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The Geography of Jobs: How Proximity to a Prestige Labor Market Shapes Opportunity for Computer Science Degree Holders

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Abstract: A computer science degree is seen as a good investment, given the lucrative calling of Silicon Valley and the ever-growing demand for software engineers. Yet, it is unclear whether all computer science degree holders fare equally well on the job market. This study explores how the routing of computer science (CS) students to specific educational geographies plays a major role in determining their career trajectories post-graduation. Using a new survey for recent computer science graduates of three public universities in Texas, I measure labor market outcomes for CS degree holders along three metrics: salary, job location, and job title. Results from 157 respondents show that alumni from universities near a major tech hub are more likely to earn higher wages in desirable job markets compared with graduates from a university located far from a dense tech hub. Although most previous studies have focused on gender and racial disparities within the high-tech industry, I provide a new lens to understand how inequality manifests through geographic segregation and leaves even high-skilled job seekers vulnerable to spatial mismatch between their place of residence and proximity to desirable, elite jobs.

Keywords: race; STEM; inequality; education

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1. Introduction

Previous research has demonstrated that job matching for STEM job seekers tends to be better in particular mid-sized metro regions where there is a deep concentration of STEM jobs such as San Jose, CA, Seattle, WA, and Austin, TX (Wright et al. 2016). Those regions overlap with major tech epicenters, colloquially referred to as Silicon Valley and its various satellite counterparts (Moretti 2013; Wright et al. 2016). Working in these geographic regions benefits all those in the local economy, including providing higher wages for *all* workers, and increased opportunities to innovate in highly specialized fields (Moretti 2013; Wright et al. 2016).

Furthermore, living in one of these "brain hubs" is professionally advantageous: not only are workers exposed to knowledge spillover, they produce better quality work (Moretti 2013). Software engineers living in a prestige city, even those working in non-elite companies, are exposed to new ideas and are privy to knowledge spillovers in a way that their colleagues living far from a tech hub are not (Moretti 2013; Wright et al. 2016). Because of these advantages, working in one of these tech hubs is particularly attractive for workers and establishes the importance of *where* someone works as a potential mechanism for understanding high-tech inequality. A second spatial variable that is less explored but which may help explain disparities on the high-tech labor market is the location of educational institutions and whether their proximity to a STEM hub confers advantages to its students on the labor market.

Despite the role geography and density of job opportunity plays in job matching, inequality research on the stratification of high-tech labor markets has primarily focused on gender and racial disparities in software engineering (Abbate 2012; Ensmenger 2015;

Alegria 2019; Alfrey and Twine 2017; Margolis et al. 2011; Chavez 2020). Job matching in STEM fields is particularly significant because (a) it reveals who is able to pursue degree-relevant jobs and (b) it provides insight into the variability among STEM jobs in terms of salaries, promotion ladders, and prestige. Interrogating variability in specific job outcomes can help shed light on how workers are sorted on the high-tech labor market and which characteristics can propel job seekers into desirable career opportunities. This project introduces a new lens on occupational inequality, geography, in order to understand how highly skilled workers are matched to jobs in the high-tech industry. Because this field is particularly inclined to agglomerate and is closely tied to geographic regions (Moretti 2013), I focus on the ways geographic positioning of postsecondary institutions impacts the school-to-work transition for computer science (CS) degree holders. That is, are the job opportunities of potential software engineers in some ways shaped by their institution's proximity to a nearby tech hub?

Using original survey data from Texas public universities, I assess how CS degree holders differ in opportunities to transition into desirable jobs. I first identify the geographies of labor markets that scholars have determined as particularly promising for tech workers. I then analyze original survey data on recent CS graduates to assess the determinants of the graduates' success at their first job post-college using three key metrics: salary, work region, and job title. My findings reveal that the location of a university sorts workers into geographically and racially segregated labor markets. Alumni from universities located in high-tech hubs are significantly more likely to work in the same high-tech hub or to travel to another one, whereas graduates from a university in a peripheral region very rarely find jobs in a dense STEM labor market. Results shed light on disparities between Hispanic and non-Hispanic graduates in Texas as well. Hispanic computer science degree holders are more likely to be found in universities located in non-prestige tech hubs and are less likely to reap the associated labor market advantages associated with proximity to a dense STEM labor market. Consequently, they also earn less than their non-Hispanic peers in their first job post-college, even after controlling for university location.

1.1. Why Texas?

Most previous research on computer science degree earners have used national or cross-national datasets to focus on overall labor market outcomes (Sassler et al. 2017; Ma and Liu 2017), which can obscure the effects of regional characteristics such as local racial demographics and historical context such as Jim Crow segregation. Studying a specific region makes it possible to explore how local inequalities shape the labor market (see McCall 2001; McDonald et al. 2015). I situated my study in Texas for two reasons: one, it has an established and fast-growing tech scene in Austin and two, Texas has a large Hispanic workforce (Moretti 2013; Straubhaar et al. 2012; Hughs et al. 2018). There is currently limited research that focuses on the outcomes of Hispanic[1] computer scientists; most recent scholarship on race and high-tech organizations is conducted through a broadly comparative lens and is analyzed using a gendered analysis (Alfrey and Twine 2017; Alegria 2019).

Texas is also the fourth-highest producer of computer science bachelor degree holders in recent years (only California, New York, and Florida conferred more four-year degrees in 2015–2016) (National Center for Education Statistics 2018). Most research conducted on the tech industry has focused on the west coast (see Petersen et al. 2000; Cooper 2000; Alfrey and Twine 2017) and while it is critical to understand the nuances of Silicon Valley's labor force, more than 80% of software engineering jobs are located outside of the Bay Area (Rodriguez 2016; Stephens and Mahesh 2018) and drawn from demographically diverse labor pools.

Educational segregation has and continues to deeply affect the Hispanic population in Texas, and the Mexican community in Texas has faced substantially more barriers to equal education and have fewer years of formal schooling in Texas than elsewhere in the United States (Bean et al. 2015; San Miguel 2001). At the K-12 level, roughly two-thirds of

Mexican American students attend schools where more than 70% of their peers are also ethnic minorities (Valencia 2000). This segregation continues in postsecondary years; the top five universities conferring bachelor's degrees to Hispanic students in the 2017–2018 academic year are Hispanic-Serving Institutions (Latino College Completion: United States n.d.). Additionally, Hispanic software engineers are most likely to earn computer and information science degrees in co-ethnic communities far from a major tech hub (Santiago and Soliz 2012).

More recently, the state has whittled away at successful racial integration efforts at the collegiate level. Hopwood v. Texas struck down affirmative action at public universities in Texas, Louisiana, and Mississippi in 1996. In the years post-Hopwood, Texas passed the Uniform Admission Policy, more commonly known as the Top 10% law, in an attempt to ensure applicant pool diversity by automatically accepting the top ten percent of high school applicants into the public university of their choosing. This resulted in fewer Black and Hispanic applicants and offers of admission to Texas' flagship universities, Texas A&M, and University of Texas at Austin (Harris and Tienda 2010).

1.2. Inequality in the High-Tech Industry

Social scientists have long been interested in gender segregation in STEM education and job outcomes but are less likely to focus on individual disciplines and the variations within (Ma and Liu 2017; Charles and Bradley 2006). The reality is that not all STEM fields are created equal. The Bureau of Labor Statistics predicts 7800 job openings for biologists between 2016 and 2026, with the median pay hovering around USD 60,000–70,000, depending on the industry specialty. Software developers will see a whopping 118,000 jobs by 2026 with median pay in the six figures (Bureau of Labor Statistics 2019). These striking differences in gender parity and job demand provide a compelling reason to examine individual STEM fields in order to understand their specific cultural and economic realities. In particular, the academic discipline that leads to a job in software engineering, computer science, remains an anomaly even among other STEM disciplines, in terms of pay gaps over the life course among the genders (Michelmore and Sassler 2016) and the mechanisms for female occupational persistence (Sassler et al. 2017; Shauman 2017).

That computer science and its related occupational field, high-tech, has become increasingly hostile to women's entrance in the past two decades has been a focal point of much STEM research (Abbate 2012; Ensmenger 2015; Alegria 2019; Margolis et al. 2011; Wynn and Correll 2017; Wynn 2020). In particular, social scientists debate the mechanisms that shape the educational pipeline for potential tech workers (Margolis et al. 2011; Ma and Liu 2017; Morgan et al. 2013; Binder et al. 2015) and detail the particular cultural and professional obstacles that women face in the high-tech workplace (Alfrey and Twine 2017; Alegria 2019; Shih 2006, Shih 2006).

Although STEM scholars have not necessarily considered the variability of educational credentials, such as the selectivity of a university, as a critical component of their study, race and inequality scholars have long examined how women and racial minorities have trouble accessing the associated benefits of schooling on the labor market (Rivera and Tilcsik 2016; Gaddis 2015; Bowles and Gitis 2011). Royster has also documented the failures of vocational schools and instructors in providing black students the resources they extend to white students, namely mentorship, work opportunities and access to social networks during and after their training, which negatively affects job outcomes for skilled black workers (Royster 2003). Because previous studies have also documented disparate occupational outcomes for racial minorities in the tech industry (Gee and Peck 2018; Diversity in High-Tech n.d.; Chavez 2020) and given the tech industry's proclivity to recruit from both elite and proximate universities, I expect to find labor market inequality based on race, geography, and university selectivity for computer science degree earners.

1.3. The Geography of the High-Tech Industry

Wright et al.'s (2016) research finds that a density of jobs (calculated as workers per unit area), rather than a large labor market, helps highly skilled STEM workers secure work. Their analysis shows medium-sized metro regions such as San Jose, Seattle, Raleigh-Durham, Austin, and San Francisco have a denser concentration of STEM jobs and are more conducive to job matching than large STEM labor markets. This may explain why areas such as Silicon Valley are seen as desirable places for tech workers. Not only do these tech hubs offer exciting places for innovation and provide a higher quality of life (Moretti 2013), they also confer real benefits for job matching for future STEM workers.

Because most previous studies on tech workers have not taken differences in geography into account, I borrow from Wright et al.'s (2016) broader research on STEM labor markets, along with economist Enrico Moretti's insights on the geographies of jobs, to establish that particular regional ecosystems that prize innovation are particularly attractive to tech workers (Moretti 2013). Wright et al. (2016) as well as Moretti (2013) call out a similar set of "brain hubs" that have a deep concentration of knowledge workers and business investment: the San Francisco Bay Area, Austin, Seattle, and Raleigh-Durham. In this study, I refer to these cities as prestige tech hubs because working in them confers real advantages, such as job matching, career specialization, and higher salary, for those graduating with a computer science degree and who want to secure a job matching their degree (Moretti 2013). As Moretti (2013) points out, these highly innovative hubs signal that another dimension of economic and social inequality is our geographic divide.

Given the benefits associated with specific geographic regions, it also stands to reason that educational institutions located within these hubs may be particularly in tune with the industry's fast-changing demands. Multiple datasets that track the pipeline between university and tech companies indicate that while the selectivity of the university matters in sending students to tech companies, being near a major tech region also boosts the opportunities of students attending less selective institutions like San Jose State University and Santa Clara University (Hartmans 2017; Barba 2015). For instance, workers for online retail giant Amazon are more likely to have attended University of Washington and Washington State University than the highly prestigious Carnegie Mellon University (Barba 2015).

I hypothesize that it is advantageous to attend a university near a major tech region because it allows students to build their social network during college and may ease some of the spatial mismatch between job opportunities and physical location that may occur when students' hometowns are far from a tech center or they attend universities outside of a major tech hub.

Hypothesis 1 (H1). *Students who graduate from universities in a tech hub are more likely to transition into a job within a prestige tech hub than their peers who attend university outside of a tech hub.*

Additionally, because job matching is better in dense labor markets like Seattle and Silicon Valley, it is also likely that students from universities near a tech epicenter are job matching into careers that make use of their degree.

Hypothesis 2 (H2). *Students who graduate from universities in a tech hub are more likely to find degree-relevant jobs compared with their peers who attend university outside of a tech hub.*

I also examine whether the financial benefits for workers in STEM-dense labor markets apply to computer science degree holders. Because many occupational characteristics such as specialization and salary depend largely on geography (Moretti 2013), I suggest that:

Hypothesis 3 (H3). *Controlling for university attended, alumni working in a prestige tech hub earn higher salaries compared with their peers working in a non-prestige tech hub.*

Finally, because of existing research on race and high-tech job outcomes, I also expect Hispanic job seekers to be less successful in their transition into the labor market on the three previously defined job outcome metrics.

Hypothesis 4a (H4a). *Hispanic computer science degree earners will be less likely to work in prestige tech hubs.*

Hypothesis 4b (H4b). *Hispanic computer science degree earners will be less likely to transition into degree-relevant jobs.*

Hypothesis 4c (H4c). *Hispanic computer science degree holders will earn lower salaries.*

2. Data and Methods

Because there is so little research on regional outcomes for tech workers, I created and administered a new online survey specifically for this project. My survey collected basic demographic data as well as geographic data on location of high school, college, first job after graduation, and job-related data such as the specific programming languages used at work, exact job title, and salary. I provided guidance on how to report job title by providing examples (e.g., "Senior Front-end Engineer") and also by stating that the job did *not* have to be related to their major in an effort to capture responses by those who did not find or opted out of computer science-degree related jobs. Capturing job-specific information paints a more nuanced understanding of work responsibilities and allowed for assessment of whether alumni are fully utilizing their degrees.

I contacted faculty and staff at multiple universities throughout Texas in order to introduce my project; three universities agreed to the study. I aimed to have a diversity of institution participation along two dimensions: institutional status ("elite" or "non-elite") and geographic region (tech hub, non-tech hub) (see Table 1). Although originally I had planned to have universities that occupied different combinations of these two dimensions (e.g., "elite, tech hub"; "non-elite, tech hub"), I was unable to procure responses from universities that fulfilled the "elite, non-tech hub" requirements to be a part of this study. However, the three participating universities did offer enough similarities and variations in their student population, region, and admissions selectivity to allow for an understanding of the mechanisms that impact job outcomes for CS degree holders.

Table 1. Universities by institution type and geography.

	Institution Type	Geography
Elite Central University	Elite	Tech Hub
Central State University	Non-Elite	Tech Hub
Regional University	Non-Elite	Non-Tech Hub

I worked with computer science department chairs and their administrative staff to launch the survey on the same day across the universities and conducted at least two rounds of data collection per school. Alumni who graduated from their programs between the years 2010 and 2017 and who had emails documented with the department received our survey through their university's official computer science department listserv.

Survey data was collected from March–August 2018 with an online survey created in Qualtrics. Two hundred and forty-nine alumni responded and approximately 94% of all surveyed had been employed at some point since graduation; I kept these participants and dropped all others for an analytic yield of 157 survey participants, with an overall response rate of 19%. Because opting into the department listserv is optional, my response rate was calculated based on those who had chosen to do so. There is a possibility that alumni who opted into the survey may have been a self-selecting group that was successful in having found a tech-related job and consequently felt more confident about taking the survey. My survey attempted to mitigate some of the potential hesitancy for those that were unable to find jobs in tech by encouraging everyone, regardless of job outcome, to respond to the survey. When comparing my sample to computer science departments broadly, however, it seems that any self-selection may have had minimal effects as the sample is representative of the computer science population in terms of racial and gender composition at their respective computer science departments.[2]

I recognize that I had a small sample size which limits my analysis but the response rate is fairly typical of web-based surveys (Sills and Song 2002) and my study addresses a significant hole in the research. Because few studies have focused on either regional experiences of tech workers outside of Silicon Valley or Hispanic computer scientists, I hope this study offers a new perspective to understand stratification mechanisms in the high-tech industry and inspires further study.

A quarter of survey respondents were women, higher than the national average (~18%) of female computer science degree holders in the same years (National Center for Science and Engineering Statistics 2019a). Nationwide, Hispanics earned 7–10% of computer science degrees in the years surveyed (National Center for Science and Engineering Statistics 2019b) but they made up made up 36% (n = 56) of the survey respondents in this study.

2.1. Dependent Variables: Early Career Outcomes

I measured first job outcomes in three ways in order to fully distinguish the available opportunities for computer scientists post-graduation: job location, job title, and salary.

2.1.1. Job Location

I identified four metropolitan regions relevant to my study: Seattle, the San Francisco Bay Area, Austin, and Raleigh-Durham. I relied on Wright et al.'s (2016) calculations for the highest concentration of STEM workers using location quotients, a calculation that examines geographic concentration relative to a broader population, and Moretti's (2013) definition of innovation economies to identify the SF Bay Area, Seattle, Austin, and Raleigh-Durham as the relevant tech hubs for this study. These four locations are considered desirable STEM labor markets because they have a large quantity of STEM jobs *and* a pool of knowledge workers that cannot be easily reproduced or replaced by competitors (Wright et al. 2016; Moretti 2013).

These tech hubs are metro areas rather than specific cities because some well-known tech organizations situate their campuses outside of the city proper, such as Microsoft headquarters in Redmond, Washington or the Dell campus in the Round Rock suburb just north of Austin. Not all metro regions connected to a tech city can automatically be considered a tech hub. For instance, the greater Austin region includes Pflugerville and San Marcos, but they do not have a similar density of STEM jobs or a high-tech campus that anchors the community and is a major provider of jobs.

I have identified these tech hubs as elite markets because they provide workers access, on average, to higher wages, better working conditions, and more interesting work (Moretti 2013). The distribution of elite tech jobs is particularly important to acknowledge because tech employers often capitalize on regional talent by creating distributed offices and headquarters, as well as acquiring local start-ups that then become part of larger conglomerates. Examples include Washington-based Expedia's acquisition of the Austin-based home rentals start-up HomeAway (nowVrbo) or Menlo Park's Meta (formerly Facebook) operating several software-driven campuses in Seattle, Austin, and San Francisco. The geographic spread of established tech companies and the mobility of tech workers even within these organizations make it important to recognize that multiple prestige labor markets exist outside of Silicon Valley.

Thick labor markets, or regions where there is a density of skilled workers and job opportunities, allow for more specific skill matching among employers and employees and raise wages for both skilled and nonskilled workers in the region (Moretti 2013). While other cities may have greater quantities of software jobs, the regions I define as prestige hubs are well-known among professionals as having a dense concentration of tech organizations and whose environment is heavily influenced by the proliferation of these businesses.

2.1.2. Occupation

I tracked whether a participant's first job post-graduation utilized or did not utilize their computer science degree. I examined several self-reported characteristics about their jobs. The first was the programming languages used on the job, if at all. For those that identified as some variation of a software engineer, they self-reported a fairly similar set of programming languages: Java, C#, python, JavaScript. The self-reported job title was also helpful in identifying how people were using languages. Respondents provided helpful descriptors of their titles, "Full Stack Software Engineer" or "DevOps Engineer", which provided additional support that they were in fact using their degrees. I also accepted alternative job titles that made use of similar programming languages, such as IT Program Manager and Data Integration Consultant. If an individual did not report using any programming languages at work and/or worked in service occupation jobs such as customer service, I considered them to be outside the "optimal" career path for alumni because their jobs did not require computer science degrees. Interns (n = 6) were coded with their most likely career path based on internship title.[3]

2.1.3. Salary

Software engineering is a rare job that allows college degree holders to immediately enter a middle-class lifestyle. An entry-level software developer earns in the USD 60,000–70,000 range in two of Texas' largest job markets for software engineers, Austin and Dallas, as well as in the metro region near the Texas–Mexico border, where many of the Hispanic computer science alumni surveyed find jobs after college (Annual MSA Wages 2017). I collected salary data in ordinal categories to reduce user error by restricting manual input data, and to make personal information slightly less intrusive. I converted salary bands into an interval-like variable by taking the midpoint of each salary band (i.e., using USD 35,000 for a USD 30,000–39,999 range). I capped the highest salary band at USD 170,000 and logged wages in order to normalize responses.[4]

2.2. Independent Variables

Location of degree institution is a central explanatory variable in this analysis. Two of the surveyed universities are located in or near a tech hub. These vary by institutional prestige, so I am able to distinguish "hub" effects from status effects by using a dummy indicator for hub location (1 = yes) and another for prestige institution (1 = yes). The three institutions can be described as follows:

2.2.1. Central Elite University

Central Elite University is a highly desirable university for Texans located near one of the identified tech hubs in Austin. It is ranked as a "more selective" university by the U.S. News and World Report, accepting roughly one-third of all applicants. Central Elite University houses a highly respected computer science department and its students should be guided by similar elite job-seeking behaviors as their peers at other selective universities. Previous studies also show that elite employers express a greater interest in elite students (Rivera 2015)—and in particular, white elite students (Gaddis 2015)—and provide them with career opportunities in a variety of well-paying career tracks. Hispanic students make up 22% of all computer science degree majors surveyed for this institution. Central Elite University alumni should have ample access to any of tech's premiere labor markets and should be able to secure well-paying and degree-relevant jobs post-graduation.

2.2.2. Central State University

Central State University is located within the same metro region as Central Elite State University, although it is far less selective, accepting nearly three-quarters of all applicants.

Seventeen percent of all survey respondents from Central State University were Hispanic. I consider Central State University's proximity to a major tech hub and desirable employers a particular advantage for its students. These students may also attend similar networking events as their peers from Central Elite University but their ability to translate their degrees into an elite job may be limited to the Texas market, where they benefit from local familiarity with the school's academic reputation and its alumni base.

2.2.3. Regional University

Alumni from a third university, situated near the Texas–Mexico border, also responded to the survey. Regional University shares a similar academic reputation and selectivity with Central State University but is isolated from any major tech market. Unlike Central Elite University, which attracts students both near and far because of its academic reputation, Regional University focuses on serving its local community: more than 90% of its student population comes directly from the metro region and nearly 90% of the survey respondents identified as Hispanic. Comparing Regional University and Central State University makes it possible to determine whether a university's geography has an effect on job outcomes, holding constant school prestige and selectivity.

I tracked geographic mobility through two metrics: log distance[5] between hometown and university attended, and log distance between college attended and first job.[6] Differentiating between the distances traveled makes it possible to determine which mobility behavior (i.e., leaving home to go to college, or leaving home for a first job) aligns with positive labor market outcomes.

I coded race using the dummy variables "Hispanic", and "Non-Hispanic" with the latter as the reference group. I also controlled for GPA, graduation year, and gender. I used a single measurement of SES, parental education, because it is more likely to be correctly identified by respondents, less intrusive, and has the ability to provide a long view into potential earnings over the life course (Shavers 2007; Sirin 2005). I coded parental education by their highest level of education and converted it to approximate schooling years. For instance, a doctorate degree was equivalent to 22 years of schooling, whereas those whose highest education level was elementary school were given five years of schooling in my coding scheme.[7] Vocational schooling was equivalent to an associate's degree (=14 years). I imputed eight parental education levels based on immigrant status and race.[8]

Parental support is a frequent topic in the literature on Hispanic students; high-achieving Hispanic women's success at the postsecondary level is largely attributed to mother's support (Gándara 1982), while educational attainment and labor force entrance are guided by parental expectations (Ovink 2014; Bean et al. 2015). I measured parental support in response to the following question, "Do you feel that parent/guardian (one or two) supported your decision to pursue your computer science degree?" (1 = strong supported, 5 = strongly disapproved, recoded so that the highest numbers reflected strong support). I transformed the two separate parental support variables into a single dummy variable that indicated unconditional parental support (i.e., both parents were strong supporters). A small number of cases (n = 11) were imputed using mean substitution using race and parent immigration status as reference.[9]

2.3. Analysis

Analysis includes a series of nested OLS and logistic regression models.

3. Findings

Descriptive statistics are broken down by university type in Table 2. The descriptive statistics reveal considerable differences between job outcomes across the three universities. Graduates from universities in a tech region were more likely to work in a tech hub than alumni who attend university outside of a tech hub. Only 6% of graduates from Regional U worked in one, compared with 74% of degree holders from Central Elite University and 41% of Central State University.

Table 2. Descriptive statistics for CS degree recipients from three Texas universities, 2018.

	All	Central Elite U	Central State U	Regional U
	Mean/SD	**Mean/SD**	**Mean/SD**	**Mean/SD**
Job in Tech Hub	0.52	0.74	0.41	0.06
	(0.50)	(0.44)	(0.50)	(0.23)
Degree Relevant Job	0.69	0.84	0.50	0.50
	(0.46)	(0.37)	(0.51)	(0.51)
Salary in Thousands of Dollars	75.30	92.28	62.34	44.85
	(34.75)	(31.85)	(19.13)	(25.82)
Hispanic (=1)	0.36	0.21	0.16	0.89
	(0.48)	(0.41)	(0.37)	(0.32)
Woman (=1)	0.25	0.31	0.22	0.11
	(0.43)	(0.47)	(0.42)	(0.32)
Immigrant Parent	0.35	0.37	0.22	0.42
	(0.48)	(0.49)	(0.42)	(0.50)
Mother's Education (Years)	14.23	15.22	13.91	12.06
	(3.05)	(2.41)	(2.67)	(3.61)
Father's Education (Years)	14.97	16.01	14.66	12.69
	(3.35)	(2.91)	(3.05)	(3.50)
Unconditional Parental Support (=1)	0.50	0.54	0.47	0.42
	(0.50)	(0.50)	(0.51)	(0.50)
Graduating Year	2014.69	2014.22	2015.03	2015.53
	(1.58)	(1.34)	(2.01)	(1.28)
GPA (4 Point Scale)	3.22	3.14	3.30	3.33
	(0.45)	(0.48)	(0.38)	(0.39)
Distance Traveled between High School and College (in *ln* miles)	4.39	4.83	4.82	2.93
	(1.72)	(1.64)	(1.10)	(1.57)
Distance Traveled from College to First Job (in *ln* Miles)	5.23	5.82	4.93	4.02
	(2.14)	(1.89)	(1.91)	(2.38)
n	157	89	32	36

However, alumni from Central State University and Regional University were equally likely to work in degree-relevant jobs, although those from Central Elite University were still far more likely to hold a job that fully utilized their computer science degree (84% compared with 50%). Advantages for Central Elite U alumni are also reflected by their salary: the approximate mean annual salary for these graduates was USD 92,000, well above the Texas state average for entry level software engineers (Annual MSA Wages 2017). Graduates from Central State U earned an average of USD 62,340 annually while alumni from Regional U earned below the state average, USD 44,850.

More than a third of my sample was Hispanic (n = 56)[10] and the majority were concentrated at one school, Regional University, where nearly 90% of alumni (n = 32) identify as Hispanic. Conversely, only 21% did so at Central Elite U (n = 19) and 16% at Central State U (n = 5). Regional University alumni had the least educated parents—roughly 12 years for both mother and father, whereas the most educated parents at Central Elite University had an average of 15 years of education for mothers and 16 years of education for fathers. While graduates from universities in tech hubs traveled nearly equal distances to attend college (4.83 and 4.82 log miles), alumni from Regional U were far less likely to travel (2.93 log miles).That Regional University alumni were less likely to travel to attend college and had parents who attained the least number of years in formal schooling may indicate their lower socioeconomic background and that they lacked associated advantages in social networks and social capital that may help their wealthier peers succeed on the job market.

3.1. Who Works in Prestige Tech Hubs?

I defined four regions as elite tech labor markets for the purposes of this study: Austin, San Francisco Bay Area, Seattle, and Raleigh-Durham. Table 3 models predict the probability of attaining a job within one of these four prestige tech hubs. Model 1 includes background characteristics, including race and gender, as well as parental education levels, academic achievement (GPA), and support. Net of other background characteristics, the odds of working in a prestige tech hub were 69% lower for Hispanic than non-Hispanic degree holders (exp[−1.16] = 0.31).

Table 3. Predictors of working in a prestige tech hub among recent CS degree recipients in Texas, 2018.

	Model 1	**Model 2**
Hispanic (=1)	−1.16 **	−0.34
	(0.43)	(0.55)
Women (=1)	0.33	−0.20
	(0.45)	(0.49)
Immigrant Parent	0.28	0.03
	(0.39)	(0.43)
Unconditional Parental Support	0.26	0.10
	(0.38)	(0.42)
Mother's Education (Years)	0.06	−0.02
	(0.08)	(0.09)
Father's Education (Years)	0.05	−0.00
	(0.07)	(0.08)
Year Graduated	−0.27 *	−0.13
	(0.12)	(0.13)
GPA (4 Point Scale)	−0.94 *	−0.22
	(0.46)	(0.52)
Log Distance HS to College	0.23 *	0.10
	(0.11)	(0.13)
Attended Elite Institution		1.39 **
		(0.49)
Attended University in Tech Hub		2.03 *
		(0.95)
_cons	548.49 *	270.14
	(249.74)	(269.85)
N	157	157
pseudo R^2	0.178	0.276

Note: Values are coefficients from logistic regression models. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

Race effects disappeared when institution location was controlled for (Model 2), suggesting that while there was no racial gap among those attending a university in a tech hub, Hispanic students were less likely to attend university in a tech hub. Hypothesis 4a is not supported.

While attending an elite institution is an indicator of whether students transition into jobs in a prestige tech hub, simply attending university in a tech hub confers real benefits. The results demonstrate that students who graduated from an institution located in a prestige hub were more likely to work in any of the four identified tech hubs, supporting hypothesis 1. Alumni from universities in a tech region were 7.6 times more likely than their peers from Regional University to work in a tech hub.[11]

In order to understand in more detail migration patterns of students to tech hubs, I document which of the four tech hubs were available to students from the three universities (Figure 1). University location may play a large part in determining where students find work after because around half of students from all three universities tended to stay nearby upon graduation. Forty-eight percent of recent graduates from Central Elite University (n = 43) stayed within the Austin metro region, while half of Central State University graduates did so (n = 16). Similarly, 53% of students from geographically distant Regional

University (n = 19) stayed near their university's metro region. Central Elite University alumni were most likely to have access to the prestige tech labor market and most likely to move out of state for prestige jobs: more than 76% of Central Elite University graduates landed in a prestige tech hub, with more than a quarter finding jobs in Seattle or the San Francisco Bay Area. Graduates from Central State and Regional University never moved into the prestige labor market in California although one survey respondent from Central State University found work in Seattle. These details reveal that the benefits conferred from attending university in a major tech hub are somewhat limited to regional advantages unless the university is also elite.

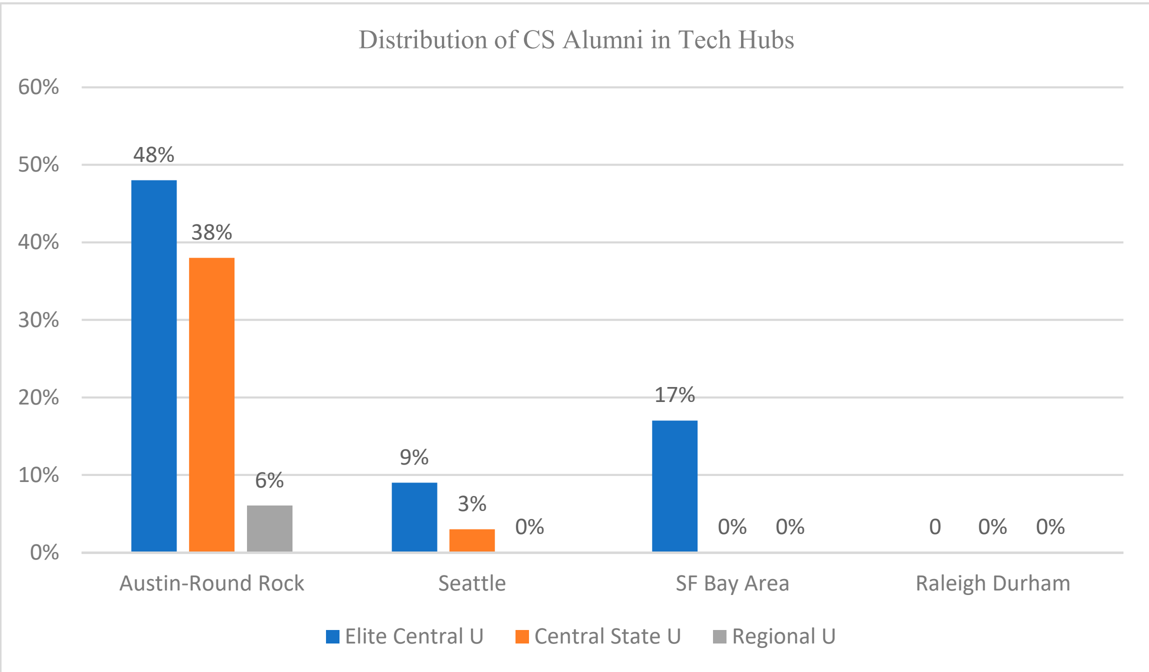

Figure 1. Distribution of CS Alumni in Tech Hubs.

3.2. Who Works in Software Development?

Table 4 examines graduates who were able to find careers that made use of their computer science degree. Hispanic job seekers faced no penalty (Hypothesis 4b not supported), nor did those who attended universities outside of a major tech hub. This is inconsistent with Hypothesis 2, which suggests that alumni from universities located in high-tech hubs are more likely to find degree-relevant jobs than their peers from a peripheral institution. That is, students who earn computer science degrees from similarly selective universities may be evenly advantaged translating their educational capital onto the labor market. Alumni from elite universities saw a significant advantage on the job market; although institution location may not impact likelihood of attaining a degree-relevant job, institutional prestige did.

Mother's education and attending an elite educational institution both contributed to the likelihood of finding a job that fully utilized a CS degree. Whereas previous social science research tended to measure intergenerational mobility between fathers and sons, these results suggest that maternal socioeconomic background and educational capital are critical components in predicting future generations' occupations (Blau and Duncan 1978; Hauser 1978; Xie 1992).

Table 4. Predictors for working in a degree-relevant occupation among recent CS degree recipients in Texas, 2018.

	Model 1	**Model 2**
Hispanic (=1)	−0.15	0.34
	(0.45)	(0.61)
Woman (=1)	−0.08	−0.52
	(0.49)	(0.55)
Immigrant Parent	0.22	−0.01
	(0.40)	(0.43)
Unconditional Parental Support	0.47	0.30
	(0.38)	(0.41)
Mother's Education (Years)	0.24 **	0.21 *
	(0.09)	(0.10)
Father's Education (Years)	−0.07	−0.12
	(0.07)	(0.08)
Year Graduated	0.04	0.20
	(0.13)	(0.14)
GPA (4 Point Scale)	0.32	1.00 +
	(0.46)	(0.54)
Log Distance HS to College	0.17	0.12
	(0.12)	(0.14)
Attended Elite Institution		2.07 ***
		(0.55)
Attended University in Tech Hub		0.03
		(0.75)
_cons	−90.05	−402.55
	(257.06)	(284.30)
n	157	157
pseudo R^2	0.096	0.188

Note: Values are coefficients from logistic regression models. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$.

3.3. What Predicts Salary?

Table 5 explores salary determinants associated with first job post-university. Institutional prestige is a consistent predictor of salary. Controlling for basic demographic data, those who attended an elite university earned 39% more annually than their peers attending non-elite universities (Model 2). Alumni from educational institutions in a major tech region also saw a bump in pay, earning 32% more annually than their peers at Regional University (Model 2); after controlling for the students' geographic mobility between their hometowns, universities, and place of first job, these alumni earned 70% more (Model 5).

Model 3 shows that the ability to travel for a first job post-college significantly increased financial returns. The significant interactions revealed in Model 4 show that this relationship was particularly strong for graduates of the regionally peripheral institution. This suggests that geographic mobility is especially important for those coming from universities far from a major tech center. Finally, those working in a tech hub (Model 4) saw a weakly significant boost (at $p < 0.1$) even after controlling for working in a degree-relevant job.

Surprisingly, holding a degree-relevant job was not a significant predictor of higher wages. Previous economic research has noted the importance of living in certain geographic centers, where the majority of the labor force is well-educated and whose financial success derives primarily from innovation by knowledge workers (Moretti 2013). In those areas, the thriving labor market increases the wages and opportunities of *all* workers in the area, not just those working in the innovation sector (Moretti 2013). That is, geography may play a larger role in determining wages than job title or responsibilities.

Hispanic alumni see a persistent significant salary disadvantage throughout the four models; even after controlling for spatial variables, university type, demographic characteristics and work region, they earned around 22% less than their non-Hispanic peers.

Hypothesis 4c is supported; Hispanic computer science degree earners face a significant earnings penalty.

Table 5. Predictors for salary of CS degree recipients in Texas, 2018.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Hispanic (=1)	−0.43 ***	−0.21 +	−0.20 +	−0.22 *
	(0.10)	(0.11)	(0.10)	(0.09)
Woman (=1)	0.06	−0.07	−0.07	−0.01
	(0.10)	(0.10)	(0.09)	(0.08)
Immigrant Parent	0.15 +	0.08	0.08	0.07
	(0.09)	(0.08)	(0.08)	(0.07)
Unconditional Parental Support	0.07	0.02	0.04	0.03
	(0.08)	(0.08)	(0.08)	(0.07)
Mother's Education (Years)	0.02	0.00	−0.00	−0.01
	(0.02)	(0.02)	(0.02)	(0.01)
Father's Education (Years)	0.00	−0.01	−0.01	−0.01
	(0.02)	(0.01)	(0.01)	(0.01)
Year Graduated	−0.04	−0.01	−0.00	−0.00
	(0.03)	(0.03)	(0.03)	(0.02)
GPA (4 Point Scale)	−0.11	0.07	0.05	−0.05
	(0.10)	(0.10)	(0.10)	(0.09)
Distance from High School to College (in *ln* Miles)	0.06 *	0.02	−0.00	−0.04
	(0.03)	(0.02)	(0.03)	(0.02)
Attended Elite Institution		0.39 ***	0.34 **	0.23 *
		(0.10)	(0.10)	(0.10)
Attended University in Tech Hub		0.32 *	0.08	0.70 ***
		(0.15)	(0.17)	(0.19)
Distance Traveled between Hometown and University (in *ln* Miles)			0.06 *	−0.10 **
			(0.02)	(0.03)
Distance Traveled from College to First Job (in *ln* Miles)				0.17 ***
				(0.03)
Works in Tech Hub (=1)				0.15 +
				(0.08)
Degree-Relevant Job (=1)				0.11
				(0.09)
_cons	90.04	13.78	7.03	6.74
	(54.88)	(52.23)	(51.39)	(45.94)
n	157	157	157	157
adj. R^2	0.230	0.354	0.377	0.521

Note: Values are coefficients from logistic regression models predicting the natural log of annual salary. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

I had originally expected to find a female disadvantage in wages considering research that attributes women's attrition from STEM occupations due to pay dissatisfaction (Hunt 2015) and a previous national study that tracked women with advanced STEM degrees who entered professional industry and found that they earned roughly USD 12,400 less annually than their male peers within the first two years of earning their degrees (Shauman 2017). However, I did not find a significant gender salary gap. Two explanations may help explain differences in labor market outcomes: income disparities may occur later in the career (Michelmore and Sassler 2016) and the selection of participants varied between the studies. I focused on one particular academic discipline and industry whereas both Shauman (2017) and Hunt (2015) focused on the broader STEM labor force. My findings support previous research by Trond Petersen, Ishak Saporta, and Mar-David L. Seidel which found that job and salary offers within a mid-size technology company were based on meritocratic measures between men and women (Petersen et al. 2000).

4. Discussion

Computer science degree holders do not all reap the same returns from their educational investment, despite literature that touts the importance of selecting high-paying college majors over institution (Carnevale et al. 2017) and the widespread belief that the STEM fields are meritocratic (Xie and Goyette 2003; Margolis et al. 2011). This study finds that the routing of students to specific educational geographies plays a major role in determining their career trajectory post-graduation: I find that alumni from universities near a major tech hub are more likely to earn higher wages in desirable job markets compared with graduates from a university located far from a dense tech hub. Furthermore, the selectivity of the university creates additional advantages for alumni in geographic placement; only students from Elite Central University were able to garner a job in the heart of Silicon Valley.

Jobs in these prestige tech hubs are desirable precisely because of their location, proximity to other skilled workers and subsequent knowledge spillover benefits, as well as the density of opportunity. This study suggests that an elite labor market for tech workers is mostly available to those who already have the resources to attend university in a major tech hub or who are fortunate enough to grow up near one. High-skilled laborers such as computer scientists are also vulnerable to spatial mismatch between their place of residence and proximity to desirable, elite jobs.

Because most recent graduates found work near their degree-granting university, students who attended school near a major prestige tech hub were advantaged in finding well-paying jobs in an elite labor market over their peers who attended school in other locations. Surprisingly, alumni from universities in a prestige tech hub were not more likely to work in degree-relevant jobs than their peers who attended a university far from a tech hub. This suggests that a university's geographic proximity to a thick labor market does not guarantee a spike in best-fit career outcomes for computer science degree holders.

That university selection is such an important indicator of job outcomes is a key contribution of this project. Previous scholarship has not focused on the significance of degree-granting institution as a means to explain job inequality for tech workers. Erin Cech, Brian Rubineau, Susan Silbey, and Caroll Seron found no difference in intentional job persistence across a similar STEM field, engineering, in four schools of varying institutional selectivity, proximity to a nearby STEM hub, and student demographics in Massachusetts (Cech et al. 2011). However, whereas Cech's research surveyed students prior to graduation and used predicted behavior, I documented alumni's movement into the labor market post-graduation. This could account for the difference in findings; it is very likely that students who persist in a highly rigorous major similarly *want* to pursue the most fitting and financially rewarding occupation, even if they are unable to do so.

I find that among three public universities across Texas, Hispanic computer scientists do well on two of three job outcome metrics *once institution location is controlled for*: finding degree-relevant jobs and working in a prestige tech hub. For the third metric, salary, Hispanic alumni earn significantly less across all models even after controlling for various social capital characteristics. Because the Hispanic computer scientists surveyed were less likely to attend university in a prestige tech hub—only 42% of all Hispanics surveyed attended a university in a prestige tech hub compared with 96% of non-Hispanics—this suggests that racial segregation along geographic lines at the undergraduate level needs to be seriously considered as a mechanism for explaining different STEM labor market outcomes. Computer science students who attend institutions in the tech periphery may miss out on prestige career pipelines curated between the university and potential employers in STEM-dense labor markets. Furthermore, studies suggest that racial minorities are held to higher professional standards than their white peers and often require more established credentials, such as attendance at a highly selective university in order to compete with less qualified white candidates (Wilson 1997; Wingfield 2012). These factors may further impact the ability of alumni from lesser known universities outside of a major tech region to find work in highly desirable tech hubs.

5. Conclusions

Research on inequalities in engineering has mostly concentrated on one axis of inequality, gender segregation (Abbate 2012; Charles and Bradley 2006; Chow and Charles 2019; Sassler et al. 2017) although more recent studies have examined race as well (Alegria 2019; Alfrey and Twine 2017; Shih 2006). This study builds on previous inequality literature on STEM by introducing the importance of postsecondary institution location in determining labor market outcomes. Because students tend to stay near their universities for their first job post-graduation, their labor market is in large part shaped by regional opportunities, particularly for students who attend non-elite institutions. These spatial disparities especially impact potential Hispanic tech workers in Texas, who are most likely to earn computer and information science degrees in co-ethnic communities far from a major tech hub (Santiago and Soliz 2012).

It is critical that STEM researchers begin contextualizing the cumulative (dis)advantages education plays in transitioning students to the high-tech labor force and how regional history shapes where people are sorted to work. Although this paper examines which individuals may be placed in environments that are more likely to transition them to degree-relevant occupations in prestige cities, it does not address cultural considerations that may impact Hispanic students in their job search process and university selection (see Desmond and Turley 2009; Ovink and Kalogrides 2015; Ovink 2014).

There are many paths forward for future research on geographic segregation, educational inequality, and race. One path forward is to examine how local geographies create inequalities within the high-tech industry. Future research could also qualitatively examine how computer science students and alumni select universities and how they frame job preferences which may help explain differences in job outcomes for potential software engineers. Although I have relied on one non-elite university in this article to suggest a general pattern, future research with better access to more universities can help refine or develop new theories for how students move into tech jobs.

If tech employers truly want to invest in cultivating a diverse workforce, developing smaller satellite offices that are integrated into larger regional offices in elite tech cities may alleviate some of the persistent racial inequities in the workforce. These satellite offices could potentially help alumni develop professional networks in major tech hubs and provide them with firsthand experience of tech culture. These skills and professional training should make these workers from peripheral labor markets more competitive in the elite labor market.

It should also be noted that not all software developers *want* to work in Silicon Valley, Seattle or any of the prestige tech hubs. Although I operationalize movement into one of these regions as an optimal career path, I recognize that CS degree holders have a variety of priorities and career options. For instance, alumni may see more value in growing and contributing to a regional software community. However, it is important for any tech worker to have *equal access* to prestige labor markets because the most innovative technologies generally develop in those geographic locations. The exposure to these skills and processes help tech workers stay current with the evolving standards and best practices in software engineering and establishes them as desirable job candidates.

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Informed Consent Statement: Informed consent was obtained from all subjects in study.

Data Availability Statement: Anonymized data collected from this study are available upon reasonable request. The data is not publicly available due to privacy concerns.

Conflicts of Interest: The author declares no conflict of interest.

Notes

1 I used the term Hispanic for several reasons. First, the term "Hispanic" is preferred over the term "Latino" in Texas by a 6-to-1 ratio. Elsewhere in the country, Hispanic is still the preferred term, although by a much lower ratio of 2-to-1 (Lopez 2013). Second, I ran my survey during an especially troubling time for Mexican immigrants and Mexican Americans, and I purposefully chose not to collect information on specific racial affiliation as I surveyed alumni whose hometowns are located near the Mexico border. Although I use the term "Hispanic", the majority of Hispanics in Texas I surveyed are Mexican origin and as such, I focus on this group's experiences.

2 Confirmed either via email with department chair, through internal department documents, or through publicly available documentation.

3 Omitting interns did not alter regression results except for the salary regression, where Hispanic race and working in a core software role are no longer significant at the ten percent level.

4 Using caps between USD 150,000 and USD 170,000 does not alter regression outcomes; it is highly unlikely alumni in early career jobs earn more than this amount. Original survey salary categories were: Less than USD 25,000; 2. USD 25,000–34,999; 3. USD 35,000–49,999; 4. USD 50,000–59,999; 6. USD 60,000–69,999; 7. USD 70,000–79,999; 8. USD 80,000–89,999; 9. USD 90,000–99,999; 10. USD 100,000–149,999; 11. USD 150,000+.

5 I used log distance because an additional mile traveled becomes decreasingly relevant as distance increases.

6 For international students, I capped unlogged values at 2340 miles, the greatest domestic distance.

7 I had one case in which one alumna had same-sex parents; in this case, because both parents had equal education levels, I distributed their educational years across "mother's education" and "father's education". Omitting this case did not affect results.

8 Running the regressions without the imputations did not alter outcomes.

9 Omitting parental support imputations did not alter outcomes.

10 The non-Hispanic sample was mostly white (n = 66) with a smaller number of Asians (n = 29); only 5 individuals identified as black, Native American, other, or did not answer the question.

11 Exp(2.03) = 7.6.

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