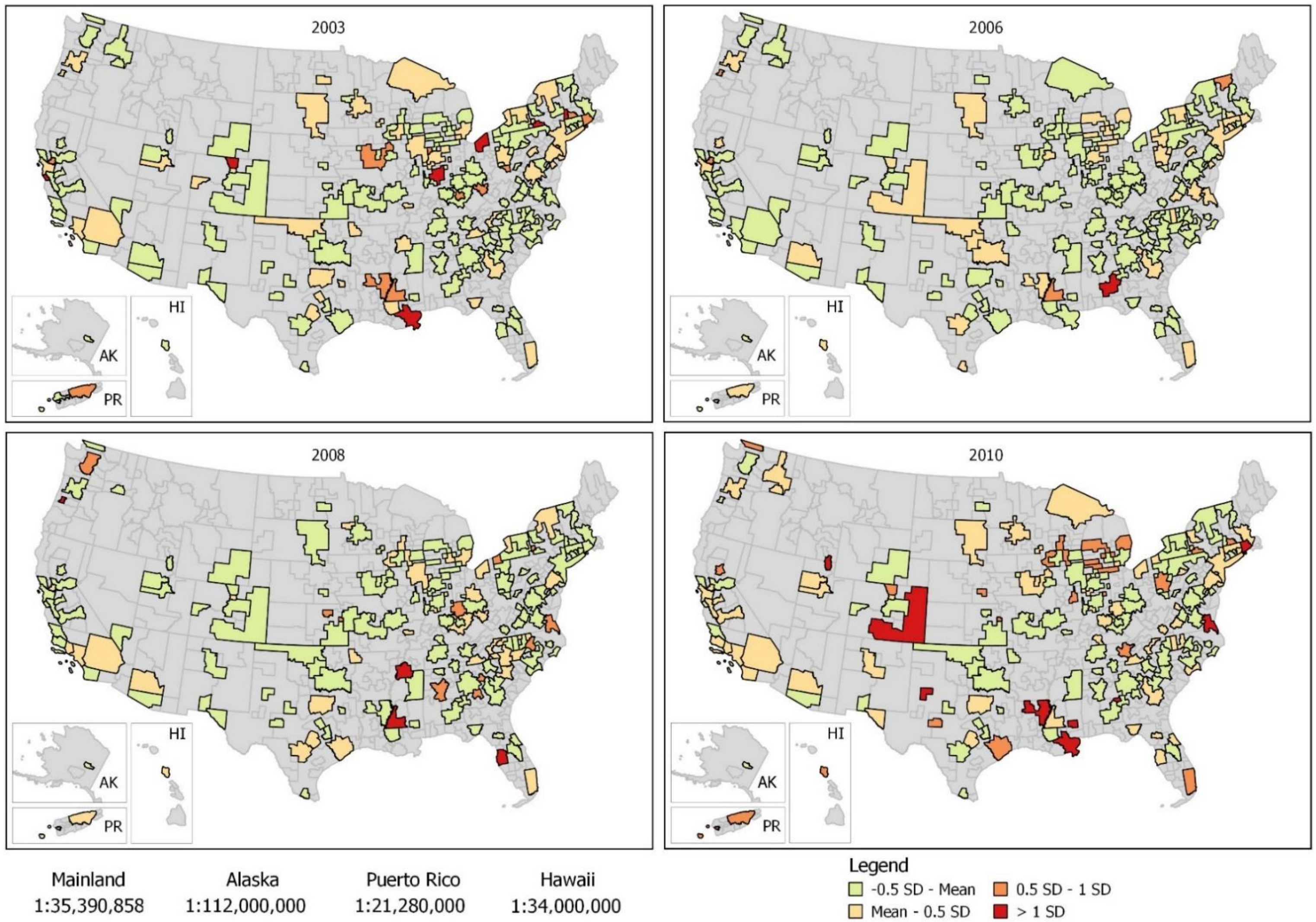

FIGURE 26: Average unemployment rate by college location and cohort

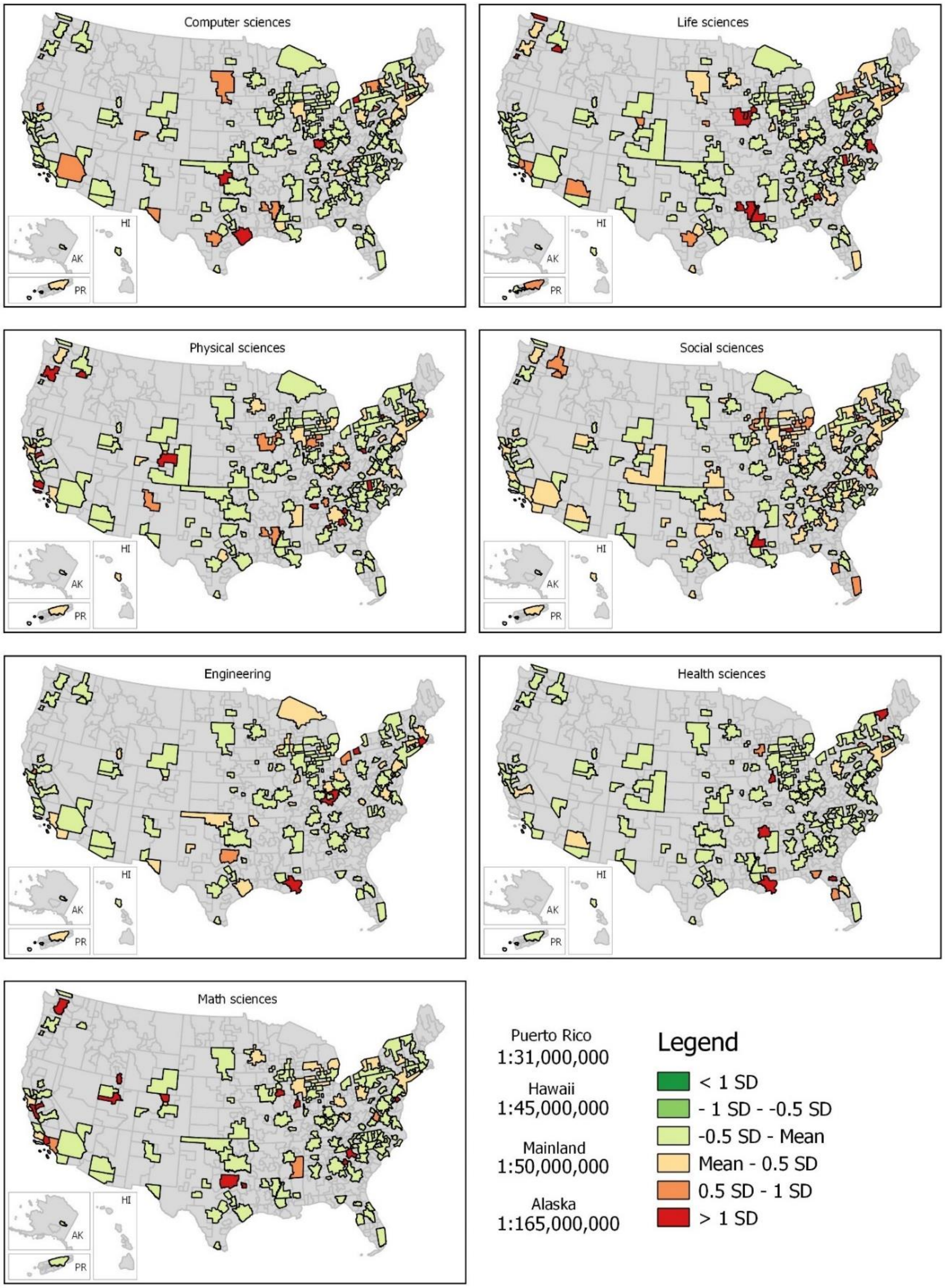

FIGURE 27: Average unemployment rate by college location and major.

The spatial patterns of unemployment by college major are presented in Figure 27. Unemployed computer science graduates are more likely to attend colleges in Oklahoma City, OK; Louisville, KY; Houston, TX; Erie, PA; San Antonio, TX; Riverside CA, East South and Northwest Massachusetts non-metropolitan areas. However, computer science graduates from other areas have a below average unemployment compared to all other STEM majors. Unemployed life science graduates are clustered in the Mideast, New England, Mississippi, Louisiana and concentrated in isolated locations – Macon, GA; Corvallis, OR and Virginia Beach, VA. More than 70 percent of college locations have lower than STEM average unemployment rate for physical science graduates. College locations with a considerably higher share of unemployed physical science graduates are all urban areas – Portland, OR; Modesto, CA; Huntsville, AL; Ithaca, NY; Macon, GA; Greensboro, NC; Denver, CO and Athens, GA.

Generally, unemployment is uncommon among engineering majors. The few areas of concentration are Erie, PA; Providence, RI; New Orleans, LA; Santa Cruz, CA; Dallas, TX; and Central Kentucky non-MSA. Health science graduates are the least likely to be unemployed. Their unemployment only averages higher for graduates from New Orleans, LA; Urbana-Champaign, IL; Gainesville, FL; Memphis, TN and Northern Vermont non-MSA. Only 20 percent of college locations average with higher unemployment for math degree holders. They include Provo, UT; Greenville, SC; Athens, GA; Dover, DE; Logan, UT; Modesto, CA; Tyler, TX; and San Jose, CA;, as areas with highest relative share of unemployed math science graduates.

d. Summary

Overall, several patterns can be drawn: First, the data show significant variations across geographic areas. The correlation between labor market outcomes and different geographic characteristics suggests further investigation on the college location, such as industrial structure, macro-economic strength, STEM labor force concentration, and spatial proximity to STEM employment clusters. Second, sub-disciplines have different labor market outcomes depending on where the colleges are located. In addition to findings from earlier chapters that engineer and health majors enjoyed higher and stable job earnings, low rates of underemployment and unemployment, the results from this chapter suggested that these sub-disciplines also had spatial advantages, earning more in places where salaries are lower than the national average. However, stagnant labor markets and low salaries are prevalent all over the country for social and life sciences, in comparison with other STEM graduates. Third, this chapter does not account for race/ethnicity and gender into the spatial description; however, as we have observed in earlier chapters, gender and racial composition differs significantly across majors, we can expect that the spatial differences in earnings, underemployment, and unemployment had significant implications for racial minorities and women. The next chapters will look into the interaction between these different parameters.

CHAPTER VII: FINDINGS FROM REGRESSION ANALYSIS OF THE TOTAL SAMPLE

1. Job earnings model

This section examines how salaries are contingent upon the characteristics at different levels. During the exploration stage, I start from the unconditional model - Model 0. The unconditional model, which is the one-way ANOVA, provides information on the amount of variation in the outcome that exists within and between institution-locations. The unconditional model indicates that 91.4 percent of variance occurs at level 1 and 8.5 percent at level 2 (Table 8).

TABLE 8: Unconditional model (Y= ln(Salary))

Variable	*B*	*t*-ratio	
Intercept	10.576079 (0.008)	1313.569***	
Random Components	*SD*	Variance	χ^2
Level-2 Residual Variance	0.19889	0.03956	2836.464
Level-1 Residual Variance	0.64922	0.42149	

Then, three models are conducted (refer to Table 10): Model 1 includes only the individual set of controls; Model (2) includes individual and institutional characteristics; and Model (3) includes the full set of variables: individual, institutional, and geographic characteristics. By adding additional predictors to the models 1 and 2, I can check how the model fit improved compared to the unconditional model, and how the relationship between the outcomes and factors at different levels changes.

The variance components for the three models are provided in Table 9. As shown here, by adding individual characteristics in Model 1, the unexplained variance on the level-2 decreases by 75.3 percent. This indicates that the addition of individual factors substantially improves the model fit. The level-2 variance residual decreases by another 45.5 percent when college-location characteristics are added to the model, which suggests that college-level factors explain a considerable amount of variance in earnings between institutions.

In Model 3, the residual variance of level-2 decreases by 26.2 percent, which makes the level-2 unexplained variance smaller than residual variance component of null model by 90.1 percent. Overall, every subsequent model demonstrates a significantly improved goodness-of-fit compared to the null model.

TABLE 9: Variance components for Models 1-3

		Random Components	
		Level-2 Residual Variance	Level-1 Residual Variance
Model (1)	*SD*	0.09873	0.54779
	Variance	0.00975	0.30007
	χ^2	1804.46***	
Model (2)	*SD*	0.07288	0.54816
	Variance	0.00531	0.30048
	χ^2	1577.15***	
Model (3)	*SD*	0.06265	0.54823
	Variance	0.00392	0.30055
	χ^2	1497.67***	

a. Individual level characteristics

Table 10 provides the regression results from the three models. In model 1, most of demographic factors have a significant effect on individuals' post-graduation earnings. Specifically, being married is significantly associated with higher individuals' salary (β =0.045, p<0.01). It is consistent with previous studies where marriage has been found to be economically beneficial by many researchers (Ahituv & Lerman, 2007; Chun & Lee, 2001; Ribar, 2004). Even though the sample is restricted to individuals under 30 years old, age positively and significantly affects person's earnings (β =-0.013, p<0.01). This is also consistent with previous research that finds older labor force members generally have more experience leading to higher wages (Card & DiNardo, 2002; Heywood &

Siebert, 2009). Researchers also find that having children has a positive effect on wages (de Linde Leonard & Stanley, 2015; Dew & Eggebeen, 2010). However, our study does not find having children to be a significant factor (β =-0.023, p=0.149).

As one important form of human capital, higher GPA is significantly related to higher salaries when controlling for other factors (p<0.01). Those with more work experience also have a significantly higher salary (β =-0.009, p<0.01), than those who have just graduated. These findings are consistent with previous literature (Jones & Jackson, 1990), as well as human capital theory (Becker, 1994). This study uses parent educational attainment as a form of social capital. It finds that parental education has a mixed influence on earnings: While a father's higher education has a positive impact on the outcome (β =-0.023, p<0.01), a mother's education is insignificant (β =-0.012, p=0.203). This finding is surprising, considering that mother's low-educational attainment level has been previously found to have negative effects on children's wages (Budig, 2002; Krein, 1986).

Interestingly, graduates who move to another state after graduation tend to have 5.6 percent higher salary than those who remain in a state where they went to college (p<0.01). Using the same dataset, Kazaqi (2016) finds that repeated migration among highly-educated labor force is associated with higher average salary. As expected, in this study, graduates who work in states with higher cost of living, indicated by regional price parities indicator, are more likely to have a higher salary (β =0.007, p<0.01). This study cannot examine the causality between migration and higher salary; however, the finding indicates that a higher spatial mobility was associated with higher economic (probably as well as social) mobility for college graduates.

College major is one of the most important factors for salary, as significant variation in labor market outcomes exist among different STEM majors. Graduates with engineering degrees are the only group that earn more than health majors (β =-0.007, p<0.01). Computer (β =-0.088, p<0.01), life (β =-0.377, p<0.01), physical (β =-0.237, p<0.01), math (β =-0.136, p<0.01) and social (β =-0.323, p<0.01) science majors earn significantly less than health. Such discrepancy in earnings among college majors follows the pattern found in Rumberger and Thomas (1993), who argue that engineering and health majors earn more than any other disciplines, including non-STEM.

Additionally, individuals employed full-year (β =-0.352, p<0.01), full-time (β =-0.777, p<0.01) and in private organizations (β =-0.038, p<0.01) earn more than those with other types of employment. Furthermore, economic recession severely impacts the job earnings. As shown in Model 1, the cohorts in 2006 (β =-0.084, p<0.01), 2008 (β =-0.038, p<0.01) and especially 2010 (β =-0.200, p<0.01) earn less than the first one.

After controlling for all other personal level characteristics, gender and race are still significant parameters for job earnings. Specifically, women earn 8 percent less than men annually (p<0.01). This is unsurprising, considering the overwhelming evidence of persisting gender pay gap (Hill, 2017). Moreover, women dominate two majors – life and social sciences – that pay the lowest wages in this sample. Nevertheless, the gender gap is smaller by 12 percent in this sample than it is reported elsewhere (Hill, 2017).

Among the racial groups, Blacks are the only group that earn significantly less than Whites (β=-0.042, p<0.01). Although Blacks are overrepresented in one of the highest paid sectors – health sciences – they still have a 4 percent lag in salaries compared to Whites. Additionally, Model 1 suggests that Asians earn slightly more (β =0.031, p=0.06) than Whites and Hispanics earn statistically similar wages to Whites. Furthermore, being foreign born is positively associated with higher job earnings (β =0.029, p=0.036).

By adding the college level factors to the model (Model 2), most of the significant predictors, except father's education, remain the same sign; however, the magnitude of coefficients changes considerably. For example, the earnings penalty decreases substantially for women (β =-0.084, p<0.01), Blacks (β =-0.037, p<0.01), computer science graduates (β =-0.085, p<0.01), and 2006 cohort graduates (β =-0.081, p<0.01). In addition, the positive effects of age (β =0.016, p<0.01) and being married (β =0.049, p<0.01) significantly increase.

By adding the location variables to the model (Model 3), female and Black are still significant factors associated with lower job earnings. Among majors, computer science (β =-0.079, p<0.01) and math (β =-0.123, p<0.01) graduates have a significantly higher salary compared to both Models 1 and 2. When comparing cohorts, the salaries in 2006 (β =-0.076, p<0.01) and 2010 (β =-0.180, p<0.01) cohorts are slightly higher than was suggested in previous models that had no location controls. While earnings are lower for 2008 cohort (β =-0.053, p<0.01) in Model 3, compared to what previous models indicate. Such changes are expected, as Black et al. (2009) find that not controlling for labor-market fixed effects, that vary by location, leads to overestimation of change in return to college education, between 1980 and 1990, by 36 percent. Similarly here, the negative effects on salaries are underestimated by 34.9 percent in 2008 cohort and overestimated by 10.6 percent in 2010 cohort in models where locational factors are omitted.

TABLE 10: Hierarchical regression results – ln(Salary)

Dependent variable: Salary in Ln	(1)	(2)	(3)
Individual level:			
Female	-0.087***	-0.084***	-0.085***
	(0.008)	(0.008)	(0.008)
Asian	0.031*	0.018	0.011
	(0.017)	(0.017)	(0.017)
Black	-0.043***	-0.037**	-0.041**
	(0.019)	(0.017)	(0.017)
Hispanic	-0.019	-0.003	-0.006
	(0.014)	(0.013)	(0.013)
Other	-0.004	-0.007	-0.015
	(0.024)	(0.022)	(0.021)
Foreign Born	0.029*	0.026*	0.019
	(0.015)	(0.015)	(0.015)
Married	0.045***	0.050***	0.050***
	(0.011)	(0.011)	(0.011)
Has children	-0.023	-0.016	-0.015
	(0.017)	(0.015)	(0.015)
Age	0.013***	0.016***	0.015***
	(0.003)	(0.003)	(0.003)
Mother has a Bachelor degree	0.012	0.009	0.009
	(0.009)	(0.009)	(0.009)
Father has a Bachelor degree	0.023**	0.016	0.016
	(0.010)	(0.009)	(0.010)
GPA	0.050***	0.051***	0.051***
	(0.005)	(0.005)	(0.005)
Months since graduation	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)
Moved out-of-state	0.057***	0.048***	0.055***
	(0.009)	(0.009)	(0.009)
Regional Price Parities (state of residence)	0.007***	0.007***	0.006***
	(0.001)	(0.001)	(0.001)
Major (health - reference):			
Computer sciences	-0.088***	-0.085***	-0.079***
	(0.027)	(0.027)	(0.027)
Life sciences	-0.377***	-0.388***	-0.376***
	(0.025)	(0.025)	(0.025)
Physical sciences	-0.238***	-0.249***	-0.234***
	(0.024)	(0.024)	(0.024)
Social sciences	-0.324***	-0.339***	-0.329***
	(0.021)	(0.022)	(0.022)
Engineering	0.079***	0.055***	0.066***
	(0.020)	(0.021)	(0.021)
Mathematical sciences	-0.136***	-0.142***	-0.129***
	(0.026)	(0.026)	(0.026)
Employer - private business	0.039***	0.035***	0.036***
	(0.011)	(0.011)	(0.011)

TABLE 10, continued.

Working full week	0.777***	0.776***	0.777***
	(0.024)	(0.025)	(0.025)
Working full year	0.353***	0.353***	0.352***
	(0.023)	(0.023)	(0.023)
Cohorts:			
2006	-0.084***	-0.080***	-0.076***
	(0.013)	(0.013)	(0.011)
2008	-0.039***	-0.039***	-0.053***
	(0.015)	(0.016)	(0.014)
2010	-0.201***	-0.202***	-0.181***
	(0.018)	(0.019)	(0.019)
University level variables:			
Enrollment		0.001***	0.001***
		(0.001)	(0.001)
Diversity index		-0.014	-0.016
		(0.019)	(0.017)
Share of Blacks		-0.053	-0.095***
		(0.044)	(0.046)
Share of Hispanics		-0.145***	-0.087*
		(0.044)	(0.046)
STEM LQ		0.039***	0.027**
		(0.012)	(0.013)
Acceptance Rate		-0.129***	-0.100***
		(0.028)	(0.029)
Private institution		0.0182	0.010
		(0.013)	(0.013)
Research/ Doctoral degree granting institution		0.026484*	0.026454*
		(0.015)	(0.015)
Area level variables:			
Diversity index			-0.154***
			(0.043)
Share of STEM employees			1.643***
			(0.543)
Proximity index			0.006*
			(0.003)
Population			0.001
			(0.005)
Unemployment			-0.018***
			(0.004)
Share of manufacturing			0.380
			(0.411)
N	19149	19149	19149
Note: Robust standard errors presented in parentheses. Significance levels: *** 1%, ** 5%, * 10%.			

b. College characteristics

By controlling for personal characteristics (Model 2), graduates' salary is positively related to larger colleges (β =0.0006, p<0.01). This was consistent with both the descriptive statistics and some prior studies (Pascarella & Terenzini, 2005). However, college ethnic diversity is not a significant factor (β =-0.013, p=0.487) any more after controlling for other characteristics, contradicting the findings from descriptive analysis. That said, in one of the most recent studies on college diversity, Hinrichs (2011) does not find any significant relationship between college diversity and future wages either. Nevertheless, the results still indicate that graduates from colleges that serve larger Hispanic population are likely to earn 14 percent less than those from the institutions with smaller share of Hispanic students (p<0.01).

The academic standards, quality and specific curriculum offers are significant factors. As shown in Model 2, graduates from colleges with STEM concentration are more likely to earn higher salaries (β =-0.039, p<0.01). Individuals who graduate from more selective colleges are more likely to earn significantly higher wages (β =-0.129, p<0.01), as well. This is consistent with most of the prior literature (Pascarella & Terenzini, 2005). Both labor market signaling and better social capital are likely to lead to increase earnings for graduates of selective colleges. Employers may pay graduates from higher status colleges more, due to brand recognizability. At the same time, elite colleges are likely to provide enhanced social capital to its graduates, which may also contribute to increased earnings (Waters, 2005, 2007).

Inconsistently with previous research, attending a private institution, as opposite to a public college, is not associated with increased earnings for STEM graduates (β =-0.039, *p*<0.01). However, graduating from a research and doctoral institutions, as opposite to non-research four-year institutions, does not have a significant influence on one's earnings at the alpha level of 0.5 (β =-0.026, *p*=0.09).

In Model 3, where personal characteristics and location factors are controlled for, university size (β =0.0004, *p*<0.01), STEM concentration (β =0.027, *p*<0.01) and college acceptance rate are still significant parameters (β =0.027, *p*<0.01). Interestingly, share of Blacks (β =-0.949, *p*<0.01) in a college becomes a significant predictor of earnings, while the share of Hispanics (β =-0.087, *p*=0.09) is not. These relationships are also predicted by the earlier descriptive analysis.

c. Location characteristics

Model 3 provides the results of location characteristics after controlling for personal and college factors. Unlike college diversity, the ethnic diversity of the place where the college is located presents a significant negative relationship to post-graduation earnings (β =-0.154, *p*<0.01), which is consistent with the descriptive analysis. This finding is surprising, considering that many researchers find that cultural diversity leads to increase in wages in the region (Ottaviano & Peri, 2005, 2006). Moreover, other results suggest that such diversity leads to increase in research and development activity (Niebuhr, 2010), which in turn may lead to economic gains. One of the possible explanations to this discrepancy is the level of analysis. The existing studies on ethnic diversity and wage-level are conducted at the aggregated level, estimating the effect of diversity factors on average regional earnings. The current study is conducted at the individual level. Moreover, the sample of this study is limited to a specific and relatively homogeneous population sample, which is not representative of the total labor force of a given area.

The population size is not a significant factor for graduate's salary (β =-0.0009, p=0.843). This is consistent with Black et al.'s study (2009) that find that MSA population has a marginal and insignificant influence on salaries. However, the local labor market conditions are significantly related to college graduates' job earnings. For instance, a one percent of increase in share of STEM workers in the area where a college is located increases one's salary by 164 percent (p<0.01). Regarding STEM employment, areas with concentration of high-technology employment tend to have higher average wages (Freedman, 2008), which may explain such a substantial wage premiums for graduates in those areas. As shown in Figure 28, the predicted job earnings for genders differ when the percentage of STEM increases in a college area. As STEM concentration increases in a metropolitan area, the salary disparities between men and women decrease.

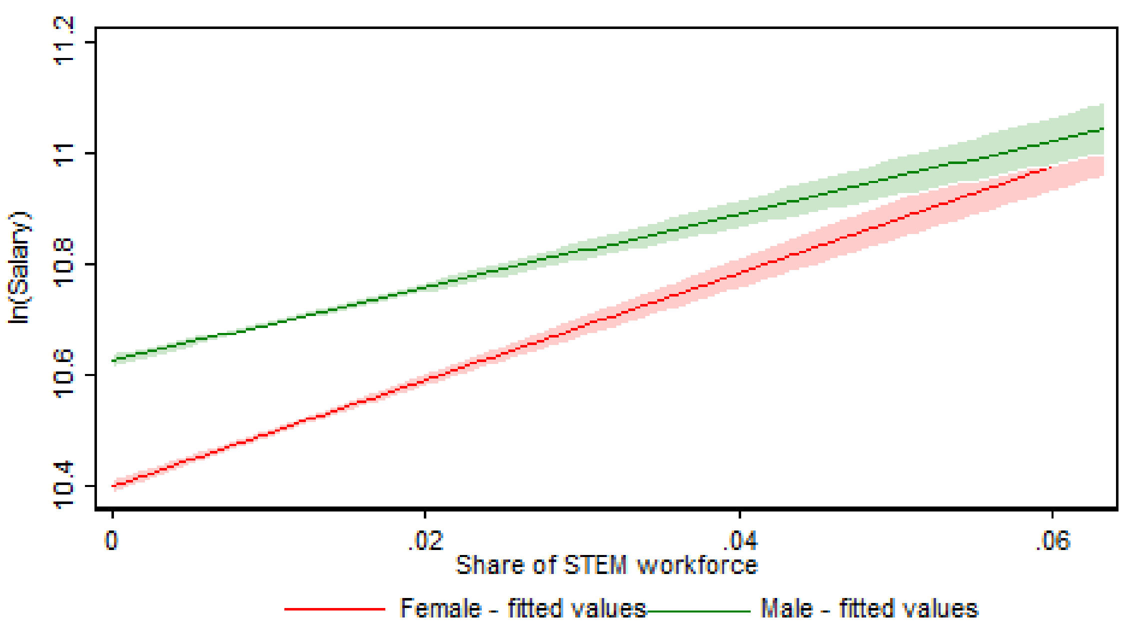

FIGURE 28: Predicted values of ln(Salary) by gender and STEM workforce concentration

Similarly, proximity to labor markets that hire a considerable number of STEM workers is slightly associated with higher post-graduation salary (β =0.0005, p=0.08). Considering that more than 70 percent of graduates stay in the state where they went to college, closeness to places with higher share of STEM employment may constitute a better job market for these graduates.

Overall, the results indicate that a significant portion of the between-college differences in salary can be attributed to college geographical factors. Indeed, the addition of location variables explained 26.2 percent more of level-2 residual variance, compared to controlling only for institutional variables. Graduates from locations that specialize in STEM have a higher salary, while those from the areas with higher unemployment rate and racial diversity tend to earn significantly less. This geographic dimension has never been explored in previous studies.

2. Underemployment

This section presents the MLM results on underemployment and unemployment analyses. The regressions results are provided in Table 11. At the individual level, female (β =0.242, p<0.01), black (β =0.347, p<0.01) and the foreign born (β =0.234, p=0.048) are more likely to work part-time involuntarily, while individuals whose father has a bachelor degree (β =-0.184, p=0.049), have higher GPA (β =-0.184, p=0.020), has more experience (β =-0.170, p<0.01) and moved out-of-state post-graduation (β =-0.353, p<0.01) are less likely to be underemployed. The gender effect is consistent with previous research that women are more likely to work part-time (Kalleberg, 2000) and reluctance to move for another job (Bielby & Bielby, 1992). The gender and racial differences are consistent with what is found with the job earning models.

There is no significant difference in underemployment prospects between majors, with exception of engineering graduates. Engineering graduates are 69 percent less likely to be underemployed than health science graduates (β =-1.158, p<0.01). Again, this result indicates the advantage of engineering majors who also earn higher salaries than most other STEM sub-disciplines.

The temporal trend is similar to that in the salary model and consistent with the descriptive analyses. Graduates in 2006 cohort are 1.48 times more likely to underemployed than those in 2003 cohort (β =0.391, p<0.01). The odds for the 2010 cohort increase even more (β =0.907, p<0.01). As indicated earlier by the description, this temporal trend reflects the economic recession effect.

Unlike the results from the salary models, none of the higher education institutional factors are significant predictors for underemployment. In contrast, the macro economic conditions at the places where the colleges are located make the differences. For example, a STEM specialization in the college location is negatively related to underemployment (β =-15.205, p<0.01). That is, in a regional labor market that is specialized in STEM industries, it is easier for graduates to find full-time employment. On the contrary, a larger workforce employed in manufacturing is significantly related to a higher probability of underemployment (β =-6.700, p=0.05). It reflects that concentration of manufacturing sectors may present an unfavorable job market for STEM graduates whose specialization does not align with jobs in these industries.

Figure 29 presents the predicted probability of underemployment for gender groups (30A) and racial groups (30B) as the STEM workforce percentage increases in an area where a college was located. As shown here, both men and women benefit significantly from STEM employment concentration, however even though women are affected the most by this factor, the underemployment gap persists even in areas with very high STEM concentration. As for racial differences, areas with low STEM employment on average have more part-time workers across all groups, with Blacks being the most likely to be underemployed and Asians the least. However, when looking at areas specialized in STEM industries, underemployment decreases for everybody, but, it especially benefits Black graduates.

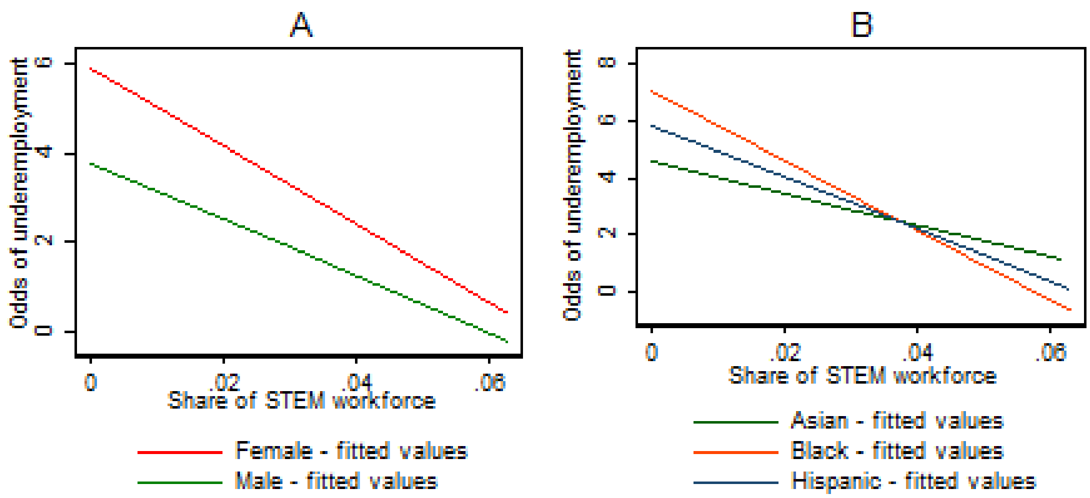

FIGURE 29: Predicted odds of underemployment by gender, race/ethnicity and STEM workforce concentration

Overall, underemployment of college graduates is to a large extent determined by the local or regional labor market characteristics of the area where the college was located. None of the college level variables have a significant effect on the outcome. Moreover, the comparison of explained variance indicated that geographical characteristics explain 83.4 percent of variance at level-2, while controlling for all other factors.

3. Unemployment

The unemployment model (Table 11) suggests slightly different results compared to underemployment model. Asian (β =0.406, p<0.01) and Black (β =0.291, p<0.01) graduates are more likely to be unemployed than their White counterparts. This corresponds with descriptive averages of unemployment across racial groups that shows that Asians and Blacks are more likely to be unemployed than Whites. Considering that both Asian and Blacks are overrepresented in STEM sectors that are in constant shortage of labor – computer and health sciences, respectively – they have higher rates of joblessness in other sectors.

At the individual level, married graduates are more likely to be employed (β =-0.353, p<0.01), but those who have children are in the opposite position (β =0.126, p=0.03). This is consistent with previous studies on effects of marriage and parenthood on employment status (Livanos, Yalkin, & Nuñez, 2009; Stjärnfäldt, 2016; Waite, Haggstrom, & Kanouse, 1986). Both graduates with higher GPA (β =-0.178, p<0.01) and more experience (β =-0.023, p<0.01) have a better luck in the labor market. Additionally, older graduates are more likely to be jobless (β =-0.072, p<0.01). Computer (β =0.676, p<0.01), life (β =0.981, p<0.01), physical (β =0.940, p<0.01), social (β =0.943, p<0.01), engineering (β =0.477, p=0.03), and math (β =-0.736, p<0.01) science graduates are all more likely to be unemployed than health sciences, which again is likely due to the perpetual shortage of nursing workers.

Among cohorts, graduates in 2006 cohort (β =-0.438, p<0.01) are the least likely to be unemployed and the 2010 are the most (β =-0.518, p<0.01). This confirms the previous findings on STEM joblessness, where Langdon et al. (2011) states that STEM graduates have experienced higher unemployment during two latest economic recessions.

At the university institutional level, graduates from colleges with larger Black student population are 1.33 times more likely to be unemployed (β =-0.290, p=0.02), if holding other conditions the same. Also, surprisingly, graduates from the research and doctoral-degree granting colleges are more likely to be jobless (β =-0.269, p=0.02) as well. No other significant factors at the college level are identified.

Similar to the salary and underemployment models, at the college location, share of STEM workers has a negative impact on the odds of unemployment (β =-13.445, p<0.01). This is consistent with localization theory and Freedman's (2008) findings on job hopping of workers in high-tech clusters. As shown by Figure 30, like underemployment, odds of unemployment in association of STEM concentration vary by gender, with women benefiting from such specialization more than men (31A). Similarly, Black graduates are positively affected by attending college in a STEM cluster area more than other minorities (31B). Obviously, gender and racial disparities change significantly with the change of STEM employment concentration.

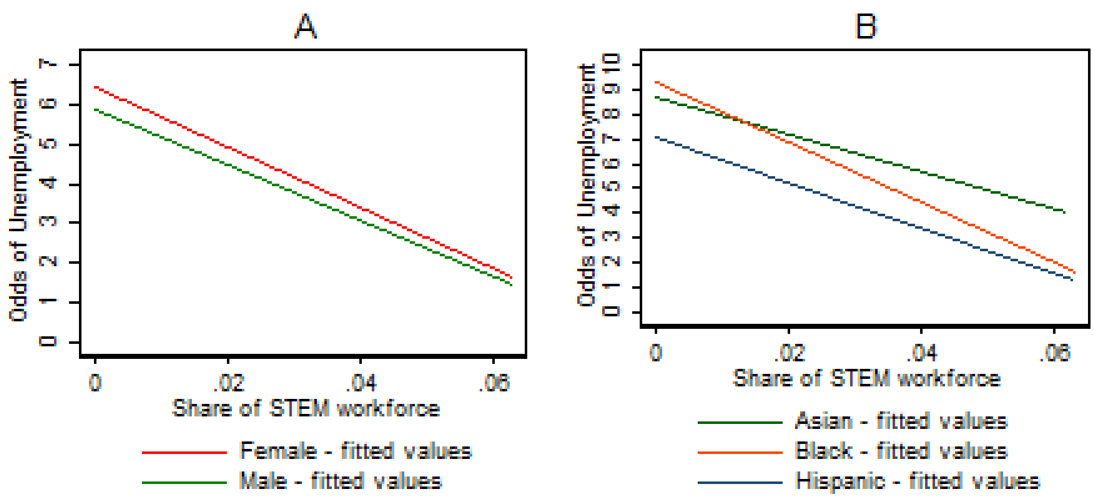

FIGURE 30: Predicted odds of unemployment by gender, race/ethnicity as STEM workforce concentration increases

Areas specialized in manufacturing are more likely to have more unemployed graduates (β =7.377, p=0.02). Similar to the underemployment model, the overall effect of locational factors on unemployment outcome are substantial. Specifically, geographical parameters at the level 2 explain 24.2 percent of variance, while institutional variables explained 23.5 percent.

TABLE 11: Hierarchical regression results – underemployment and unemployment models.

Fixed effects	Dependent variable:	
	Underemployed	Unemployed
Individual level:		
Female	0.242***	0.051
	(0.086)	(0.075)
Asian	-0.091	0.406***
	(0.155)	(0.125)
Black	0.347***	0.291**
	(0.135)	(0.122)
Hispanic	0.126	0.101
	(0.132)	(0.117)
Other	0.287	0.455***
	(0.196)	(0.148)
Foreign Born	0.234***	0.170*
	(0.118)	(0.102)
Married	-0.192	-0.353***
	(0.125)	(0.104)
Has children	0.045	0.277**
	(0.143)	(0.126)
Age	-0.012	0.072***
	(0.028)	(0.025)
Mother has a Bachelor degree	0.069	-0.071
	(0.093)	(0.078)
Father has a Bachelor degree	-0.184***	0.035
	(0.093)	(0.080)
GPA	-0.105***	-0.178***
	(0.045)	(0.039)
Months since graduation	-0.017***	-0.023***
	(0.001)	(0.005)
Moved out-of-state	-0.353***	-0.127
	(0.101)	(0.084)
Regional Price Parities (state of residence)	0.003	0.002
	(0.001)	(0.005)

TABLE 11, continued.

Major (health - reference):		
Computer sciences	-0.330	0.676**
	(0.234)	(0.255)
Life sciences	0.116	0.982***
	(0.195)	(0.228)
Physical sciences	0.128	0.940***
	(0.197)	(0.232)
Social sciences	0.237	0.943***
	(0.175)	(0.215)
Engineering	-1.158***	0.477**
	(0.202)	(0.215)
Mathematical sciences	-0.375	0.736***
	(0.269)	(0.261)
Employer - private business	-0.067	
	(0.089)	
Cohorts:		
2006	-0.107	-0.439***
	(0.126)	(0.106)
2008	0.392***	-0.056
	(0.141)	(0.120)
2010	0.908***	0.519***
	(0.144)	(0.114)
University level variables:		
Enrollment	0.001	-0.002*
	(0.001)	(0.001)
Diversity index	0.353*	0.125
	(0.192)	(0.106)
Share of Blacks	0.193	0.693***
	(0.347)	(0.254)
Share of Hispanics	0.482	0.419
	(0.416)	(0.292)
STEM LQ	-0.161	-0.040
	(0.114)	(0.091)
Acceptance Rate	0.131	-0.167
	(0.265)	(0.210)
Private institution	-0.020	-0.156
	(0.116)	(0.098)
Research/ Doctoral institution	-0.090	0.269***
	(0.133)	(0.103)

TABLE 11, continued.

Area level variables:		
Diversity index	0.567	0.275
	(0.390)	(0.314)
Share of STEM employees	-15.204***	-13.445
	(5.89)	(4.988)
Proximity index	-0.015	0.011
	(0.031)	(0.026)
Population	0.042	0.005
	(0.039)	(0.032)
Unemployment	0.034	0.040
	(0.034)	(0.027)
Manufacturing	6.700***	7.377**
	(3.425)	(3.086)
N	19149	19149
Note: Robust standard errors presented in parentheses. Significance levels: *** 1%, ** 5%, * 10%.		

4. Summary

Among individual factors, both race and gender play major roles in all three dimensions of labor market outcomes. Female and Black graduates appear to be the most disadvantaged groups. Women are more likely to be unemployed and earn on average approximately 8 percent less than men, while Blacks earn 4 percent less than Whites and are 1.3 times more likely to be unemployed and 1.4 times underemployed. Asians had a significant disadvantage in employment as well, being 1.5 times more likely to be unemployed.

For salary, many institutional factors are significant predictors of graduate's earnings. For instance, college size, selectivity and specialization in STEM have an overwhelmingly positive relationship with job earnings, while larger Black student enrollment have an opposite effect. Institutional level characteristics are not significant factors with only larger Black student enrollment having a negative impact. The insignificance of institutional characteristics is similar to that for the underemployment model.

Location makes a lot of difference, especially for unemployment and underemployment outcomes. College area economic health and STEM specialization are the most influential determinants of graduates' early careers on geographic level. This raises a question of how higher education is involved in local and regional economic development. There is an older debate of "town and gown" which questions a HEI's role in local and regional economy. The current research indicated that college STEM graduates' labor market turnover is closely related to the regional economy.

CHAPTER VIII: ANALYSIS BY MAJOR WITHIN STEM

This chapter provides the results of analysis disaggregated by STEM sub-disciplines. Considering the heterogeneity of STEM majors included in this sample, as well as considerable variability in average earnings, unemployment and underemployment rates reported by descriptive analysis, significant differences in the outcomes between these major groups are expected.

1. Salary

    a. Computer science

GPA (β =-0.083, p<0.01), work experience (β =-0.007, p<0.01), and working full-year (β =-0.325, p<0.01) or full-week (β =-0.897, p<0.01) has a positive association with salary. After controlling for these characteristics, gender and racial differences are still significant. Women not only are underrepresented in computer science occupations, they earn significantly less than men. Specifically, after controlling for other characteristics, women earn almost 9 percent less than men. This is consistent with Beede et al. (2011). Using 2009 American Community Survey data, they find that women in computer science occupations earn 12 percent less than men when controlling for age, education and region of residence. As for racial differences, although Black (β =-0.204, p<0.01), Hispanic (β =-0.148, p=0.01) and White graduates are statistically equally represented in computer science disciplines, their salaries differ significantly, with Blacks earning 20 percent and Hispanics 14 percent less than their White counterparts.

At the institutional level, the patterns are similar to the general model. Both higher racial diversity (β =-0.189, p=0.03) and higher share of Hispanic students (β =-0.512, *p*=0.01) are associated with lower pay, while STEM specialization (β =-0.101, *p*=0.05) and college size (β =-0.002, *p*<0.01) are associated with higher post-graduation earnings. Among geographical factors, only the unemployment rate is significantly associated with the salary for computer scientists. That is, as the unemployment rate increased by 1 percent, the job earnings for computer science graduates decrease by 4 percent (β =-0.040, *p*=0.02).

b. Life science

At the individual level, those with more experience (β =0.013, *p*<0.01), who move out-of-state post-graduation (β =0.082, *p*=0.02), work full-year (β =-0.418, *p*<0.01) and full-week (β =-0.683, *p*<0.01) are likely to earn more. Graduates in 2006 (β =-0.092, *p*<0.01) and 2010 (β =-0.271, *p*<0.01) cohorts are more likely to earn less than those in 2003 cohort. After controlling for the individual characteristics, gender is still a significant factor. Female life science graduates (β =-0.148, *p*<0.01), who constitute the majority in this discipline, earn significantly less than their male counterparts. Moreover, the gender difference in pay constitute the widest gender pay gap when compared to all other majors. Beede et al. (2011) find that women with life science degrees earn only 8 percent less than men. The current study finds a much bigger gap as female life scientists earn almost 15 percent less than men. There are no significant racial difference of job earnings in life science discipline.

At the institution level, life science graduates from larger (β =0.001, *p*<0.01) and private (β =0.102, *p*=0.05) universities tend to earn more, while those who attend colleges with higher concentration of Hispanics (β =-0.016, *p*=0.01) are likely to earn significantly less. At the college location level, there are no significant factors except that ethnic diversity is negatively associated with job earnings. These negative effects are consistent with findings for all STEM graduates.

c. Physical science

Like other majors, women with physical (β =-0.112, p<0.01) science degrees earn 11 percent less than men, after controlling for other characteristics. While married individuals (β =0.099, p=0.01) tend to earn more, those with children have lesser pay (β =-0.123, p=0.03). Older physical science graduates also have a pay advantage (β =0.039, p=0.03), so as those with more experience (β =-0.394, p=0.03). Full-year workers (β =0.032, p<0.01) earn 32 percent more than those who work part-year, while those employed full-week (β =0.998, p<0.01) earn almost twice as much as than those who work part-time. After controlling for these characteristics, racial differences are not found for physical science. None of the variables at the level-2 had a significant relationship with physical science graduates' earnings.

d. Social sciences

Similar to other disciplines, GPA (β =0.045, p<0.01), work experience (β =0.001, p<0.01), and working full-year (β =0.397, p<0.01) and full-week (β =0.714, p<0.01) have a positive significant relationship with salary. Both being married (β =0.084, p<0.01) and older age (β =0.018, p<0.01) are likely to earn more, compared to single and younger graduates, respectively. After controlling for other conditions, gender is still a significant predictor. Specifically, female social science graduates earn 14 percent less than their male counterparts. (β =-0.141, p<0.01). It is worth noting that even within social sciences, women are highly concentrated in lower paying sub-disciplines as men are more likely to major in economics and related sciences that usually lead to higher paid jobs (Weinberger, 1999). Again, no significant racial differences in job earnings are identified.

Graduates in the first cohort earned 10 percent more than 2006 cohort (β =-0.102, p<0.01), 12 percent more than the 2008 cohort (β =-0.124, p<0.01) and 27 percent more than the last cohort (β =-0.273, p<0.01). This indicates that there was a downward trend in the salaries of social science graduates.

At the institutional level, only the acceptance rate was significantly related to earnings (β =-0.269, p<0.01). Among the location factors, graduates who went to college in areas with higher unemployment tended to earn less (β =-0.02, p=0.02). Furthermore, those who attended colleges in locations close to other areas with high STEM concentration (β =0.016, p<0.01) were likely to earn 16 percent more than those from more isolated areas.

e. Engineering

At the individual level, graduates who move to other state (β =0.072, p<0.01), have higher GPAs (β =0.053, p<0.01) and more experience (β =0.007, p<0.01), being married (β =0.033, p<0.01), employed in in private business (β =0.120, p<0.01), work full-year (β =0.284, p<0.01) and full-week (β =0.901, p<0.01) have a significantly higher salary than those who do not have these features. On average, 2006 (β =-0.039, p<0.01) and 2010 (β =-0.091, p<0.01) cohorts of engineering graduates have the lowest pay.

After controlling for other characteristics, female engineering graduates earn slightly less than men (β =-0.026, p=0.02), which is the smallest difference in salaries between male and female STEM graduates, even though women are largely underrepresented in this field. Again, no significant racial differences are identified.

At the institutional level, college size is positively related to engineering graduates' salary (β =0.001, p=0.02). Higher percentage of Hispanic student population has a negative relationship with job earnings (β =-0.162, p<0.01). The salary outcome of engineering graduates is impacted by many geographical factors. Specifically, racial or ethnic diversity (β =-0.206, p<0.01), proximity to STEM clusters (β =-0.011, p<0.01) and unemployment (β =-0.017, p<0.01) in the regional labor market are negatively related to engineering graduates' earnings. Share of STEM workers, on the contrary, has a positive impact (β =2.181, p<0.01). These results are similar to the general model with exception of proximity index, which has a positive effect on earning for all graduates. However, it is unsurprising, since highly specialized labor, like certain engineers, often enjoy a wage premium in more remote areas.

f. Health science

At the individual level, higher GPA (β =0.057, p<0.01), more working experience (β =0.006, p<0.01), older age (β =0.028, p<0.01), working full-year (β =0.282, p<0.01) and full-week (β =0.478, p<0.01) are positively associated with higher salary. Different from all other majors, after controlling for other characteristics, gender is not a significant factor in predicting job earnings. In fact, health science is the only major where women earn statistically equal salary with men (β =-0.050, p=0.146). This was possibly due to high concentration of women in this particular discipline, as well as a robust demand for health professionals. As shown earlier, health science is one of the most common majors among women (the other common majors are social and life sciences). Nursing and other health related professions are commonly perceived as more feminine and there was some evidence that men experienced discrimination in such occupations (Kouta and Kaite, 2011).

There are significant racial differences. Despite that Blacks are the most likely to major in health sciences than any other group, they are more likely to earn less than their White counterparts (β =-0.156, p=0.02). The literature suggested that Black nurses are being discriminated against when considered for promotion (Barbee, 1993), which may contribute to such discrepancy in earnings.

At the institutional level, college size (β =0.001, p=0.05) and acceptance rate (β =0.311, p=0.05) are positively associated with engineering graduates' pay. As for location, there is positive association with STEM specialization (β =2.863, p=0.05) and area population (β =0.041, p=0.05), at alpha level 0.10. This finding contradicts the established notion about nurses having higher salaries in remote areas.

g. Math science

Women with math science degrees have lower salaries than men with the same major (β =-0.081, p=0.03). Blacks earn significantly less (β =-0.174, p=0.02) than whites. The foreign born are likely to have higher salary (β =0.117, p=0.04) than the native born. As expected, math graduates with higher GPA (β =0.062, p<0.01), more experience (β =0.011, p<0.01), working full-year (β =0.216, p<0.01) and full-time (β =0.992, p<0.01) are more likely to earn more. Additionally, the 2006 cohort (β =-0.108, p=0.02) has the lowest earnings compared to math graduates in other cohorts.

At the college level, higher shares of Blacks (β =0.408, p<0.01) and Hispanics (β =0.454, p<0.01) has a positive relationship with math science graduates' salaries. Among the geographical factors, proximity to STEM clusters (β =0.027, p=0.04) and share of manufacturing in the college area (β =4.76, p<0.01) has a positive relationship with job earnings. But, a higher rate of unemployment has a negative impact (β =-0.06, p<0.01).

h. Summary

Women are more likely to earn less across all STEM majors, except health sciences. Moreover, the gender pay gap is the widest for within women-dominated and lowest-paid majors – life and social sciences. Generally, race has little effect on salary. However, Black graduates in computer, health and mathematical science majors tend to earn less than their White counterparts.

Family factors impact salaries for only a few majors. Married graduates with degrees in physical, social sciences and engineering sciences earn more than their single counterparts, while having children negatively affects salaries for physical major graduates. In most cases, age does not matter, with exception of social and physical sciences. Family educational background does not have any effect on graduates' pay.

Across all the majors except for life sciences, higher GPA is positively associated with post-graduation earnings. Similarly, more working experience is a significant predictor for higher salaries, regardless of specific STEM majors. Only life, math and engineering sciences tend to have a greater pay if they moved to another state after graduation. All STEM majors are more likely to have a greater pay in states with higher cost of living. Computer and engineering science majors earn more if employed in private businesses, as opposite to government institutions. All majors except computer, health and math sciences, experience pay cut during recession in the end of the decade.

In general, graduates from larger universities fare better in terms of salary, except physical, social and mathematical science majors for whom size of the institution does not make significant differences. College racial diversity is only negatively associated with computer science graduates' pay. Interestingly, school specialization in STEM positively affects only computer scientists, while other majors are not likely to benefit from this factor. Graduates with degrees in social and health sciences who graduate from more selective colleges are more likely to have higher pay. However, for other majors, college prestige does not have any significant influence. Overall, compared to individual personal characteristics and location factors, higher education institutional features are relatively not significant factors to predict STEM graduate job earnings when disaggregated results are examined.

At the college location, the population size has no significant relationship with earning of every STEM major after controlling for other characteristics. Higher unemployment has a negative relationship with computer, social, engineering and math science graduates' pay. Similarly, racial diversity is negatively associated with salaries for life and engineering science graduates. Engineering and health science graduates benefit from the concentration of STEM workforce at places where the universities are located. Proximity to areas with STEM workforce concentration benefits the salaries of social, health and mathematical science graduates. However, this factor affected engineering graduates in the opposite way. Furthermore, share of manufacturing industry has little effect on graduates' pay, with exception of math majors. The results of these models are presented in Table 12.

TABLE 12: Hierarchical regression results by major. Dependent variable: ln(Salary)

Fixed Effect	Computer sciences	Life sciences	Physical sciences	Social sciences	Engineering	Health sciences	Mathematical sciences
Individual level:							
Female	-0.086**	-0.148***	-0.113***	-0.141***	-0.026***	-0.050	-0.081**
	(0.037)	(0.033)	(0.031)	(0.018)	(0.011)	(0.035)	(0.037)
Asian	0.001	-0.068	0.074	0.034	0.005	-0.064	0.033
	(0.055)	(0.087)	(0.061)	(0.035)	(0.022)	(0.089)	(0.063)
Black	-0.205***	-0.039	-0.015	-0.022	-0.014	-0.156***	-0.174**
	(0.064)	(0.056)	(0.066)	(0.035)	(0.019)	(0.063)	(0.071)
Hispanic	-0.148***	-0.014	-0.054	0.014	0.004	-0.052	-0.039
	(0.058)	(0.047)	(0.051)	(0.025)	(0.017)	(0.081)	(0.074)
Other	0.006	-0.048	0.046	-0.017	0.002	-0.076	-0.126
	(0.086)	(0.071)	(0.072)	(0.048)	(0.025)	(0.071)	(0.130)
Foreign Born	-0.004	0.070	-0.064	0.036	-0.008	0.108	0.117**
	(0.048)	(0.057)	(0.054)	(0.032)	(0.019)	(0.071)	(0.056)
Married	0.045	0.026	0.100***	0.085***	0.033***	0.017	0.001
	(0.046)	(0.045)	(0.039)	(0.023)	(0.013)	(0.052)	(0.049)
Has children	0.016	-0.041	-0.124**	0.024	-0.030	-0.015	0.018
	(0.056)	(0.070)	(0.057)	(0.028)	(0.021)	(0.047)	(0.058)
Age	0.028	0.009	0.039***	0.018***	0.001	0.029*	-0.011
	(0.010)	(0.011)	(0.012)	(0.007)	(0.004)	(0.011)	(0.014)
Mother has a Bachelor degree	0.031	-0.010	-0.051	0.030	0.004	-0.021	0.036
	(0.037)	(0.043)	(0.035)	(0.021)	(0.011)	(0.039)	(0.045)

TABLE 12, continued.

Father has a Bachelor degree	-0.021	-0.040	0.015	0.040*	0.018	0.016	-0.003
	(0.037)	(0.042)	(0.017)	(0.021)	(0.011)	(0.040)	(0.046)
GPA	0.083***	0.024	0.042**	0.045***	0.053***	0.057***	0.062***
	(0.019)	(0.020)	(0.017)	(0.009)	(0.006)	(0.021)	(0.019)
Months since graduation	0.008***	0.013***	0.008***	0.010***	0.008***	0.007***	0.011***
	(0.002)	(0.020)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Moved out-of-state	-0.013	0.083***	0.041	0.026	0.072***	-0.030	0.085*
	(0.039)	(0.032)	(0.032)	(0.021)	(0.011)	(0.043)	(0.044)
Regional Price Parities (state of residence)	0.010***	0.006***	0.006***	0.007***	0.003***	0.009***	0.008***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Employer - private business	0.061***	-0.033	0.006	-0.027	0.120***	0.045	0.023
	(0.060)	(0.031)	(0.043)	(0.022)	(0.015)	(0.041)	(0.040)
Working full-year	0.325***	0.419***	0.322	0.398	0.284***	0.282***	0.216***
	(0.110)	(0.057)	(0.044)	(0.037)	(0.050)	(0.098)	(0.054)
Working full-week	0.897***	0.683***	0.998	0.714	0.901	0.478***	0.992
	(0.119)	(0.061)	(0.051)	(0.039)	(0.077)	(0.076)	(0.111)

TABLE 12, continued.

Cohorts:							
2006	-0.111	-0.092***	-0.064	-0.102***	-0.040***	-0.066	-0.108***
	(0.051)	(0.034)	(0.042)	(0.021)	(0.015)	(0.057)	(0.046)
2008	-0.089	-0.052	-0.007	-0.124***	-0.008	-0.059	-0.059
	(0.063)	(0.039)	(0.046)	(0.029)	(0.017)	(0.068)	(0.052)
2010	-0.042	-0.271***	-0.197***	-0.273***	-0.090***	-0.153	-0.123*
	(0.070)	(0.072)	(0.053)	(0.042)	(0.023)	(0.078)	(0.065)
University level variables:							
Enrollment	0.002***	0.002***	0.001	0.001	0.001***	-0.001**	0.001
	(0.001)	(0.001)	(0.001)	(0.022)	(0.001)	(0.001)	(0.001)
Diversity index	-0.189***	-0.097*	-0.025	0.036	-0.008	-0.032	0.103*
	(0.087)	(0.055)	(0.056)	(0.047)	(0.011)	(0.026)	(0.054)
Share of Blacks	0.175	-0.260	-0.086	-0.145	0.022	-0.143	0.408***
	(0.142)	(0.161)	(0.132)	(0.117)	(0.046)	(0.206)	(0.147)
Share of Hispanics	-0.512***	-0.395***	0.091	0.011	-0.162***	-0.067	0.454***
	(0.202)	(0.189)	(0.148)	(0.115)	(0.046)	(0.108)	(0.175)
STEM LQ	0.101**	0.043	0.010	0.019	0.017	0.013	-0.036
	(0.052)	(0.046)	(0.041)	(0.026)	(0.016)	(0.013)	(0.045)
Acceptance Rate	-0.133	-0.004	-0.011	-0.269***	-0.047	-0.311**	0.051
	(0.125)	(0.106)	(0.096)	(0.025)	(0.035)	(0.156)	(0.118)
Private institution	0.074	0.102***	0.028	0.018	0.001	-0.045	0.002
	(0.051)	(0.053)	(0.043)	(0.028)	(0.019)	(0.039)	(0.049)

TABLE 12, continued.

Research/ Doctoral degree granting institution	-0.001	-0.002	0.088	0.005	-0.023	0.102*	0.058
	(0.059)	(0.049)	(0.047)	(0.033)	(0.020)	(0.056)	(0.060)
Area level variables:							
Diversity index	-0.277	-0.394***	-0.155	-0.059	-0.206***	0.067	-0.077
	(0.194)	(0.341)	(0.135)	(0.082)	(0.049)	(0.151)	(0.152)
Share of STEM employees	-1.54	0.699	1.176	0.653	2.181***	2.863*	3.814
	(2.825)	(2.212)	(2.046)	(1.325)	(0.608)	(1.666)	(2.771)
Proximity index	-0.002	0.005	0.006	0.016**	-0.011***	0.012	0.027**
	(0.015)	(0.009)	(0.011)	(0.006)	(0.004)	(0.013)	(0.013)
Population	-0.009	0.001	0.012	0.001	-0.008	0.041*	-0.003
	(0.018)	(0.018)	(0.014)	(0.008)	(0.005)	(0.023)	(0.017)
Unemployment	-0.040***	-0.009	-0.009	-0.021**	-0.017***	-0.011	-0.058***
	(0.018)	(0.016)	(0.013)	(0.009)	(0.005)	(0.017)	(0.017)
Manufacturing	1.001	-0.507	1.093	0.295	0.247	-1.067	4.756***
	(1.789)	(1.272)	(1.298)	(0.811)	(0.549)	(1.794)	(1.678)
N	1115	2052	1705	5751	6365	1199	962
Note: Robust standard errors presented in parentheses. Significance levels: *** 1%, ** 5%, * 10%.							

2. Underemployment

At the individual level, female life (β =0.485, p<0.02) and social (β =0.248, p<0.03) science graduates are more likely to be underemployed than their male counterparts. Again, these are the STEM disciplines that are dominated by women. Among the racial groups, only Black (β =0.507, p<0.01) social science and Hispanic (β =2.143, p<0.01) mathematical science graduates are more likely to be underemployed. Higher grades do not matter, but only for computer (β =-0.682, p<0.01), health (β =-0.319, p=0.04) and engineering (β =-0.338, p=0.02) graduates, which are the three highest paid STEM majors in this sample.

Social science majors with more experiences (β =-0.21, p=0.02) and those who move to other state after graduation (β =-3.43, p=0.03) have more chances of being employed full-time. This indicates that for social science graduates it takes more time and spatial mobility to secure full-time employment. Similarly, engineering graduates who leave their college state are less likely to be underemployed (β =-1.107, p<0.01). Computer science (β =-1.031, p=0.02) graduates are less likely to be underemployed if employed in private business, but health science (β =0.953, p=0.02) graduates fared better when employed in the public sector.

Underemployment among recent graduates follows the similar temporal trend of their earnings. Almost every major except computer sciences and math experience higher underemployment during the recession cohort. Health (β =1.934, p=0.02) and life (β =1.169, p<0.01) science graduates are affected by recession the most, as they are the most likely to be underemployed by the end of 2000s.

Only very few institutional level variables are significant in predicting the likelihood of graduates' underemployment. Engineering (β =-0.670, p=0.05) and health (β =-0.849, p=0.05) majors who graduated from colleges with higher STEM specialization are less likely to be underemployed. Social science graduates who attended less selective institutions are more likely to work part time (β =0.76355, p=0.05). Among the location factors, physical science graduates who went to college in areas with high concentration of STEM workers are not just likely to earn more, but also less likely to be underemployed (β =-42.168, p=0.04). Moreover, areas with higher concentration of manufacturing industries significantly increases the likelihood of underemployment among engineering graduates (β =19.747, p=0.05).

Overall, underemployment is more common among women with degrees in already lower paid fields – social and life sciences. As indicated earlier, women are more likely to concentrate in social and life sciences. In particular, higher GPA and college specialization in STEM are significantly associated with getting a full-time job in higher paid fields (such as health, engineering and computer sciences). For all other majors, however, these factors do not matter. Geographical factors affect only engineering and physical science graduates' employment situation. STEM specialization decreases underemployment for physical science graduates by two times. Graduating in areas with higher concentration of manufacturing is likely to increase the chances of part-time employment for engineering majors. Results from these models are provided in Table 13

3. Unemployment

After controlling for other characteristics, no significant gender disparities in the probability of unemployment are identified in sub-disciplines. Among the racial groups, Asian graduates with degrees in life (β =1.065, p<0.01), physical sciences (β =0.742, p=0.03) and health (β =-1.479, p=0.04) are more likely to be unemployed than their White counterparts. Similarly, Blacks (β =0.561, p=0.04) and the foreign born (β =0.369, p=0.03) with engineering degrees are more likely to be jobless than Whites and the native born with the same major. This follows the patterns from results of the general model, where both Blacks and foreign born are found to have a disadvantage in employment.

Married social science graduates (β =-0.686, p<0.01) are more likely to be employed. Higher GPA decreases the social science and engineering graduates' odds of unemployment by 0.29 and 0.25 points, respectively. Graduates with life (β =-0.038, p<0.01), physical (β =-0.049, p<0.01) and engineering (β =-0.022, p<0.01) science degrees significantly benefit from more work experiences, while computer (β =-0.961, p<0.01) and engineering (β =-0.472, p<0.01) science graduates are more likely to secure employment if they move to another state after graduation. These results are different from underemployment model where engineering graduates do not benefit from any of these factors. Moreover, only graduates with engineering (β =0.604, p<0.01) and math (β =1.590, p<0.01) degrees experience higher unemployment in the last cohort when compared to the earlier cohorts. This is interesting, considering that all other labor market outcomes are negatively affected in the last cohort across almost all major groups. In other words, unemployment is more prevalent during recession only for graduates in certain fields.

At the institutional level, engineering graduates (β =-0.005, p<0.01) from larger colleges are more likely to be employed than those from smaller schools. Racial diversity has little effect on graduates' employment prospects, with exception of engineering graduates who are more likely to be unemployed if they attend a racially diverse college (β =0.405, p=0.02) or institutions with higher shares of Hispanics (β =1.183, p=0.03). Similarly, graduates with life science degrees (β =0.405, p=0.02) from colleges with a higher proportion of Black students (β =2.759, p<0.01) are more likely to be jobless. Surprisingly, engineering (β =0.538, p=0.03) and health (β =1.183, p=0.04) graduates who attend research and doctoral granting institutions are more likely to be unemployed than their counterparts who attend other types of colleges. In prior studies, the effects of Carnegie classification were inconsistent, including all positive, negative and insignificant influence of schools with higher classification on various learning and labor market outcomes (Pascarella & Terenzini, 2005).

Among the location factors, a larger population size is significantly associated with higher rate of unemployment for computer science graduates (β =0.325, p=0.04). When unemployment in the college area is higher, the likelihood of unemployment increases for physical science graduates as well (β =0.222, p=0.03). In addition, racial diversity has a negative relationship with computer (β =4.006, p<0.01) and engineering (β =1.507, p=0.03) graduates. Furthermore, engineering graduates from areas with a larger manufacturing industry are considerably more likely to be unemployed (β =12.347, p=0.05). In contrast, the proportion of STEM workforce in the college area significantly decrease the odd of joblessness for social science graduates (β =-19.002, p=0.02).

In sum, unemployment is the only outcome examined in this study that is not affected by gender in the disaggregated models. That said, Asians are significantly disadvantaged in fields where they are underrepresented. Moreover, the model appears to fit the best with engineering graduates, as factors at all levels are significantly related to their employment status. Similar to the underemployment model, engineers are more likely to be jobless if graduated in areas that specialize in manufacturing and are more racially diverse. Social scientists are the only group that benefited from STEM employment concentration in a college area. Results from these models are provided in Table 14.

TABLE 13: Hierarchical logistic regression results by major. Dependent variable: underemployment

Fixed Effect	Computer sciences	Life sciences	Physical sciences	Social sciences	Engineering	Health sciences	Mathematical sciences
Individual level:							
Female	-0.428	0.485**	0.243	0.248**	0.163	-0.062	0.497
	(0.460)	(0.252)	(0.246)	(0.129)	(0.249)	(0.362)	(0.515)
Asian	-0.438	-0.079	-0.196	-0.291	0.350	-0.446	1.315
	(0.732)	(0.499)	(0.416)	(0.236)	(0.382)	(0.633)	(0.989)
Black	0.766	-0.102	-0.233	0.507***	-0.087	0.807*	1.120
	(0.606)	(0.454)	(0.540)	(0.192)	(0.500)	(0.469)	(0.859)
Hispanic	-0.488	0.215	-0.205	0.071	0.293	0.173	2.143***
	(0.801)	(0.336)	(0.408)	(0.188)	(0.406)	(0.501)	0.580222
Other	0.433	0.059	0.881**	0.351	-1.036	0.407	(omitted)
	(0.918)	(0.483)	(0.441)	(0.271)	(1.032)	(0.604)	
Foreign Born	-0.023	0.252	0.686*	0.016	0.508*	0.505	-0.351
	(0.565)	(0.392)	(0.362)	(0.189)	(0.272)	(0.520)	(0.743)
Married	-0.013	0.094	-0.099	-0.209	-0.594*	-0.031	-0.178
	(0.447)	(0.290)	(0.385)	(0.203)	(0.359)	(0.408)	(0.465)
Has children	-0.493	-0.409	-0.193	0.232	-0.120	0.281	-0.185
	(0.632)	(0.482)	(0.548)	(0.204)	(0.425)	(0.432)	(0.706)
Age	0.076	-0.056	-0.060	0.006	0.075	-0.245**	0.162
	(0.106)	(0.087)	(0.100)	(0.040)	(0.098)	(0.122)	(0.119)

TABLE 13, continued.

Mother has a Bachelor degree	0.013	0.007	-0.326	0.177	0.030	0.372	0.296
	(0.401)	(0.240)	(0.294)	(0.139)	(0.282)	(0.341)	(0.566)
Father has a Bachelor degree	-0.636	0.019	0.058	-0.252*	-0.094	-0.110	-0.449
	(0.424)	(0.225)	(0.283)	(0.144)	(0.282)	(0.373)	(0.589)
GPA	-0.682***	-0.055	0.091	-0.058	-0.338**	-0.319**	0.233***
	(0.211)	(0.121)	(0.146)	(0.065)	(0.146)	(0.158)	(0.102)
Months since graduation	0.013	-0.020	-0.018	-0.021**	-0.014	-0.018	-0.015
	(0.027)	(0.016)	(0.019)	(0.009)	(0.017)	(0.019)	(0.026)
Moved out-of-state	-0.104	-0.146	-0.127	-0.343**	-1.107***	-0.372	-0.620
	(0.440)	(0.253)	(0.266)	(0.163)	(0.309)	(0.374)	(0.626)
Regional Price Parities (state of residence)	-0.014	0.007	0.007	0.007	-0.030*	0.021	-0.016
	(0.023)	(0.015)	(0.017)	(0.008)	(0.017)	(0.018)	(0.027)

TABLE 13, continued.

Employer - private business	-1.031**	-0.087	0.083	-0.055	-0.286	0.953**	0.249
	(0.445)	(0.239)	(0.261)	(0.133)	(0.285)	(0.447)	(0.434)
Cohorts:							
2006	-0.837*	0.411	0.041	-0.122	-0.783**	1.279*	-0.548
	(0.492)	(0.345)	(0.351)	(0.202)	(0.344)	(0.736)	(0.677)
2008	0.044	0.951**	-0.127	0.594***	-0.043	0.981	-0.079
	(0.580)	(0.392)	(0.409)	(0.216)	(0.358)	(0.801)	(0.678)
2010	0.098	1.170***	0.850**	0.997***	0.903**	1.934**	1.389*
	(0.727)	(0.416)	(0.402)	(0.223)	(0.358)	(0.791)	(0.738)
University level variables:							
Enrollment	0.002	0.003	0.003	0.001	-0.006*	-0.004	0.006
	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.009)
Diversity index	0.835	0.950*	0.274	0.524	0.637*	0.021	1.018
	(0.843)	(0.562)	(0.565)	(0.204)	(0.372)	(0.374)	(1.548)
Share of Blacks	0.952	1.220	1.214	-0.833	-0.120	0.569	-2.335
	(1.146)	(1.026)	(0.954)	(0.754)	(1.192)	(1.221)	(3.015)
Share of Hispanics	1.813	-0.370	-1.295	0.889	1.600	-0.131	-2.782
	(2.020)	(1.255)	(1.195)	(0.632)	(1.064)	(1.166)	(2.423)

TABLE 13, continued.

STEM LQ	0.097	0.104	0.128	-0.093	-0.670**	-0.849**	-0.455
	(0.402)	(0.324)	(0.327)	(0.186)	(0.348)	(0.482)	(0.698)
Acceptance Rate	-1.998	-0.393	0.899	0.764**	-0.617	-0.054	0.572
	(1.224)	(0.723)	(0.770)	(0.408)	(0.672)	(1.170)	(1.421)
Private institution	-0.139	0.176	0.163	-0.045	-0.040	-0.653	0.375
	(0.459)	(0.329)	(0.341)	(0.193)	(0.341)	(0.407)	(0.695)
Research/ Doctoral degree granting institution	-0.139	-0.390	0.178	-0.105	0.438	0.725*	-1.324
	(0.585)	(0.348)	(0.352)	(0.216)	(0.421)	(0.416)	(0.907)
Area level variables:							
Diversity index	0.118	-0.217	-0.141	0.907	1.201	2.180	4.337*
	(1.951)	(0.902)	(1.131)	(0.630)	(1.068)	(1.339)	(2.389)
Share of STEM employees	-37.846	-19.709	-42.168**	-7.961	-18.139	4.117	9.106
	(28.335)	(14.730)	(21.732)	(9.052)	(14.675)	(20.853)	(27.001)
Proximity index	-0.029	0.032	0.039	-0.053	0.141	-0.140	0.033
	(0.136)	(0.083)	(0.093)	(0.047)	(0.092)	(0.120)	(0.174)

TABLE 13, continued.

Population	0.255	-0.154	0.067	0.072	0.103	0.127	0.158
	(0.207)	(0.096)	(0.107)	(0.062)	(0.109)	(0.150)	(0.243)
Unemployment	0.043	0.036	0.058	0.072	-0.090	0.025	-0.123
	(0.183)	(0.096)	(0.102)	(0.052)	(0.083)	(0.118)	(0.261)
Manufacturing	19.468	12.924	-3.429	1.755	19.747**	3.475	14.921
	(17.475)	(9.102)	(10.345)	(5.654)	(11.095)	(12.204)	(14.847)
N	1115	2052	1705	5751	6365	1199	962
Note: Robust standard errors presented in parentheses. Significance levels: *** 1%, ** 5%, * 10%.							

TABLE 14: Hierarchical logistic regression results by major. Dependent variable: unemployment

Fixed Effect	Computer sciences	Life sciences	Physical sciences	Social sciences	Engineering	Health sciences	Mathematical sciences
<u>Individual level:</u>							
Female	-0.178	0.307	-0.139	-0.012	0.253 *	-0.177	-0.449
	(0.367)	(0.207)	(0.235)	(0.122)	(0.151)	(0.518)	(0.329)
Asian	0.003	1.066***	0.742**	0.170	0.429*	1.479**	0.629
	(0.563)	(0.373)	(0.372)	(0.203)	(0.235)	(0.600)	(0.639)
Black	0.947*	-0.939	-0.097	0.184	0.560**	1.035	0.470
	(0.509)	(0.596)	(0.519)	(0.180)	(0.247)	(0.643)	(0.573)
Hispanic	0.543	0.173	0.358	0.060	0.045	-1.290	0.101
	(0.538)	(0.339)	(0.361)	(0.190)	(0.232)	(1.532)	(0.557)
Other	-0.311	0.103	1.299 ***	0.386	0.486	-0.056	-0.093
	(1.032)	(0.450)	(0.352)	(0.251)	(0.315)	(0.816)	(0.761)
Foreign Born	-0.345	-0.428	0.340	0.268	0.369**	-0.071	-0.180
	(0.464)	(0.395)	(0.323)	(0.179)	(0.185)	(0.674)	(0.549)
Married	0.400	-0.380	-0.094	-0.687 ***	-0.236	-0.829	-0.313
	(0.412)	(0.307)	(0.302)	(0.203)	(0.185)	(0.617)	(0.473)
Has children	0.057	0.769 **	0.177	0.207	0.139	0.560	0.725
	(0.491)	(0.311)	(0.397)	(0.200)	(0.281)	(0.653)	(0.510)

TABLE 14, continued.

Age	0.126	0.117 *	0.139*	0.063	0.007	0.036	0.083
	(0.081)	(0.065)	(0.078)	(0.043)	(0.056)	(0.139)	(0.123)
Mother has a Bachelor degree	-0.130	0.091	0.0369	-0.096	-0.103	-0.901	-0.035
	(0.334)	(0.204)	(0.251)	(0.133)	(0.156)	(0.579)	(0.379)
Father has a Bachelor degree	0.346	0.218	-0.135	-0.064	0.129	0.339	-0.380
	(0.351)	(0.219)	(0.262)	(0.133)	(0.153)	(0.445)	(0.414)
GPA	-0.197	-0.064	0.081	-0.206 ***	-0.280 ***	-0.175	-0.162
	(0.152)	(0.103)	(0.117)	(0.070)	(0.082)	(0.235)	(0.195)
Months since graduation	-0.028	-0.038 ***	-0.049 ***	-0.007	-0.022**	-0.035	-0.034*
	(0.019)	(0.014)	(0.014)	(0.008)	(0.010)	(0.030)	(0.019)
Moved out-of-state	-0.961 **	0.107	0.056	0.109	-0.472***	-0.469	0.188
	(0.380)	(0.224)	(0.237)	(0.150)	(0.152)	(0.584)	(0.379)
Regional Price Parities (state of residence)	0.027	0.006	-0.011	-0.007	0.006	0.024	0.044**
	(0.021)	(0.012)	(0.013)	(0.008)	(0.009)	(0.026)	(0.020)
Cohorts:							
2006	-0.214	-0.095	-0.022	-0.589 ***	-0.853 ***	-0.576	0.734
	(0.378)	(0.283)	(0.356)	(0.172)	(0.206)	(0.713)	(0.451)

TABLE 14, continued.

2008	-0.654	0.298	0.385	0.082	-0.234	-0.198	0.714
	(0.633)	(0.315)	(0.364)	(0.191)	(0.220)	(0.839)	(0.593)
2010	0.174	0.494	0.200	0.500	0.604***	0.037	1.590 ***
	(0.465)	(0.316)	(0.363)	(0.194)	(0.201)	(0.745)	(0.567)
University level variables:							
Enrollment	-0.001	0.001	-0.001	-0.001	-0.005***	0.003	-0.002
	(0.005)	(0.003)	(0.003)	(0.002)	(0.002)	(0.006)	(0.006)
Diversity index	-0.122	0.358	-0.281	0.031	0.405**	-0.192	-0.089
	(0.588)	(0.285)	(0.456)	(0.125)	(0.172)	(0.516)	(0.380)
Share of Blacks	1.424	2.759***	-0.740	0.659	0.551	-1.047	-0.467
	(1.013)	(0.892)	(1.016)	(0.435)	(0.545)	(1.266)	(1.443)
Share of Hispanics	0.288	0.892	-1.447	-0.271	1.183**	-0.321	-1.462
	(1.524)	(0.818)	(1.065)	(0.580)	(0.523)	(1.500)	(1.706)
STEM LQ	0.055	-0.201	-0.095	0.157	-0.219	-0.963	-0.622
	(0.360)	(0.239)	(0.268)	(0.159)	(0.208)	(0.732)	(0.580)
Acceptance Rate	-0.382	-0.732	-0.666	0.197	0.035	-0.525	0.089
	(1.008)	(0.520)	(0.675)	(0.389)	(0.415)	(1.354)	(0.867)
Private institution	0.316	0.341	0.231	-0.122	-0.089	-0.011	-0.624
	(0.384)	(0.279)	(0.295)	(0.180)	(0.213)	(0.575)	(0.514)

TABLE 14, continued.

Research/ Doctoral degree granting institution	0.125	0.085	0.375	-0.088	0.538**	1.183**	0.326
	(0.437)	(0.284)	(0.319)	(0.182)	(0.228)	(0.574)	(0.554)
Area level variables:							
Diversity index	4.006***	0.934	-1.279	-0.829	1.507**	0.192	-1.412
	(1.413)	(0.896)	(0.934)	(0.558)	(0.630)	(1.957)	(1.491)
Share of STEM employees	-1.244	8.405	-2.99	-19.002**	-24.359	-9.623	10.453
	(26.429)	(14.024)	(14.140)	(9.494)	(9.390)	(28.608)	(19.331)
Proximity index	-0.075	-0.055	0.039	0.027	0.0165	0.026	-0.008
	(0.128)	(0.070)	(0.077)	(0.044)	(0.056)	(0.136)	(0.114)
Population	0.325**	-0.081	-0.018	-0.046	0.060	-0.046	-0.056
	(0.161)	(0.107)	(0.104)	(0.056)	(0.066)	(0.166)	(0.157)
Unemployment	0.007	0.045	0.222**	0.019	-0.030	0.240	0.018
	(0.138)	(0.068)	(0.095)	(0.051)	(0.050)	(0.166)	(0.152)
Manufacturing	0.159	8.560	9.869	8.178	12.347**	-27.897*	12.550
	(15.104)	(8.568)	(9.533)	(5.216)	(6.793)	(15.779)	(11.931)
N	1115	2052	1705	5751	6365	1199	962
Note: Robust standard errors presented in parentheses. Significance levels: *** 1%, ** 5%, * 10%.							

CHAPTER IX: DISCUSSION AND CONCLUSION

Many researchers have examined individual and college's role in STEM students' post-graduation success in the labor markets (Pascarella & Terenzini, 2005). For example, at the individual level, research finds that gender (Beede et al., 2011; Buffington, Cerf, Jones, & Weinberg, 2016; Chen, 2009), race (Beede et al., 2011; Broyles & Fenner, 2010), parental level of education (Roksa & Arum, 2012), GPA (Jones & Jackson, 1990; Xu, 2013) and major (J. Altonji, Blom, & Meghir, 2012; Gerhart, 1990; Melguizo & Wolniak, 2011) is associated with graduates' labor market outcomes. At the institutional level, research finds that graduates from large colleges (Pascarella & Terenzini, 2005) and selective colleges (Thomas, 2000) have better outcomes than students who attend smaller and less selective colleges. However, previous research has not taken into account of the local or regional labor market conditions in the college area.

This project examines recent graduates' early career experiences through the analysis of four cohorts of STEM Bachelor's degree recipients with a special attention to geographical factors that contribute to such experiences. Salary, underemployment and unemployment are the outcomes of interest. The individual level factors examined in this study are a set of demographic characteristics, family background, major, performance in college (GPA), work experience and cohort. The institutional level factors in examination include higher education institution type, size, selectivity, racial diversity, and level of STEM specialization. Among the geographical predictors, there are macro-economic strength, racial diversity, population size, STEM workforce concentration, proximity to areas with larger STEM labor markets, and share of workers in manufacturing industries.

1. How do STEM graduates perform in the labor market over time and space?

    a. Job earnings

When comparing the salary/earning outcome between cohorts, it is evident that STEM graduates in the second half of 2000s experience a considerable decrease in earnings, especially in the last cohort. This is consistent with prior research on temporal trends in STEM salaries (Langdon et al., 2011), which states that STEM employees experience salary reduction during recessions. However, the geographical distribution of salary decline varies substantially across college locations. For instance, in the early 2000s, STEM graduate's salary in the vast majority of college locations only slightly deviates from the national mean; at the same time, the job earnings of last two cohorts vary significantly depending on where the graduates attend college. During the last recession, graduates from colleges in the South, Western New England and Rocky Mount areas are affected the most.

Men have a considerable advantage in job earnings compared to women. Additionally, male and female graduates are largely segregated by college major, which may have affected the average salaries and gender pay differences. For example, women dominate social and life sciences - the lowest paid fields. However, even within these majors, men have a wage premium. On the other hand, average salaries are higher for women in health and engineering compared to men with similar degrees. Unlike life and social sciences, these fields are drastically different in gender composition, with health being dominated by women and engineering by men; nevertheless, they both still are the highest paid fields for women. Averages salaries decrease for both women and men in the late 2000s; but, for women this drop is much smaller than for men, as the gender pay gap decreases from 7.7 percent in the 2006 cohort to 2.6 percent in the 2010 cohort.

There were also pay differences between racial and ethnic groups. Asian graduates had higher average earnings across all STEM disciplines, followed by Whites, Hispanics and Blacks. Computer and math sciences were the fields where the pay gaps across racial groups were the largest. Additionally, engineering, computer science and health were the highest paid fields for all races, except Asian who earned more in math related fields than in health. On average, earnings decreased for all groups during recession, with health and engineering graduates having the smallest reduction in pay. Overall, the pay gap between minorities (except Black graduates) and Whites increased during recession, while the salary difference between Asians and Whites reached 26 percent, in favor of the former.

b. Underemployment

Underemployment among STEM graduates have gradually increased over the decade. In the first two cohorts, underemployment is more evenly distributed across the country. During the economic downturn, graduates from certain college regions are disproportionally more likely to work part-time involuntarily than graduates from other areas. The areas with highest rate of STEM underemployment are mainly in the Pacific Northwest, Mideast and certain areas in the South.

Underemployment is more common among women than men, especially in female dominated fields. Underemployment is more prevalent for men than for women in health fields. Conversely, female graduates are more likely than men to be underemployed in physical science fields. Social and life sciences are the fields with higher-than-average underemployment rate for both genders. Engineering graduates of both genders were the least likely to work part-time. Recession affected underemployment of men and women differently. While more women, in all fields but computer science, work part time during recession than previously, men have a sharp increase in underemployment only in few fields, social and physical sciences.

Average rates of underemployment also differ by race/ethnicity. All racial and ethnic minorities are more likely to be underemployed than Whites in all fields. Again, engineering field is the most immune to underemployment, while social and life sciences have the largest number of the underemployed across all groups. Underemployment has grown in almost all fields for all the groups during recession, with math and physical science majors being hurt the most.

c. Unemployment

Unlike salary and underemployment outcomes, unemployment is higher for STEM graduates in the first and last cohorts. In both cohorts, the unemployed disproportionally graduate from colleges in the Midwest, Louisiana and Mississippi regions; however, during the recession, many college areas on the East Coast are also among those with a higher number of unemployed graduates.

Although unemployment varies by major and cohort, more men than women are unemployed during the study period. The distribution of unemployed graduates across majors and cohorts follows the distribution patterns of the lower-paid individuals. For example, unemployment is the most prevalent among social and life science graduates, with women being more likely to be unemployed in life sciences and men being more likely to be jobless in social sciences. Both men and women with health degrees are the least likely to be unemployed, which again mirrors the distribution of salaries. Overall, graduates in highly-paid fields (e.g., heath and engineering) that often have shortage of workers are the most immune to unemployment, regardless of gender. Expectedly, there are more unemployed of both genders in the last cohort, than in the previous three cohorts.

For racial differences, unemployment is much less prevalent among Whites than any other group. Moreover, for Whites, differences in unemployment among sub-disciplines and cohorts are considerably smaller than for other groups. In addition, Asian graduates, although the highest paid group, have the highest unemployment rate among all the racial groups. Hispanic graduates are the second least likely to be unemployed and have exceptionally low unemployment in health sector. Cohort-wise, unemployment has grown almost in every field for all groups but for Blacks who enjoyed lower unemployment rates in the majority of the fields.

2. How are the labor market outcomes associated with individual, institutional and geographic locational characteristics?

   a. Job earnings

Graduate's salary depends on many factors. At the individual level, gender, race, marital status and age influence recent graduates' pay. Compared to men, women are severely disadvantaged. Compared to Whites, Blacks earn significantly less. Human capital, such as GPA and work experiences, are positively associated with earnings. This is consistent with prior research on how college grades and experience affect further earnings (Jones & Jackson, 1990). Graduates with health and engineering degrees have the highest pay in this sample. On average, the last three cohorts of STEM graduates earn significantly less than the first one.

At the university level, in line with previous research, college size, STEM specialization and selectivity are all positively related to salary (Pascarella & Terenzini, 2005). Concentration of Black students, on the other hand, has the opposite effect, which also supports the prior findings on labor market experiences among HBCU graduates (Fitzgerald, 2000). Among the college locations, racial diversity and unemployment rate at the college area are negatively related to earnings. In contrast, the share of STEM workforce and proximity to other areas that employ larger numbers of STEM employees has an overwhelmingly positive impact on salary.

The gender and racial disparities in job earnings significantly vary across STEM sub-disciplines. For instance, female graduates have a significant earnings disadvantage compared to males with any STEM degree, except health sciences. Such results are not surprising, considering the well documented gender inequalities in STEM labor market. Blacks earn less only in computer, physical and mathematical science fields. Hispanics have a disadvantage only in computer science. Demographic factors (e.g., age and marital status) are positively associated with salaries of only physical, social and engineering graduates. However, months that passed since graduation have a positive effect on pay regardless of major. This suggests that time spent in labor force either working or looking for job, increases one's chances of having higher salary. Another factor that positively affects earnings of all STEM graduates, but for life science majors, is college GPA. Furthermore, during recession, salaries have decreased almost in all fields except for computer science and health.

College size is a positive predictor of salaries for majority of majors – computer, physical and engineering, while health science graduates are the only group that is likely to earn more if graduated from a smaller institution. Unlike most prior research, the results suggest that graduates from private institutions do not have a pay advantage, with the exception of graduates with life science degrees. College selectivity is important for salaries of only social and health science graduates.

The effects of location factors vary by major. Salaries of engineering, math and social science graduates are affected by the location factors the most. For instance, social sciences and math graduates from areas close to STEM clusters are more likely to have higher pay than those in more remote areas. However, this effect is opposite for engineering graduates. Higher unemployment rate presented a disadvantage for graduates in most fields, except for health physical and life science majors. Finally, college areas with STEM employment concentration are positively related to earnings in engineering and health fields.

b. Underemployment

Women are more likely to be underemployed than men. Black graduates generally have a higher chance of being underemployed than white. Foreign born status is also associated with higher likelihood of working part-time. Family factors have little influence on underemployment, except for father's education. That is, the graduates whose father has a college degree are significantly less likely to be underemployed. Overwhelmingly, higher grades are likely to lead to a full-time job. Graduates with more experience, as measured by time since graduation, are predominantly employed full-time. When contr3olled for all other variables, graduates in the two last cohorts are significantly more likely to work part-time.

On average, college characteristics offer little explanation for the underemployment outcome. The only factor that influences chances of part-time work is college diversity, which is positively associated with underemployment. College location factors have more predicting power on underemployment than the characteristics of college. Overall, the proportion of STEM employees at the college location negatively associates with involuntary part-time employment. Share of manufacturing employment in the college area, on the other hand, is positively associated with higher probability of underemployment.

When analyzing STEM majors separately, graduates with engineering degrees are the least likely to be underemployed. Women with life and social science degrees have a significant employment disadvantage. Blacks are more likely to be underemployed only in social science and, to lesser extent, health science fields. Additionally, the effects of parental education and post-graduation experience pertains only to social science graduates. Higher grades result in higher pay only for computer, engineering and health science graduates.

Disaggregated analysis also reveals that some institutional factors significantly associate with underemployment in certain fields. For example, college STEM specialization significantly decreases the likelihood of underemployment for graduates with engineering and health degrees; and selectivity of college is negatively associated with underemployment for social science graduates. Among the location factors, concentration of STEM workforce has a negative relationship with underemployment for physical science graduates. Additionally, concentration of manufacturing significantly increases the likelihood of underemployment only for engineers.

c. Unemployment

The predictors that affected graduates' employment prospects somewhat differ from those that influenced underemployment outcome. On average, women are as likely to be unemployed as men. Asian graduates do not experience any disadvantage in terms of salary and full-time employment, however, they are significantly more likely to be unemployed. Blacks have a major disadvantage in employment compared to Whites. Additionally, unlike underemployment, unemployment odds are greatly impacted by family factors, such as marital status and children. While being married decreases one's odds of unemployment, having children present a reversed effect. Interestingly, older graduates are not just likely to earn more, they are also more likely to be unemployed. Similar to other outcomes, higher grades and more experience are significant predictors of post-graduation employment. In addition, the 2006 cohort is the least likely to be unemployed and the 2010 is the most. Langdon et al. (2011) also finds that aggregated STEM employment suffered during the recent economic downturn.

At the college level, only the proportion of Black students and college research/doctoral status positively influences unemployment odds. College size, on the other hand, is negatively associated with joblessness. Among location factors, only share of manufacturing workforce in a college area negatively affects unemployment outcome.

Health science graduates are the most likely to find a job. Female engineers have a slight disadvantage compared to men with the same degree. Asians are more likely to be jobless than Whites in majority of disciplines, engineering, health, life and physical sciences. Among the disciplines, unemployment prospects of social science and life science graduates are positively affected by marital status having children, respectively.

Additionally, temporal trends in unemployment vary by major. Only social and engineering graduates are significantly less likely to be jobless in 2006, compared to the 2003 cohort. Math and engineering graduates are the only groups that have had the higher unemployment during economic recession.

When looking at STEM majors separately, it is evident that unemployment of engineering graduates is greatly associated with many college factors. For example, graduating from racially diverse, research and doctoral granting institutions, and colleges with larger Hispanic populations increases the likelihood of unemployment for engineering majors. Moreover, racial diversity increases the likelihood of unemployment for computer science and engineering graduates. Social science graduates benefit from STEM workforce concentration. Among the college locations, computer science graduates are more likely be unemployed when graduated from colleges in smaller and more racially homogeneous areas. Physical science graduates have higher odds of being employed if they graduated from the areas with lower unemployment rate.

3. How does geography matter?

In the literature of college choice, where the location of college is concerned, studies have mainly focused on the college's proximity to home, preference for certain landscape and lifestyle, in-state or out-of-state location, in addition to institutional factors such as college rankings, prestige, tuition etc. At the same time, prior research on post-graduation labor market outcomes has solely focused on human capital and higher education institutional characteristics, with little attention to the role of college location and its characteristics. Results from this study suggests that the location of colleges does not only matter when choosing college, but also has profound impacts when they go to the job markets after graduation.

Labor force mobility has declined considerably over the past decades. This is largely attributed to various factors that prevent people from moving. For example, low housing supply in areas with many job opportunities is likely to drive prices up and increase the entry barrier (Schleicher, 2016). Therefore, for graduates who are just starting their careers and often have limited professional networks and spatial mobility, and fewer resources including both financial and social capital, which institution and which location that they graduated from can directly interfere their experiences of seeking and starting full time work.

The results of this study indicate that location and its characteristics have a substantial effect on all the three dimensions of career outcomes explored in this study. Location attributes help to explain 26 percent of variance between colleges for salary outcome. Moreover, for underemployment and unemployment outcomes, geographical factors exceed the predicting power of institutional level variables. This suggests that the large part of between-college differences in graduate's labor market outcomes is attributed not just to academic settings, but to higher education institutions' location and associated conditions.

Among geographic factors, local economic characteristics have the most significant influences on graduates' early careers. Colleges located in the areas that employ large numbers of STEM workers produce higher paid and fully-employed graduates, so as colleges located closer to STEM employment clusters. On the other hand, higher unemployment rate in places where colleges are located have a damaging effect on the employment opportunities and job earnings. These impacts from the college geographic locations are consistent with Glaeser et al. (1992) concept of localization effect. According to their perspective, concentration of one industry in an area creates a favorable environment for knowledge creation and diffusion. They argue that such industry clustering leads to increased competition that aids economic and innovative progress. Additionally, Freedman (2008), who studied localization of software publishing industry, also finds that salaries are higher in clusters, so as the likelihood of finding a job.

There are also other possible explanations for the impacts of STEM employment concentration on graduates' early careers. First, colleges located in smaller towns produce more specialized labor than the local economy can absorb. Manning and Petrongolo (2011) find that interest in jobs decays with distance. Therefore, the excess supply of STEM graduates may drive unemployment and underemployment up and consequently decrease salaries.

Second, graduates who attended colleges in places that specialize in STEM industries and the places with healthier local economies have more opportunities to get an internship or other professional training during college. These experiences add values to their competitiveness in the labor market after graduation. Indeed, prior literature suggests that students of urban colleges are most likely to have a professional part-time job (Price et al., 2003) and having this experience on a resume favorably impacts their employment after college (Sagen et al., 2000).

Third, the relationships between institutions and communities surrounding them are found to be very important for both student and employers. For instance, Rosenbaum

(1984) argues that close partnership between colleges and employers lead to better job placement of graduates of such colleges, as well as more streamlined recruitment for companies. He also notes that such relationships usually occur locally. Graduates from institutions that are connected to local employers are preferred not just during recruitment efforts, but also in the future when these employees are being considered for promotion. A lot has changed in job search and recruitment strategies since Rosenbaum wrote his study. The Internet and other technologies have widened the access to job opportunities for graduates and, at the same time, given the companies new ways to look for talent across the world. Nevertheless, data from company profiles on a job networking site, e.g., LinkedIn, confirm Rosenbaum's arguments. For example, many large technology corporations (i.e. Apple, Microsoft, Oracle etc.) that hire a lot of STEM talent, did most of their recruitment locally, from institutions with various selectivity and prestige (Pearlstein, 2014).

Fourth, there may be an indirect influence of college location on graduate's careers. For instance, some studies suggest that colleges in remote locations have staffing difficulties and high turnover of instructional and academic support staff (citations). This can negatively impact students' learning process, social network building, and, in turn, post-graduation outcomes.

Finally, labor force mobility is at the historically low level right now, as only 30 percent of graduates in the national sample crossed the state-line after graduation (Moretti, 2012). It is safe to assume that many graduates stay at or near areas where they attended college after graduation, where they attempt to secure employment. Therefore, the spatial inflexibility is likely to hinder graduates' early career in areas with weak economy and scarce opportunities in STEM employment.

4. Significance and Implications

This study offers several contributions to the literature on labor force development, higher education, and regional development in the United States. This study integrates a spatial component into an intersectional framework to better understand the spatial dimensions of labor market outcomes for the recent college graduates. This spatial approach to study post-graduation early employment is largely overlooked, as place is rarely being accounted as a separate factor in higher education's impacts on students.

a. Significance

Research on higher education. Various resources provide extensive information on colleges for prospective students and their parents. It covers almost every aspect of what different institutions have to offer; however, data on job placements and other post-graduation indicators are often absent. Recently, the federal government started a program that ranks universities by early labor market outcomes of its graduates (Bidwell, 2015, June 24). This study contributes to existing body of research on higher education through examination of the labor market experiences of recent college graduates, with a focus on location where they obtained higher education degrees.

To my knowledge, this is the first study that factors in socio-economic characteristics of college location to explain the post-graduation career-experiences. The results of this study suggest that previous models without considering the role of college location have overestimated the role of individual and institutional predictors by more than 20 percent. For instance, most of prior studies agreed on the importance of student's GPA and college selectivity for future earnings. These results indicate that their explanatory power decreases significantly when geographical predictors are introduced. These factors are still significant in the current study; however, their explanatory power reduces when geographical predictors are included. Along the same lines, the negative impacts of recent recession are overestimated by almost 36 percent in models without controlling for college location. This confirms prior findings on importance of geographic controls when estimating returns to education. (Black et al., 2009).

Labor market studies. Previous studies have highlighted human capital and social capital at the individual level and multiple factors at the higher education institutional level; however, they have not sufficiently examined the college location factors. For STEM in particular, previous research has highlighted the importance of STEM education in labor market outcomes, it has not simultaneously assessed the multiscalar factors, nor has it examined the sub-disciplines within the STEM from a comparative perspective. The current study provides a detailed, timely, comparative study to simultaneously examine the multi-dimensional and multi-scaled factors that impact STEM graduate early career experiences and particularly highlighted the geographic location of their colleges that is seldom examined in existing literature.

In addition to salary, two other dimensions of labor market experiences are explored in this study, underemployment and unemployment. Both unemployment (Abel et al., 2014) and underemployment (Scurry & Blenkinsopp, 2011) among recent college graduates received a popular attention, both in public media and academia, during last economic recession. In both cases, general economic conditions are blamed for worsening graduates' career outcomes. Both the current study and prior research identified many factors that contribute to inadequate employment, most notably is the college major (Carnevale, Cheah, & Strohl, 2013). Different from earlier studies, however, results from the current research suggest that, location-wise, unemployment and underemployment are the most prevalent among graduates from areas with higher presence of manufacturing industries, predominantly located in the rust belt. On the other hand, higher concentration of STEM employment, focused mainly in the coastal areas, leads to decreased underemployment.

This study also contributes to the scholarship on racial and gender disparities in the labor markets. For instance, the results show that gender pay gap is contingent on local industry specialization. Similarly, pay gaps between underrepresented minorities and Whites are reduced in places with higher STEM employment presence. Considering that such pay gaps are not uniform across the country, these findings are important for further understanding the spatial differences in earnings and other career outcomes. Additionally, the results of this study confirm prior findings on gender differences in unemployment during the latest recession. For example, similar to Sahin, Song, and Hobijn (2010), the current study finds that women have a much lesser disadvantage in terms of employment during and after the 2007 recession. However, after recession, women’s earnings were negatively affected to the lesser extent than men’s. Sahin et al. (2010) argue that this disparity is likely due to the more profound adverse influence of the recession on male-dominated fields. Results from this study do not support this conclusion, as women fared better in terms of earnings reduction, in every field including those dominated by men.

<u>Methodology</u>. Another novelty of this project lies in its methodology and usage of the privileged restrictive data. The restrictive dataset is largely underutilized and probably

this is the first time to be used for this type of analysis. First, the NSRCG datasets have the largest number of cases (suitable for this study) compared to similar programs, like Baccalaureate and Beyond Longitudinal Study and National Longitudinal Survey of Youth, which is very important when conducting spatial analysis. Second, it provides an extensive variety of parameters pertaining to both graduates and their educational history. Finally, microdata with geographic identification are extremely rare, not to mention a temporal dimension.

Besides NSRCG, this study integrates other datasets, such as IPEDS, OES and US Census data, to supplement the analysis with relevant variables. Further, a two-level hierarchical modeling is employed in this study to incorporate individual, institutional, and locational (and regional) factors. This approach perfectly suits the nested nature of the data and allows the comparison of within and between college-location effects. The current study provides a unique and multidimensional analyses of early career experiences of college graduates. Such an innovative methodological design provides a useful example for labor market research, higher education studies, and regional sciences.

b. Policy implications

Higher education. The results of the research have significant policy implications. Science and technology are the main drivers of modern economies across the world. A highly skilled and educated labor force is a key for development in these fields. Omnipresent shortages of such workers results in competition for talent at every level – regional, national and international. Therefore, it is critical to keep the investment in programs promoting the underrepresented populations in STEM education and careers. It not only benefits the society as a whole, but also reduces pay disparities across gender and race to achieve equitable growth. As shown by this study, women and racial minorities have already achieved pay parities in certain STEM fields. Collaborating on STEM initiatives with local communities and pre-K-12 schools could help to increase participation and reduce barriers related to educational preparation for the underrepresented groups.

Because significant differences in graduates' outcomes between higher education institutions are attributed to their locations, organizations that attempt to rank schools based on such outcomes have to account for differences in labor market conditions among various college locations. This is especially important when comparing the early career outcomes, as recent graduates are likely to stay in a college area for some time after graduation. Additionally, early career premiums related to area STEM concentration may not necessarily lead to mid-career advantages 10 or 20 years after graduation. Therefore, using early labor market outcomes as a main indicator of college quality, disregarding location and graduates' mid-career experiences, may be unfair to well-performing colleges in disadvantaged geographic locations and vice versa.

<u>Labor market and regional development.</u> As much as technology is a very global phenomenon, it is also localized and concentrated in a few major hubs across the US and the rest of the world. These technology hubs generally also have stronger economies, higher average wages, and better standard of living. Moreover, these benefits can be transferred to workers in other industries and occupations in the same locations (Moretti, 2012). Prior studies (Anselin, Varga, & Acs, 1997; Youtie & Shapira, 2008) find that universities play crucial part in regional development of research and innovative sectors. Knowledge spillovers created by higher education institutions facilitate growth in high-

technology industries. Indeed, universities have played major roles in the early establishment of many technology companies. The famous example is Alphabet (aka Google) that was born out of Stanford and Facebook was launched in Harvard. It suggests that local STEM talent development helps to ignite regional technology sector; however, Fallah et al. (2013) find no evidence of such effects, arguing that universities only help to create human capital, rather than knowledge spillovers.

The results of this study indicate a highly unequal success in landing a job, having full-time employment or competitive salary between areas with practically no STEM presence and major STEM hubs. It confirms that simply producing locally un-demanded STEM talent causes diminished early labor market advanteges for such graduates. Therefore, the integration between higher education and regional development is crucial to fully utilize human capital and promote high-tech, high-growth industry as well. Technology startups may provide training and employment opportunities for recent STEM graduates. Therefore, college administrators, local authorities and higher education policy makers are recommended to invest in college-affiliated innovation parks and incubators to enable more efficient integration of research into industry, facilitate economic growth and create jobs for graduates and local community at large.

Diversity initiatives targeted at STEM education should account for specifics of local labor markets that graduates enter after they finish college. For example, Figure 31 illustrates how much the predicted salary of a hypothetical STEM college graduate changes depending on college selectivity and employment concentration in a college location. This hypothetical graduate is assumed to be Black female with other conditions set at the mean of the national sample across cohorts. As shown here, the earnings vary dramatically depending on college quality and location. Although graduates from more selective colleges receive a salary premium regardless of area STEM concentration, the magnitude of pay gap between graduates from very selective to non-selective colleges increases significantly in STEM employment clusters. The prediction suggests that, for underrepresented minorities, college area economy structure is extremely important in determining their early career outcomes. This information could be useful for prospective STEM students and their parents in deciding where to go to college. Though attending a prestige college provides earning benefits after graduation, in many cases graduating from a less selective (and often more affordable) school located in a STEM hub may lead to similar or even better early labor market experiences.

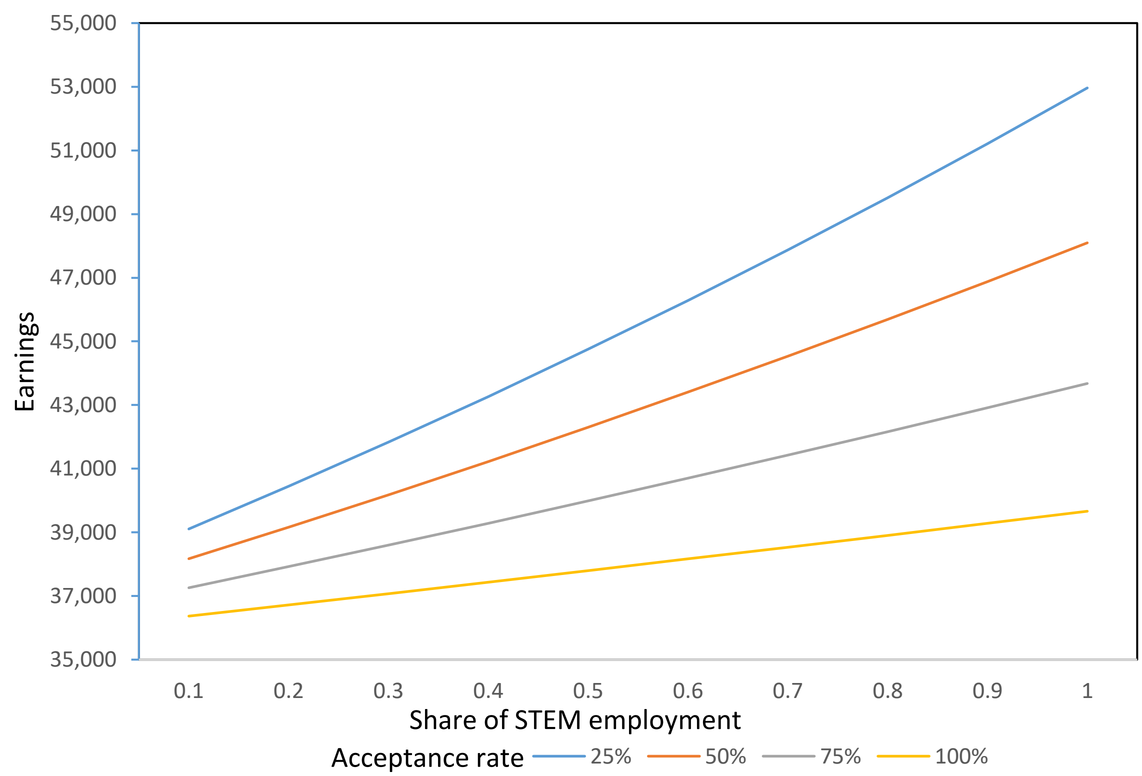

FIGURE 31: Predicted earnings of Black female graduates with the change of college acceptance rate and the STEM employment concentration in the college location

5. Limitations and further research

This study has a few limitations. (1) There is no available control for graduates' residence at the time the survey was taken. The omitted factors that pertain to location of residence may help to further differentiate the effects of where individuals go to college and where they are being employed. Moreover, exclusion of such controls may have inflated the importance of college area controls included in this study. Thus, further research needs to employ other datasets that have indicators pertaining to the current area of residence (on a smaller scale) and characteristics related to them. In addition, as this study finds post-graduation migration has a positive influence on graduate's early careers, it is still unknown how this happens. Especially, the current data do not allow examining whether it is people seek good jobs and, then, migrate; or people migrate first and then find good jobs; or simultaneously. This simultaneity suggests that more research on labor-force migration is required to understand the relationship between college location economic conditions and out-migration of graduates. Overall, there is no information at what point and how local STEM specialization factors into graduates' academic or post-graduate career. Future research with qualitative case studies could be useful in this aspect.

(2) When analyzing the disaggregated outcomes by major, disciplines are aggregated into larg common groups. Such aggregation may absorb differences within these major groups. For instance, civil engineers may have higher unemployment rate than any other engineers during the recent recession. Similarly, prior research suggests that economists earn significantly more than any other social science graduates. Future studies need to

concentrate on differences within these larger groups of disciplines, to see whether there are significant differences in outcomes between sub-disciplines.

(3) The data does not indicate whether graduates ever transferred between schools. This uncertainty may complicate the assessment of both institutional and geographical effects in cases when a graduate attended more than one college in different locations. Unfortunately, such distinctions are out of scope of this study.

(4) There are some limitations concerning methodology used in this study. Considering that this study is focused on three distinct blocks of predictors – individual, institutional and location – a three-level HLM would be a better fit for this study. In the current study, there are only a few areas that include more than one university and the sample size is insufficient to set up a three-level framework. Future research could be possible to explore the geographical impacts on labor market experiences with a larger sample size of universities across locations.

Additionally, utilizing ordinal regression may be useful in research of employment status of graduates, where unemployment, underemployment and full-time employment indicators exist on an ordinal scale. In addition to estimating the strength of the effect that predictors have on the employment status, ordinal regression helps to predict how much change in independent variable leads to change in employment situation (i.e. underemployed to fully employed).

Many STEM graduates work in occupations outside their fields of study (Hyer, 2014). Controlling for occupational mismatch may be useful in assessing to what extent working in a job unrelated to college major influences earnings and employment opportunities. As online education is becoming more common, taking into account the mode of education (online vs. face-to-face) is crucial for accessing geographic effects. This is important especially because graduate of online colleges may have never been to a place where school (headquarter) is located.

Finally, this study used four cohorts to explore temporal trends. Since each cohort combined graduates from multiple years, variation in outcomes from year to year may be more accurate than differences between cohorts.

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APPENDIX 1

List of disciplines
Computer sciences
Computer and information sciences
Computer science
Computer systems analysis
Information services and systems
OTHER computer and information sciences
Life sciences
Animal sciences
Food sciences and technology
Plant sciences
OTHER agricultural sciences
Biochemistry and biophysics
Biology, general
Botany
Cell and molecular biology
Ecology
Genetics, animal and plant
Microbiological sciences and immunology
Nutritional science
Pharmacology, human and animal
Physiology and pathology, human and animal
Zoology, general
OTHER biological sciences
Environmental science or studies
Forestry sciences
Mathematical sciences
Applied mathematics
Mathematics, general
Operations research
Statistics
OTHER mathematical sciences
Physical sciences
Chemistry, except biochemistry
Atmospheric sciences and meteorology
Earth sciences

Geology
Geological science, other
Oceanography
OTHER physical sciences
Astronomy and astrophysics
Physics
Social sciences
Educational psychology
Clinical psychology
Counseling psychology
Experimental psychology
Psychology, general
Industrial and organizational psychology
Social psychology
OTHER psychology
Agricultural economics
Economics
Public policy studies
International relations
Political science and government
Anthropology and archeology
Criminology
Sociology
Area and ethnic studies
Linguistics
Philosophy of science
Geography
History of science
OTHER social sciences
Engineering
Chemical engineering
Architectural engineering
Civil engineering
Computer and systems engineering
Electrical, electronics and communications engineering
Industrial and manufacturing engineering
Mechanical engineering
Aerospace, aeronautical and astronautical engineering

Agricultural engineering
Bioengineering and biomedical engineering
Engineering sciences, mechanics and physics
Environmental engineering
Engineering, general
Geophysical and geological engineering
Materials engineering, including ceramics and textiles
Metallurgical engineering
Mining and minerals engineering
Naval architecture and marine engineering
Nuclear engineering
Petroleum engineering
OTHER engineering
Health
Audiology and speech pathology
Health services administration
Health and medical assistants
Health and medical technologies
Medical preparatory programs (e.g. pre-dentistry,-medical,-veterinary)
Medicine (dentistry, optometry, osteopathic, podiatry, veterinary)
Nursing (4 years or longer program)
Pharmacy
Physical therapy and other rehabilitation/therapeutic services
Public health (including environmental health and epidemiology)
OTHER health and medical sciences

APPENDIX 2

List of geographic areas	
1	Abilene, TX
2	Aguadilla-Isabela, PR
3	Albany-Schenectady-Troy, NY
4	Albuquerque, NM
5	Ames, IA
6	Ann Arbor, MI
7	Athens-Clarke County, GA
8	Atlanta-Sandy Springs-Roswell, GA
9	Atlantic City-Hammonton, NJ
10	Auburn-Opelika, AL
11	Augusta-Richmond County, GA-SC
12	Austin-Round Rock, TX
13	Balance of Lower Peninsula of Michigan nonmetropolitan area
14	Baltimore-Columbia-Towson, MD
15	Baton Rouge, LA
16	Bellingham, WA
17	Binghamton, NY
18	Birmingham-Hoover, AL
19	Blacksburg-Christiansburg-Radford, VA
20	Bloomington, IN
21	Boston-Cambridge-Nashua, MA-NH
22	Boulder, CO
23	Bowling Green, KY
24	Bridgeport-Stamford-Norwalk, CT
25	Buffalo-Cheektowaga-Niagara Falls, NY
26	Capital/Northern New York nonmetropolitan area
27	Carbondale-Marion, IL
28	Central Kentucky nonmetropolitan area
29	Central Missouri nonmetropolitan area
30	Central-Southeast Wyoming nonmetropolitan area
31	Champaign-Urbana, IL
32	Charlotte-Concord-Gastonia, NC-SC
33	Charlottesville, VA
34	Chattanooga, TN-GA

35	Chicago-Naperville-Elgin, IL-IN-WI
36	Chico, CA
37	Cincinnati, OH-KY-IN
38	Cleveland-Elyria, OH
39	College Station-Bryan, TX
40	Columbia, MO
41	Columbia, SC
42	Columbus, GA-AL
43	Columbus, OH
44	Corvallis, OR
45	Cumberland, MD-WV
46	Dallas-Fort Worth-Arlington, TX
47	Davenport-Moline-Rock Island, IA-IL
48	Deltona-Daytona Beach-Ormond Beach, FL
49	Denver-Aurora-Lakewood, CO
50	Detroit-Warren-Dearborn, MI
51	Dover, DE
52	Durham-Chapel Hill, NC
53	East Georgia nonmetropolitan area
54	East South Dakota nonmetropolitan area
55	East Washington nonmetropolitan area
56	Eastern and Southern Colorado nonmetropolitan area
57	El Paso, TX
58	Erie, PA
59	Fairbanks, AK
60	Fargo, ND-MN
61	Fayetteville-Springdale-Rogers, AR-MO
62	Fort Collins, CO
63	Fresno, CA
64	Gainesville, FL
65	Grand Junction, CO
66	Greensboro-High Point, NC
67	Greenville-Anderson-Mauldin, SC
68	Harrisburg-Carlisle, PA
69	Harrisonburg, VA
70	Hartford-West Hartford-East Hartford, CT
71	Hattiesburg, MS
72	Houston-The Woodlands-Sugar Land, TX

73	Huntington-Ashland, WV-KY-OH
74	Huntsville, AL
75	Indianapolis-Carmel-Anderson, IN
76	Iowa City, IA
77	Ithaca, NY
78	Kalamazoo-Portage, MI
79	Kansas City, MO-KS
80	Knoxville, TN
81	La Crosse-Onalaska, WI-MN
82	Lafayette-West Lafayette, IN
83	Lansing-East Lansing, MI
84	Las Cruces, NM
85	Las Vegas-Henderson-Paradise, NV
86	Lawrence, KS
87	Lexington-Fayette, KY
88	Lincoln, NE
89	Logan, UT-ID
90	Los Angeles-Long Beach-Anaheim, CA
91	Louisville/Jefferson County, KY-IN
92	Lubbock, TX
93	Lynchburg, VA
94	Macon, GA
95	Madison, WI
96	Manhattan, KS
97	Mayaguez, PR
98	McAllen-Edinburg-Mission, TX
99	Memphis, TN-MS-AR
100	Miami-Fort Lauderdale-West Palm Beach, FL
101	Michigan City-La Porte, IN
102	Milwaukee-Waukesha-West Allis, WI
103	Minneapolis-St. Paul-Bloomington, MN-WI
104	Modesto, CA
105	Morgantown, WV
106	Mountain North Carolina nonmetropolitan area
107	Muncie, IN
108	Myrtle Beach-Conway-North Myrtle Beach, SC-NC
109	Nashville-Davidson--Murfreesboro--Franklin, TN
110	New Bedford, MA

111	New Haven, CT
112	New Orleans-Metairie, LA
113	New York-Newark-Jersey City, NY-NJ-PA
114	Northeast Louisiana nonmetropolitan area
115	Northeast Mississippi nonmetropolitan area
116	Northern Indiana nonmetropolitan area
117	Northern Pennsylvania nonmetropolitan area
118	Northern Vermont nonmetropolitan area
119	Northwest Massachusetts nonmetropolitan area
120	Northwest Oklahoma nonmetropolitan area
121	Norwich-New London-Westerly, CT-RI
122	Oklahoma City, OK
123	Orlando-Kissimmee-Sanford, FL
124	Oxnard-Thousand Oaks-Ventura, CA
125	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
126	Phoenix-Mesa-Scottsdale, AZ
127	Piedmont North Carolina nonmetropolitan area
128	Pittsburgh, PA
129	Pittsfield, MA
130	Portland-Vancouver-Hillsboro, OR-WA
131	Providence-Warwick, RI-MA
132	Provo-Orem, UT
133	Raleigh, NC
134	Richmond, VA
135	Riverside-San Bernardino-Ontario, CA
136	Rochester, NY
137	Sacramento--Roseville--Arden-Arcade, CA
138	Salt Lake City, UT
139	San Angelo, TX
140	San Antonio-New Braunfels, TX
141	San Diego-Carlsbad, CA
142	San Francisco-Oakland-Hayward, CA
143	San Jose-Sunnyvale-Santa Clara, CA
144	San Juan-Carolina-Caguas, PR
145	San Luis Obispo-Paso Robles-Arroyo Grande, CA
146	Santa Cruz-Watsonville, CA
147	Santa Maria-Santa Barbara, CA
148	Santa Rosa, CA

149	Seattle-Tacoma-Bellevue, WA
150	South Bend-Mishawaka, IN-MI
151	South Central Wisconsin nonmetropolitan area
152	Southeast Alabama nonmetropolitan area
153	Southeast Coastal North Carolina nonmetropolitan area
154	Southeast Iowa nonmetropolitan area
155	Southeast Kansas nonmetropolitan area
156	Southeast Oklahoma nonmetropolitan area
157	Southern Ohio non-metropolitan area
158	Southwest Massachusetts nonmetropolitan area
159	Southwest Mississippi nonmetropolitan area
160	Southwest New York nonmetropolitan area
161	Springfield, MA-CT
162	Springfield, OH
163	St. Cloud, MN
164	St. Louis, MO-IL
165	State College, PA
166	Syracuse, NY
167	Tallahassee, FL
168	Tampa-St. Petersburg-Clearwater, FL
169	Terre Haute, IN
170	Trenton, NJ
171	Tucson, AZ
172	Tyler, TX
173	Upper Peninsula of Michigan nonmetropolitan area
174	Urban Honolulu, HI
175	Vallejo-Fairfield, CA
176	Virginia Beach-Norfolk-Newport News, VA-NC
177	Waco, TX
178	Walla Walla, WA
179	Washington-Arlington-Alexandria, DC-VA-MD-WV
180	West Central New Hampshire nonmetropolitan area
181	Western Pennsylvania nonmetropolitan area
182	Winston-Salem, NC