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Is a Computer Science Degree the Golden Ticket? Effects of Race, Place, and Degree Institution on First Job Outcomes in Texas

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by

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ABSTRACT

Is a Computer Science Degree the Golden Ticket? Effects of Race, Place, and Degree Institution on First Job Outcomes in Texas

by

Tiffany Yu Chow

Research and policy efforts to increase the racial diversity of STEM fields have focused on how to prime the educational pipeline through interventions in schools and universities. This thesis focuses on recent college graduates who have successfully cleared a key hurdle and graduated with a bachelor's degree in computer science. I use original survey data from three public universities across Texas to determine whether there are differences in first job outcomes between Hispanic and non-Hispanic computer scientists on the elite tech labor market. I find that university attended is the most consistent predictor of labor market success. Differences between Hispanics and non-Hispanics in job outcomes are mostly attributable to the concentration of Hispanic computer science degree holders in a non-elite, geographically peripheral university. Controlling for university attended, Hispanics are as likely to work in a prestige tech hub and in a core software job as their white and Asian peers; however, they earn lower wages. In addition, results suggest a positive association between geographic mobility, higher earnings, and the likelihood of working in desirable, degree-related jobs. Results suggest that a closer inspection of segregational mechanisms at the post-secondary level is needed to fully understand its effects on elite job opportunities. Although a degree in computer science can provide a ticket to one of the most lucrative

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occupational fields in Texas, racial stratification within this field occurs early in the career and likely translates into long-lasting socioeconomic inequalities.

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Introduction

Computer science's increasing exclusion of women in the past two decades has been a consistent focus of research and policy on STEM education and career outcomes. This study widens the lens on the discussion of inequality within the discipline to factors predicting success in the high-tech labor market. My central research aim is to compare the career outcomes of Hispanic and non-Hispanic computer scientists during the school-to work-transition. I use original survey data from three public Texas universities to identify the determinants of obtaining elite jobs within the tech industry by examining racial, socioeconomic, and educational backgrounds, as well as geographic mobility patterns.

Tech companies offer highly competitive wages and reinforce the "best and brightest" rhetoric that underlines STEM fields and occupations (Margolis *et al* 2011, Leslie *et al* 2015). Although tech culture has long championed itself as a meritocratic field (Rodgers 1999, Crockett 1999, Evangelista 1999, Wong 2017), women and racial minorities have struggled to find a steady toehold in the industry and its related academic disciplines (Gee and Peck 2017, National Center for Science and Engineering Statistics 2017a, Evans and Rangarajan 2017). Within tech, software engineering jobs are in particularly high demand, commanding some of the largest financial returns among high tech careers. Although there has been a concerted effort to understand women and racial minorities' recession from computing fields and STEM occupations (see: Xie and Shauman 2005, Hunt 2010, Glass *et al* 2013, Ma and Liu 2017), there is limited research on those who have successfully earned computer science degrees (exception: Shih 2006, Sassler *et al* 2017). Specifically, this paper examines whether computer science degree earners generally have similar advantages on the job market or whether other driving forces contribute to differences in job outcomes.

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The labor market outcomes of Texas graduates are of particular interest because the state contains an attractive tech hub in Austin and has a unique racial legacy that makes its labor pool distinct from other major tech centers. Texas is 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) and locating my work in Texas allows for close analysis of an understudied and underrepresented group in computer science, Hispanics (NCES 2017).

This project tracks a select group of computer science degree holders during the school-to-work transition by focusing on the effects of the university attended and its impact on the career paths on the high-tech labor market. Whereas most studies looking at STEM employment outcomes are based on national data sets (Charles and Bradley 2006, Michelmore and Sassler 2016, Sassler, Michelmore and Smith 2017, Shauman 2017), my study is purposefully regional in order to surface local qualities in educational stratification and demographics. Labor market entrance is an important event for understanding both leakage from industry as well as the beginning of in-group differences within the STEM labor market (Xie and Shauman 2003, Shauman 2017, Sassler, Michelmore and Smith 2017). Early career moves also set the stage for future earnings, as occupational sorting into different career paths can often explain racial and gender pay disparities (see: Penner 2008, Morgan 2008). Job roles in tech differ strongly in industry prestige, financial returns, upward mobility, and geographic availability. I surveyed recent college graduates across three public universities in Texas to understand which computer science degree holders move into the most economically and professionally advantageous careers within this industry.

Because the tech industry is closely tied with specific geographic regions (Moretti 2013), I identify high-prestige jobs in part based on location. Prestige job destinations

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include Silicon Valley, Seattle, New York, and Austin; a high-status occupation would be a core tech role in software development, such as software engineering or product management. Median salaries for these roles average in the low six figures across the country (Anon 2018a, Ricketts 2017). Job outcome results address whether lingering inequalities impact labor market opportunities for Hispanic degree earners in a supposedly meritocratic industry. Using multidimensional metrics of labor market success: job title prestige, geographic location and wages, delivers a more holistic picture of how these graduates are faring post-degree. I examine whether there are in-group differences in tech labor market entrance for computer science majors. I find that race is not a direct predictor of job outcomes once similar educational opportunities are controlled for; instead, degree institution is the most consistent indicator of where students enter the labor market, how much they earn, and what their responsibilities at work are.

Why Texas?

Although Texas is not often on the forefront of popular imagination on tech, the industry has grown immensely in the past decade. Once a sleepy town with only two major highways, Austin has become a high prestige tech destination. The popular conference, South by Southwest, most well known for its concerts and music festival, added an "Interactive" event to its lineup during the heyday of the dot com boom (Anon 2018b) and is considered a premier networking event among the tech crowd. Dell, headquartered in the Austin suburb of Round Rock, is a major economic contributor of the metro region. In the late 90s, nearly 50 percent of Round Rock's revenues came from the company; in recent years, the number is closer to 30 percent (Jacobs 1999, Osborn 2013). The state's contribution to tech innovation and human capital needs to be carefully and contextually assessed alongside that of Silicon Valley, particularly as Austin's popularity grows among

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software engineers[1] looking for highly specialized roles, lower cost of living, and a well-established tech labor market.

Despite Austin's position as a vibrant and active tech hub, it remains understudied. Most research conducted on the tech industry has focused on the west coast. While it is a critical to understand the nuances of Silicon Valley's labor force, over 80 percent of software engineering jobs are located outside of the Bay Area (Rodriguez 2016, Stephens and Mahesh 2018) and draw from demographically diverse labor pools. Washington D.C., for instance, employs roughly 15%[2] black workers in the computing and mathematical occupations, many of whom work for the federal government either directly or as a client (Ruggles *et al* 2018, Wong 2017).

Texas' legacy of racial segregation differentiates it from states with comparable Mexican-origin populations. In addition to formal segregation between white and black Texans, Jim Crow laws were often applied to Mexican Americans, and communities were often segregated three ways: black, Hispanic, and white (Valencia 2000). As a result, the Mexican community in Texas has faced substantially more barriers to equal education and have the fewest years of formal schooling compared with co-ethnics elsewhere in the United States (Bean *et al* 2015, San Miguel 2000). Hispanic[3] graduates are both an understudied group in STEM research and the largest racial minority group in Texas. Their educational

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[1] Software engineers are also known as developers and programmers. I use these terms interchangeably throughout this paper.

[2] Calculated for years between 2013-2016 using IPUMS.

[3] I use 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 migrants 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

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and occupational outcomes will have an enormous impact on the future of the Lone Star state and its viability as an innovation and high-tech center. It is important to recognize the unique historical legacy with discrimination *Tejanos*, or Texas of Mexican descent, face and to study their experiences in STEM separately from their co-ethnics elsewhere.

Educational segregation has and continues to deeply affect the Hispanic population in Texas. At the K-12 level, roughly two thirds of Mexican American students attended schools where over 70% of their peers are also ethnic minorities (Valencia 2000). This segregation continues in post-secondary years; the two universities in Texas that awarded the most number of bachelor's degrees to Hispanic students in 2014 are majority Hispanic institutions, where over 80% of the student body identified as Hispanic (Latino College Completion: United States). In response to longstanding discrimination, activist groups such as the League of United Latin American Citizens have campaigned for equal educational opportunities since the early twentieth century (San Miguel 2000, Johnson 2011). Prior to the rapid influx of Mexican immigrants in the 1920s, the state employed a *laissez-faire* attitude with the education of Tejano children, allowing local authorities to take the lead (San Miguel 2000). This large new wave of immigrants during and after Mexico's civil war forced state officials to finally consider the education of these students; educators also took this as an opportunity for disseminating assimilationist ideals, such as English only instruction (San Miguel 2000).

Most importantly, the Mexican population was perceived to be a critical component of the labor force and all efforts were made by educational leaders and locally influential farmers to keep them as laborers (San Miguel 2000). Although no official segregation laws existed, the majority of schools segregated at the request of white parents, who did not want

term "Hispanic," the majority of Hispanics in Texas I surveyed are Mexican origin and as such, I focus on this group's experiences.

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their children educated alongside Mexican youth (San Miguel 2000). Mexican students who attempted to attend white schools were often denied, either by hostile environments, intentional withholding of transportation resources, or outright rejection (San Miguel 2000). Although key court cases began chipping away at de facto segregation, it wasn't until 1970 when *Cisneros v Corpus Christi Independent School District* established Mexican Americans as a protected ethnic group under the desegregation laws of *Brown v. Board of Education* (San Miguel 2000).

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. However, the Top 10% law did not increase underrepresented minorities at the prestigious flagship universities, Texas A&M (TAMU) and University of Texas at Austin (Long and Tienda 2010). Instead, racial diversity was at its peak under affirmative action whereas the Top 10% law has had a negative effect on Hispanic and black enrollment at both flagship institutions (Harris and Tienda 2010) because these students are less likely to automatically qualify for college admission under the 10% law and are less competitive than their peers with higher standardized test scores who earn non-guaranteed admission (Tienda and Niu 2006). Additionally, because of the high growth of eligible college applicants, Hispanic and black application rates have declined over time, which has led to fewer enrollees (Harris and Tienda 2010) and fewer opportunities for Hispanic college graduates to reap the benefits associated with prestigious universities. However, college attended may not be the most important factor in predicting future earnings. A study by the Center on Education and the

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Workforce argues that across the University of Texas system, major selection is the most important predictor of income, with students receiving degrees in high-paying majors at open-access institutions outearning students in more selective universities enrolled in low-paying majors (Carnevale *et al* 2017). My study questions whether degree selection is the most meaningful predictor of earnings or whether other factors significantly impact labor market outcomes during early-career.

Competing cultures

To the best of my knowledge, this study is the first to focus specifically on Hispanic labor force entrance in the tech industry. Research has broadly shown that for non-white tech workers, social isolation can take a toll (Alfrey and Twine 2017) and that the experiences of Mexican American professionals vary widely (Aguis Vallejo 2003). Jody Agius Vallejo's interviews with middle-class Mexican Americans in the Los Angeles region illuminates the experiences of Hispanic professional workers in majority white industries (Agius Vallejo 2003). Agius Vallejo found that among her interview subjects, those raised in working class environments could not fully integrate into a company's social environment. Instead, these upwardly mobile workers faced professional setbacks, such as being hidden from client view or left out of critical meetings, and experienced racially charged, discomfiting conversations with colleagues (Agius Vallejo 2013). Although interview subjects raised in middle-class homes also experienced racial and immigration based stereotyping, they almost never attributed racialized remarks as intentionally hurtful (Agius Vallejo 2013). Rather, Agius Vallejo describes the latter subjects as those who benefited from "social whitening" and were able to cross racial boundaries based on their middle-class upbringing (Agius Vallejo 2013). Agius Vallejo's study suggests that smooth

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integration into a predominantly white work culture rests on previous cultural integration into white, middle-class society[4].

The ability to socialize and communicate with colleagues in tech is particularly important. Despite the stereotype that programmers are loners, in actuality their work is team-oriented and communal. That is, software developers must be fluent in the dominant culture of the industry. Developers rely on their colleagues to review their code before they are allowed to submit their work into the main code repository ("pull request"), work as a unified team to quickly fix bugs or work on a feature together ("swarming") and host "lunch and learn" sessions where their colleagues can ask questions about newly implemented techniques and socialize. Their role requires a mutual trust in each other's ability to deliver code on time but also necessitates similar views in ranking technical priorities and on the product development process.

Kanter (1977/1993) has previously demonstrated how companies use workforce homogeneity in order to build trust, particularly in times of uncertainty (Kanter 1977/1993). Silicon Valley tech culture succeeds in part because its technological innovations necessitates risk-taking and failure ("fail fast, fail often"), which sets a baseline for workplace instability, where jobs and even companies often face potential shuttering. It makes sense, then, that Silicon Valley's workforce is *more* homogenous than the overall private industry sector (Diversity in High Tech) and that white men dominate the dominant culture of the industry as well as the popular American imagination of *who* belongs in computer science and high-tech organizations (Thébaud and Charles 2018, Wynn and Correll 2017, Margolis *et al* 2011, Ensmenger 2015, Abbate 2012).

[4] Although there is a significant Asian population within tech culture, Asians and Asian Americans are underrepresented in executive positions and have more difficulty accessing mainstream jobs. I would argue that they do not set the precedent for culture within tech organizations. (Gee and Peck 2017, Shih 2006).

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Educational institutions have long been identified as incubators for cultural training and capital accumulation. They also hold another important distinction in determining job outcomes: universities have the ability to shape the attitudes and aspirations of college students (Binder, Davis and Bloom 2016). Binder and colleagues' interviews with students at Stanford and Harvard Universities found that students *learn* which jobs are considered high-status through university culture and therefore acceptable to pursue (Binder, Davis and Bloom 2016). It is unclear whether less selective universities also encourage their students to specific high-prestige careers as aggressively as prestigious universities, although Rivera's study on on-campus recruiting among elite professional service firms suggests that there are demand-side constraints for non-elite students seeking elite jobs (Rivera 2015). The Binder *et al* study includes students from all backgrounds and racial groups and finds no discernable differences in attitudes and belief systems in identifying these desirable, high-wage jobs. However, there is some evidence that racial groups access different cultural values even on the same campus.

Maya Beasley's research with Stanford students a few years earlier sheds light on how black students determine viable career paths. Beasley's research finds that African American students who socialize in mostly segregated networks at the collegiate level are more likely to aspire to racialized careers, such as occupations geared toward helping their community or jobs with a relatively larger portion of black workers compared with their co-ethnics in more integrated networks (Beasley 2011). That is, despite the general understanding of elite jobs as defined by university culture, black students at highly selective institutions also take into account how their career choices fit into their value system. An open question is whether Hispanic computer science degree holders from elite schools follow different career trajectories than their white and Asian peers.

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In this study, I use original survey data on recent computer science graduates from three Texan universities to address some of the knowledge gaps identified above. First, I explore race and class differences in early career outcomes, including variations in salary, access to software development occupations, and high-prestige labor markets. Second, I examine the extent to which divergences between Hispanic and non-Hispanic degree holders can be attributed to differences in their distributions across universities and/or the geographic distance between tech hubs and their communities of origin. Finally, I offer notes on how research can better understand the marginalization of underrepresented minorities in elite tech careers.

Method and Analytical Strategy

Data Collection

Previous research on computer science degree earners have used national or cross-national datasets to focus on overall labor market outcomes (exception: Cech *et al* 2011), which may obscure regional patterns. Previous qualitative research by Margolis and colleagues have demonstrated the importance of studying how geographically close educational institutions can vary widely in student body demographics and preparation for academic success in computer science (Margolis *et al* 2011). I build on Margolis and Cech's efforts in focusing on regional outcomes in order to understand the variety of labor market experiences for Hispanic degree holders in Texas. Because there is so little research on this population of computer scientists, it was necessary to create a new survey specifically for this project. My survey is unique in that it not only focused on the alumni's personal background, but that it also collected data on the specific programming skills being used, location of work, and exact job title. Capturing this information paints a more nuanced understanding of work responsibilities and whether alumni are fully utilizing their degrees.

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I "cold-emailed" faculty and staff at multiple universities throughout Texas in order to introduce my project; three universities agreed to the study. I worked with 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. All alumni who graduated from their programs between the years 2010-2017 received our survey through their university's official computer science department listserv. Survey data was collected between March -August 2018 with an online survey created with Qualtrics. 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 153 survey participants.

Of these institutions, one is a selective university with a highly ranked computer science program situated in a prestige tech hub, while another is a less selective university located in the same metropolitan region. The third participating university is located in a non-prestige tech hub and is also a less selective institution. The resulting sample is representative of the computer science population in terms of race and gender composition at their respective computer science departments.[5] 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 2017a). Nationwide, Hispanics earn between seven and nine percent of computer science degree in the years surveyed (National Center for Science and Engineering 2017b); overall, Hispanics made up 38 percent of the respondents, reflecting the demographics of the surveyed computer science departments.

Dependent variables

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

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I measure first job outcomes three ways in order to fully distinguish the available opportunities for computer scientists post-graduation: job location, occupation, and salary. Information on the relative desirability of job titles and location is based on a combination of opportunities for tech-related careers and key organizations that have anchored the local tech scene, media reports, and my own experience working within the tech sector.

Job Location

I identify four prestige markets relevant to my study: Seattle, the San Francisco Bay Area, Austin, and New York. These geographic locations are generally considered elite labor markets by workers in the tech industry (Roose 2018, Oremus 2013, Hayes 1988, Lipton and Brasfield 2017). Employment in an elite market is desirable because it provides 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 Austin's HomeAway (a competitor to AirBnB) or Menlo Park's Facebook operating several software-driven campuses in Seattle, Austin, San Francisco, and New York. The geographic spread of established tech companies and the mobility of tech workers even within these organizations makes 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 raises 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 selected are well-

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known among professionals as having a dense concentration of tech organizations and whose environment is heavily influenced by the proliferation of these businesses. Living in a prestige city or what economist Enrico Moretti calls a “brain hub” is not just a symbolic badge of honor. Geographic proximity to smart and successful people has real consequence: it leads to higher levels of innovation as well as better quality of work (Moretti 2013). Software engineers living in a prestige city, even those working in non-elite companies, are exposed to new ideas and privy to knowledge spillovers in a way that their colleagues living far from a tech hub are not. It is generally known that working in these centers provide career mobility, greater networking opportunities, and higher salaries.

Occupation

Working in software development as an engineer, product manager (PM) or data scientist are all desirable paths stemming from a computer science degree. I track whether a participant enters one of these occupations, or takes a job outside one of these core professional roles. At early career, engineers, PMs, and data scientists earn similar salaries. Elite organizations often require PMs to have strong technical backgrounds and data scientists leverage their background in programming languages. For the purposes of this paper, I consolidated these occupations into a single “software development” category in order to track who obtained degree-relevant jobs. Other technical roles, such as quality assurance engineers or database administrators are considered outside of the core professional tech jobs since none of these jobs require computer science degrees. Computer science degree holders are overqualified for these positions. Similarly, non-technical positions are also low degree utilization jobs and therefore outside the “optimal” career path for alumni in terms of financial compensation and career mobility.

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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 in the $60-70k 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 find jobs after college (2017 Annual MSA Wages). 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 $35k for a $30k-$39,999 range). I capped the highest salary band[6] at the $170,000).[7]

Independent variables

I coded race using the dummy variable "Hispanic" to track Hispanic and non-Hispanic (white and Asian) outcomes. I collapsed white and Asian students into a "non-Hispanic" category because white (n=66) and Asian (n= 29) tech workers have similar trajectories during early-career (Gee and Peck 2018, Sassler, Michelmore and Smith 2017). I dropped all other race categories because there were too few black (n= 2) and Native American (n=1) respondents. Three individuals chose not to racially identify. I grouped mixed-race persons with their non-white racial identity.[8]

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[6] Using caps between $150,000 and $170,000 does not alter regression outcomes; it is highly unlikely alumni in early career jobs earn over this amount.

[7] Original survey salary categories were:
Less than $25,000 2. $25,000-$34,999 3. $35,000-$49,999 4. $50,000-$59,999 6. $60,000-$69,999
7. $70,000-$79,999 8. $80,000-$89,999 9. 90,000-$99,999 10. $100,000-$149,999 11. $150,000+

[8] Half of the individuals in the dropped race categories attended University A and earned at least $80,000. The other half attended University B and earned a maximum of $79,999.

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The definition and operationalization of socioeconomic (SES) status has long been contested by social scientists (Duncan, Featherman, and Duncan 1972, Ensminger and Fothergill 2003, White *et al* 1993, Hauser 1994, Sirin 2005, Berzofsky 2014), although three main proxies have remained consistent over time with regards to measuring student outcome based on SES background: parental education, parental occupation, and household income (Sirin 2005, Berzofsky *et al* 2014). I use 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 (Sirin 2005, Shavers 2007). I coded parental education on a scale approximating schooling years. For instance, a doctorate degree was equivalent to 22 years of schooling, whereas those whose highest education level was elementary school was given five years of schooling in my coding scheme. Vocational schooling was equivalent to an associate's degree (=14 years). I imputed eight parental education levels based on immigrant status and race.[9] I had one case in which one alumna had same-sex parents who had the same level of education; in this case, I assigned the same educational years to parent two and categorized parent two as the other gendered parent.

I chose universities based on academic reputation and geographic distance to a tech center. Tracking geographic proximity to a prestige tech center makes it possible to test whether this is an advantage in the elite job market post-graduation. Second, academic reputation matters because previous research has shown how elite employers invest in and recruit from highly-ranked universities (Rivera 2015) and that students from these schools tend to desire prestige jobs, such as tech work (Binder *et al* 2016). Furthermore, we know

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Similarly, due to the small sample size, I dropped my sole gender non-binary subject. Their salary was over $100,000.

[9] Running the regressions without the imputations does not alter outcomes.

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that students coming from these schools have obvious advantages in the job market although these advantages are often distributed inequitably across the student population (Gaddis 2015). Below, I introduce the three universities I have selected for this study.

University A: Elite, Tech Hub

	Highly selective	Tech Hub
University A	✓	✓
University B		✓
University C		

University A would be considered a prestige institution. It is ranked as a "more selective" university by the U.S. News and World Report, accepting roughly one-third of all applicants. University A 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 prestigious career tracks. University A 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.

University B: Non-elite, Tech Hub

University B is located within the same tech hub metro region, although it is far less selective, accepting nearly three quarters of all applicants. One fifth of all survey respondents from University B are Hispanic. I consider University B's location a particular advantage for its students because of the school's close proximity to desirable employers. These students also share similar social and professional networks with their peers at University A. Alumni from University B may find the most success translating their degree into a elite job within the context of a local prestige labor market (e.g. Austin) due to

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regional understanding of the school's academic reputation and its alumni base. Employers in California, for instance, may have organizational ties and preferences for its own regionally strong universities.

University C: Non-elite, Peripheral region

Alumni from a third university (C), situated near the Texas-Mexico border, also responded to the survey. University C shares similar academic reputation and selectivity as University B, but is isolated from any major tech market. Unlike University A, which attracts students both near and far because of its academic reputation, University C focuses on serving its local community: over 90 percent of its student population come directly from the metro region and nearly 90 percent of its survey respondents identify as Hispanic. Comparing University B and C makes it possible to determine whether a university's geography has an effect on job outcomes, holding constant school prestige and selectivity.

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

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number of cases (n=11) were imputed using mean substitution using race and parent immigration status as reference.[10]

Previous literature on post-secondary education suggests that the pursuit of higher education is often facilitated by the ability to live at home (Desmond and Turley 2009, Ovink and Kalogrides 2015). A number of reasons exist, including the cost of education, cultural desires, and parental request (Desmond and Turley 2009, Ovink and Kalogrides 2015). It is unclear whether the same reasons that compel students to stay close to home factor in their job search process. Minority communities may be at a larger disadvantage on the job market because of spatial friction (Stoll 2010), that is, a lack of specialty skilled jobs in the job seeker's immediate community. Using high school city as a proxy for hometown location, I calculated the log distance[11] travelled for first job capped to capture job mobility of survey respondents.[12] I also control for GPA, graduation year, and gender.

Analytic Strategy

Analysis involve a series of nested regression models. The first accounts for background characteristics, the second for human capital, and the third for first job outcomes. Logistic regressions were used for all analysis except salary, which used OLS regression.

Findings

[10] Omitting parental support imputations does not alter outcomes.

[11] I use log distance because the majority of students travel fewer than 500 miles from home, and additional miles past a distance threshold diminishes in value. For instance, it is generally equally cumbersome to travel 1000 miles and 1002 miles whereas traveling between fewer miles may be exaggerated at lower values.

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

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Descriptive statistics are broken down by race in Table 1 and by university in Table 2. There are significant differences in salaries and likelihood of working in a prestige tech hub between Hispanic and non-Hispanic individuals (Table 1). The approximate mean salary for Hispanics is $58,000 (below the entry-level average of $70,000 in most major Texas cities (2017 Annual MSA Wages); non-Hispanics earn a mean of $84,000 at their first job. White and Asian alumni are more likely to work in a prestige tech hub: 62 percent compared with their Hispanic peers at 32 percent. Interestingly, there is no statistically significant difference in finding a job working in software development (61 percent compared with 72 percent), which suggests that while Hispanic alumni are successfully finding industry-relevant jobs, they are taking on less lucrative positions in non-elite tech hubs. Human capital characteristics also differ sharply within this group comparison. Non-Hispanics are more likely to have higher GPAs and travel further for their first job. Hispanic graduates also have less educated parents: roughly two years of education separates the parents of non-Hispanic students from Hispanic students.

Table 2 presents descriptive statistics by university. Graduates from University C, a majority Hispanic institution, differ significantly from their peers at University A, in nearly every way, except for parental support and parent immigration status. The average mean salary for University A alumni was $91,000, the highest of all three universities. University B trails with an average of $64,000 and University C alumni earn $45,000. 50 percent of alumni from University C entered a core software profession, whereas 84 percent of the respondents from University A did. Interestingly, students from University C were slightly more likely to place in a software job than their peers at University B (45%), although this difference was not statistically significant. Alumni differences for University B and C were concentrated in salaries and the likelihood of working in a prestige hub.

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I plotted where alumni found their first jobs post-college using Google Maps' publicly available Application Programming Interface (API). Figures A-F[13] show where alumni found their first jobs post-college, broken down by race. Hispanic entry onto the labor market is represented via the blue markers, non-Hispanics red. The numbers on the markers indicate the count of alumni in a particular city. Over 80 percent of all alumni from University C stayed in Texas (Figures E and F), with no alumni moving to Seattle or Silicon Valley. Only three alumni enter the prestige tech labor markets, two in Austin and one in New York. 57 percent of alumni from University C stayed local and worked near their alma mater (graduates from other programs never relocated into this region) which suggests working for and with co-ethnics because of the region's racial demographics. Contrary to state reports on early career salaries, I find that of all employees who worked in cities near the Texas-Mexico border, only one made \$70k or above; 70% of University C working in the region earned less than \$50k. For the most part, alumni from University B (Figures C and D) also fail to break into Silicon Valley, instead taking prestige jobs in Austin (35%) and Seattle (3%). Nearly 18 percent (n=15) of University A alumni ended up in the prestigious Bay Area region; another 47% remained local to Austin (Figures A and B). Altogether, nearly 73% of all graduating students from University A find jobs in Seattle, Austin, or the Bay Area. I turn now to multivariate models to explain possible mechanisms driving these disparities. The first series of analyses explore differences in geographic outcomes.

Who works in prestige tech hubs?

[13] I provide static images in my appendix, but an online interactive map is available at https://jsbin.com/rovifix/edit?output

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I defined four regions as elite tech labor markets for the purposes of this study: Austin, San Francisco Bay Area, Seattle, and New York. I run two models to predict the probability of attaining a job within one of these four major tech markets (Table 3). My first model is comprised of background characteristics, including race and gender, as well as parental education levels and support. Interns (n=6) were coded with their most likely career path based on internship title.[14] Net of other background characteristics, Hispanics are 61 percent less likely to transition into a first job located in an elite tech hub, and more recent graduates are less likely to do so as well. Both effects disappear when distributions across institutions are taken into account. Women are as likely as men to work in these elite labor markets. Although I explored race interactions with school and gender across all regressions, my sample size was too small to draw meaningful conclusions.

The second model adds human capital characteristics: educational institution, GPA, and the log distance travelled for work from hometown. After social and educational capital investments are controlled for, only institutional attendance improves likelihood of transitioning into a prestige tech location after graduation. Being Hispanic is no longer statistically significant in predicting the likelihood of working in tech. Alumni from top-ranked computer science department of University A are 389% times more likely to work in one of the previously defined prestige tech hubs than peers at University B, whereas University C alumni are 82% less likely to land in these regions compared with those graduates. University A enables its students to access a national prestige labor market, whereas graduates from other programs are typically more confined to regional job opportunities.

[14] 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

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Who works in software development?

Table 4 examines graduates who are able to find careers that make use of their computer science degree. Model 1 suggests that mother's education predicts occupational pathway: for every additional year of maternal education the likelihood of her child working in a prestige software role increases by 26%. There are no job role differences by gender or other background characteristics. Moving onto Model 2 and taking into account human capital, graduates from University A are roughly 8 times more likely to enter a prestige career path in tech. Mother's education is similarly important in Model 2; an increase in maternal education boosts the probability of working in software development by 33%. Father's educational attainment, however, significantly lowers the likelihood of alumni working in software development by 18%. This was an unexpected result and requires further research. Furthermore, whereas previous social science research tends to measure intergenerational mobility between fathers and sons, these results suggest that women's socioeconomic background is a critical component in predicting future generation's occupational status (Hauser 1978, Xie 1992).

Interestingly, there is no significant difference between alumni from University B and C. It is surprising that University B alumni are *not* more significantly likely than respondents from University C to enter core software jobs, given University B's geographic positioning in a major tech region. These two universities share comparable academic rankings and acceptance rates (60-70 percent), which may help explain similarities regarding alumni occupational paths. I discuss whether geographical proximity has any impact on job outcomes further below. One possible reason for the relatively low attainment of core tech jobs amongst University B alumni is that they may find it more difficult to compete with students from University A for internships and jobs.

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Finally, geographic mobility to first job is also a significant predictor of working in software development although its effects may be difficult to interpret given the bidirectional relationship between distance travelled for job and holding a core software job. Alumni may use their own funds and travel to find a job that meets the narrow requirements of a prestige job in tech or may be singled out and incentivized to accept a job opportunity far from their hometown.

What predicts salary?

Table 5 explores salary determinants associated with first job. Once again, race is a significant predictor of earnings prior to controlling for human capital (Table 5). Hispanics earn \$21,190 *less* than their white and Asian peers when only considering personal characteristics such as gender and parental educational attainment. Once GPA and distance travelled are controlled for, Hispanics earn \$10,130 less than their non-Hispanic peers. Introducing first job outcomes to the regression (Model 3) does not reduce this salary differential: Hispanics earn \$11,620 less than their white and Asian colleagues.[15] 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 \$12,400 less annually than their male pees within the first two years of earning their degrees (Shauman 2017). However, I did not find a significant wage handicap. Two explanations may help explain differences in labor market outcomes: income disparities may occur later in the career

[15] Running a race and university interaction did not have significant results and are not displayed, which suggests students attending the same school tend to earn similar wages. Coefficients for Hispanic x University A and Hispanic x University C are -10.73 and -5.93 respectively.

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(Michelmore and Sassler 2016) and the selection of participants vary between the studies. I focus on one particular academic discipline and industry whereas both Shauman and Hunt focus 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, Saporta, and Seidel 2000).

Wage discrepancies are additionally explained by human capital investments and first job outcomes. Model 2 and 3 reveal that university attended is a salient indicator of financial returns. Alumni from the highly ranked University A outearn their peers by a significant amount: alumni from this program earn roughly $14,580 more than graduates of University B, once job outcomes and other educational investments are accounted for. Although there is not a significant difference in wages between alumni from University B and C, recent graduates from University C earn $6,950 less than their peers at non-elite University B.

The ability to travel for work also increases financial returns, as does working in a major tech hub and finding a core software development job. Working in major tech hub increases financial returns by $8,950 while working in a core software development role is associated with an additional $1,208 in wages. What these indicators suggest is that job title and geographic mobility to a prestige tech hub, along with institution, play a major role in determining financial rewards within tech.

Discussion

Computer science degree holders do not all reap the same returns from their educational investment. Texas' history with segregation can be seen reflected in its educational system, where the majority of Mexican American students attend K-12 schools where 70% or more

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of their peers were racial minorities in the 1993-1994 school year and are also more likely to be taught by noncertified teachers (Valencia 2000). The dismantling of Texas' affirmative action programs has further disadvantaged Mexican American and other racial minorities at the post-secondary level; under the 10% law, racial minorities are now less likely to attend one of Texas' nationally reputable flagship institutions (Harris and Tienda 2010). The opportunity to attend an elite institution has profound consequence on the high tech labor market: I find that alumni from a highly selective university is more likely to succeed in obtaining core software jobs and earn high wages in desirable job markets. The ability to relocate for work improves the likelihood of working in software development and leads to higher financial returns. I find no evidence that Hispanic computer scientists are directly disadvantaged in their access to prestige tech hubs and core software jobs, although they consistently earn lower wages than their white and Asian peers.

Surprisingly, alumni from University B were not more likely to become software developers than their peers at University C. This suggests that a university's geographic proximity to a thick labor market does not guarantee a hike in best-fit career outcomes for computer science degree holders. However, University B's location helps its alumni to secure more work in prestige labor markets compared with University C. This may explain University B's advantage in securing higher salaries. In short, academic rankings may partially explain similarities in occupational pathing whereas geographic proximity to a local tech scene increases the proportion of alumni entering prestige markets. Both University A and B are located in the same tech-heavy metro region and are significantly more likely to send alumni into high-prestige cities than University C. Alumni from University C remain particularly vulnerable to racial segregation after graduation, with nearly 60 percent of graduates working in predominantly Hispanic regions. Further research

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is needed to understand the dynamics between prospective tech employees and the process of determining viable job opportunities on the labor market.

That university selection is such an important indicator of job outcomes is somewhat surprising. 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 and student demographics in Massachusetts (Cech *et al* 2011). However, whereas Cech's research surveys students prior to graduation and uses 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: finding degree-relevant jobs and working in a prestige tech hub once differences in distribution across universities are taken into account. For all outcomes, university attended is the key predictor. University C, which is a predominantly Hispanic institution (nearly 90% of its computer science department is Hispanic) fares the least favorably across the three metrics used in this study.

This suggests that a) the routing of students to specific post-secondary institutions is important and impacts career trajectory in a meaningful way and b) racial segregation at the undergraduate level needs to be seriously considered as a mechanism for explaining different STEM labor market outcomes. Computer science students who attend non-elite institutions in the tech periphery may miss out on prestige career pipelines curated between the university and potential employers. 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

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qualified white candidates (Wingfield 2013, Wilson 1997), which may further impact the ability of University C alumni to find work in highly desirable organizations and job roles.

That race does not play a significant role in determining labor market outcomes is a somewhat deceptive finding since college students in this study are stratified in their attendance of secondary institutions by race. As my research shows, being Hispanic does not mean less willingness or ability to pursue a technically rigorous career in software. While these results do not rule out the effect of cultural values on job outcomes at less selective institutions or the impact of ethno-racial preferences prior to college attendance, such as the effects of attending segregated secondary schooling (Braddock 1980, Butler 2010), Hispanic identity and culture does not appear to be a master determinant of job outcomes. In all cases, the university attended is the most important factor in predicting occupation, salary, and job location for computer science degree holders.

Conclusion

This study builds on previous inequality literature on STEM by introducing the importance of post-secondary schooling in determining labor market outcomes. It is critical that STEM researchers begin contextualizing education and job outcomes with regional variation in mind. An outstanding research question is why alumni from University C remain in the

immediate metro region. Previous research on high-tech culture has shown that Asian immigrants are able to “circumvent discrimination” by leaving mainstream tech organizations once they hit a glass ceiling and opting to work at co-ethnic run businesses instead in order to move into managerial roles (Shih 2006). It is unclear whether Hispanic

graduates strategize about career opportunities in a similar way or whether they are influenced by community values such as the students in Beasley’s study, but these factors

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could potentially explain the lack of Hispanic entrance into labor markets where there are very few co-ethnic tech workers and business owners. Future research should examine the choices and constraints for this population to better understand how labor market decisions are made.

Although there is value in staying local to a university and growing the regional software community by establishing start-ups and new businesses, it is important for any tech worker to have equal access to prestige labor markets because the most innovative technologies generally occurs 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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Table 1: Descriptive Statistics for CS Degree Recipients from 3 Texas universities, 2018, by Race

	All N = 153 Mean/SD	Hispanic N = 57 Mean/SD	Non-Hispanic N = 96 Mean/SD	t-test
Background characteristics				
Women (=1)	0.24	0.23	0.25	
	(0.43)	(0.42)	(0.44)	
Immigrant Parent	0.36	0.42	0.32	
	(0.48)	(0.50)	(0.47)	
Mother's Education (yrs)	14.22	12.84	15.04	***
	(3.06)	(3.62)	(2.33)	
Father's Education (yrs)	14.99	13.37	15.95	***
	(3.38)	(3.36)	(3.02)	
Unconditional Parental	0.49	0.47	0.50	
Support (=1)	(0.50)	(0.50)	(0.50)	
Graduating Year	2014.69	2015.11	2014.45	*
	(1.56)	(1.48)	(1.56)	
Human capital				
University A: Elite, Tech	0.56	0.33	0.70	***
Hub (=1)	(0.50)	(0.48)	(0.46)	
University B: Non-elite,	0.20	0.11	0.26	*
Tech Hub (=1)	(0.40)	(0.31)	(0.44)	
University C: Non-elite,	0.24	0.56	0.04	***
Peripheral region	(0.43)	(0.50)	(0.20)	
GPA (4 Point Scale)	3.22	3.13	3.28	*
	(0.45)	(0.48)	(0.43)	
Log of distance (miles)	5.19	4.66	5.51	*
	(2.15)	(2.21)	(2.06)	
First Job Outcomes				
Salary (in thousands of	74.44	57.75	84.35	***
Dollars)	(33.71)	(31.42)	(31.14)	
Works in Prestige Tech	0.51	0.32	0.62	***
Hub	(0.50)	(0.47)	(0.49)	
Software Development	0.68	0.61	0.72	
	(0.47)	(0.49)	(0.45)	
QA/Web/DBA	0.14	0.18	0.12	
	(0.35)	(0.38)	(0.33)	

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Table 2: Descriptive Statistics for CS Degree Recipients from 3 Texas universities, 2018, by University Attended

	Univ A: Elite, Tech Hub N = 86 Mean/SD	Univ B: Non-Elite, Tech Hub N = 31 Mean/SD	Univ C: Non-elite, Peripheral N = 36 Mean/SD
Human Capital Characteristics			
Hispanic (=1)	0.22	0.19	0.89
	(0.42)	(0.40)	(0.32)
Women (=1)	0.30	0.23	0.11
	(0.46)	(0.43)	(0.32)
Immigrant Parent	0.38	0.23	0.42
	(0.49)	(0.43)	(0.50)
Mother's Education (yrs)	15.22	13.97	12.06
	(2.41)	(2.69)	(3.61)
Father's Education (yrs)	16.01	14.81	12.69
	(2.94)	(3.11)	(3.50)
Unconditional Parental Support (=1)	0.53	0.45	0.42
	(0.50)	(0.51)	(0.50)
Graduating Year	2014.26	2014.94	2015.53
	(1.35)	(1.97)	(1.28)
Human capital			
GPA (4 Point Scale)	3.14	3.32	3.33
	(0.48)	(0.39)	(0.39)
Log of distance (miles)	5.83	4.77	4.02
	(1.90)	(1.91)	(2.38)
First Job Characteristics			
Salary (in thousands of Dollars)	90.67	63.79	44.85
	(29.91)	(22.84)	(25.82)
Works in Prestige Tech Hub	0.73	0.39	0.08
	(0.45)	(0.50)	(0.28)
Software Development	0.84	0.45	0.50
	(0.37)	(0.51)	(0.51)
QA/Web/DBA	0.10	0.16	0.22
	(0.31)	(0.37)	(0.42)

Exponentiated coefficients; Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < .01$, *** $p < .001$

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Table 3: Predictors of working in a prestige tech hub among recent CS degree recipients in Texas, 2018 (N=153)

	Model 1	Model 2
Background characteristics		
Hispanic (=1)	0.39*	0.77
	(0.15)	(0.40)
Women (=1)	1.05	0.78
	(0.44)	(0.38)
Immigrant Parent	1.43	1.16
	(0.53)	(0.49)
Unconditional Parental Support (=1)	1.34	1.04
	(0.49)	(0.43)
Mother's Education (yrs)	1.07	1.00
	(0.09)	(0.09)
Father's Education (yrs)	1.05	1.01
	(0.07)	(0.08)
Graduating Year	0.74*	0.92
	(0.09)	(0.12)
Human capital		
University A: Elite, Tech Hub		3.89**
		(1.93)
University C: Non-elite, Peripheral Region		0.18*
		(0.14)
GPA (4 Point Scale)		0.72
		(0.36)
Log distance (in miles)		1.00
		(0.10)
Pseudo R^2	0.114	0.246

Exponentiated coefficients; Standard errors in parentheses
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < .01$, $^{***}p < .001$

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Table 4: Predictors for working in Software Development among recent CS degree recipients in Texas, 2018 (N=153)

	Model 1	Model 2
Background characteristics		
Hispanic (=1)	0.85	1.74
	(0.36)	(1.11)
Women (=1)	1.12	0.63
	(0.51)	(0.37)
Immigrant Parent	1.13	0.95
	(0.44)	(0.44)
Unconditional Parental Support (=1)	1.56	1.59
	(0.59)	(0.73)
Mother's Education (yrs)	1.26^{**}	1.33^{*}
	(0.11)	(0.15)
Father's Education (yrs)	0.95	0.82^{*}
	(0.07)	(0.08)
Graduating Year	1.04	1.30^{+}
	(0.13)	(0.21)
Human capital		
University A: Elite, Tech Hub		7.99^{***}
		(4.77)
University C: Non-elite, Peripheral Region		1.05
		(0.78)
GPA (4 Point Scale)		2.77^{+}
		(1.61)
Distance traveled for job (in hundreds of miles)		1.55^{***}
		(0.17)
pseudo R^2	0.080	0.294

Exponentiated coefficients; Standard errors in parentheses
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < .01$, $^{***}p < .001$

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Table 5: Predicting wages by salary, capped at $170,000 in thousands of dollars (N = 153)

	Model 1	Model 2	Model 3
Background Characteristics			
Hispanic (=1)	-21.91***	-11.09+	-11.62*
	(6.01)	(6.01)	(5.84)
Women (=1)	0.31	-5.99	-4.18
	(6.30)	(5.56)	(5.42)
Immigrant Parent	7.70	4.78	4.79
	(5.52)	(4.61)	(4.47)
Unconditional Parental	2.23	0.92	-0.01
Support	(5.44)	(4.54)	(4.45)
Mother's Education (yrs)	1.12	0.18	-0.30
	(1.19)	(1.00)	(0.99)
Father's Education (yrs)	0.67	-0.50	-0.18
	(1.06)	(0.89)	(0.87)
Graduating Year	-3.09+	0.50	0.12
	(1.75)	(1.54)	(1.51)
Human Capital			
University A: Elite, Tech		22.13***	14.58*
Hub		(6.12)	(6.42)
University C: Non-elite,		-9.28	-6.95
Peripheral Region		(7.98)	(7.88)
GPA (4 Point Scale)		0.67	-0.64
		(5.61)	(5.53)
Log distance (in miles)		6.07***	5.11***
		(1.10)	(1.13)
First Job Outcome			
Works in Major Tech			9.60+
Hub			(5.10)
Software Development			12.33+
(=1)			(6.99)
QA/Web/DBA			-3.27
			(7.82)
_cons	6273.43+ (3524.29)	-966.20 (3098.36)	-199.38 (3049.34)
Adjusted R^2	0.151	0.424	0.461

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Figure A – University A, Hispanic

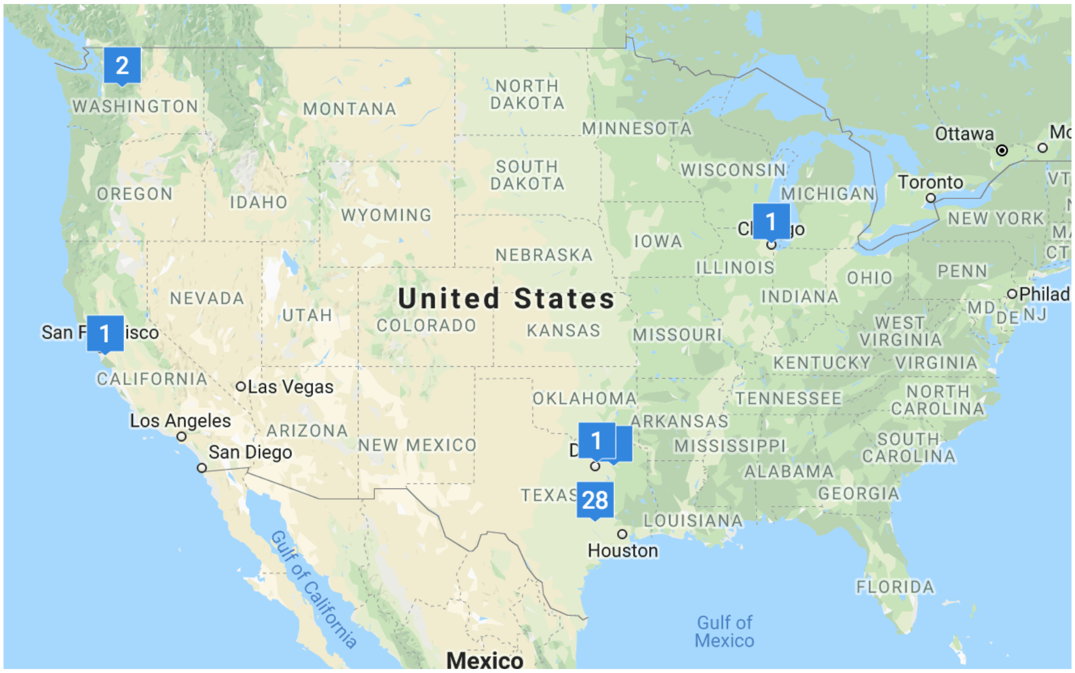

Figure B – University A, Non-Hispanic

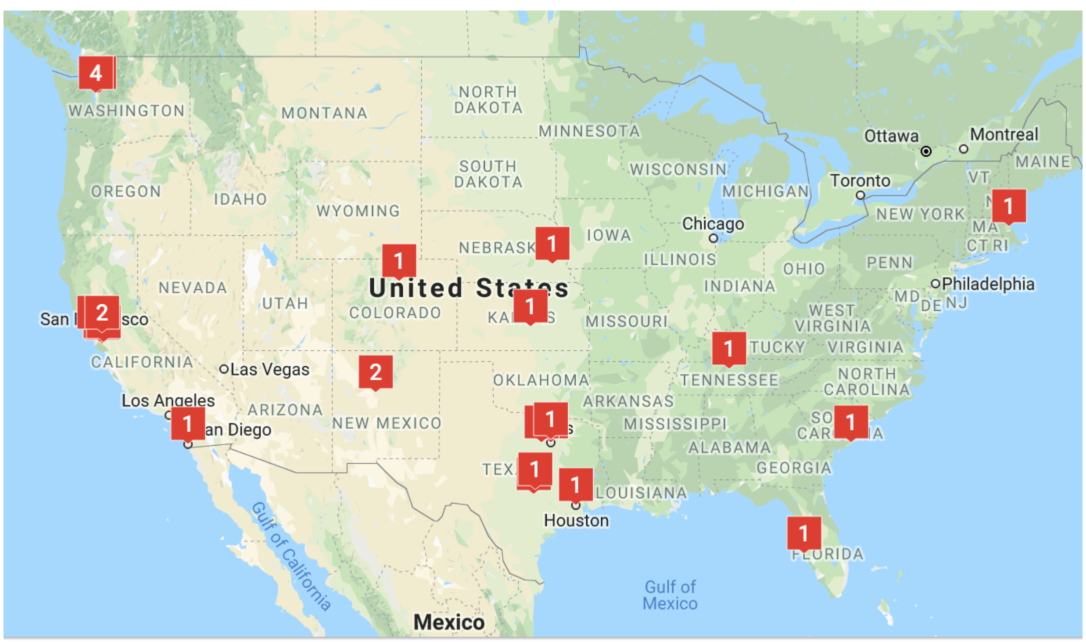

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Figure C – University B, Hispanic

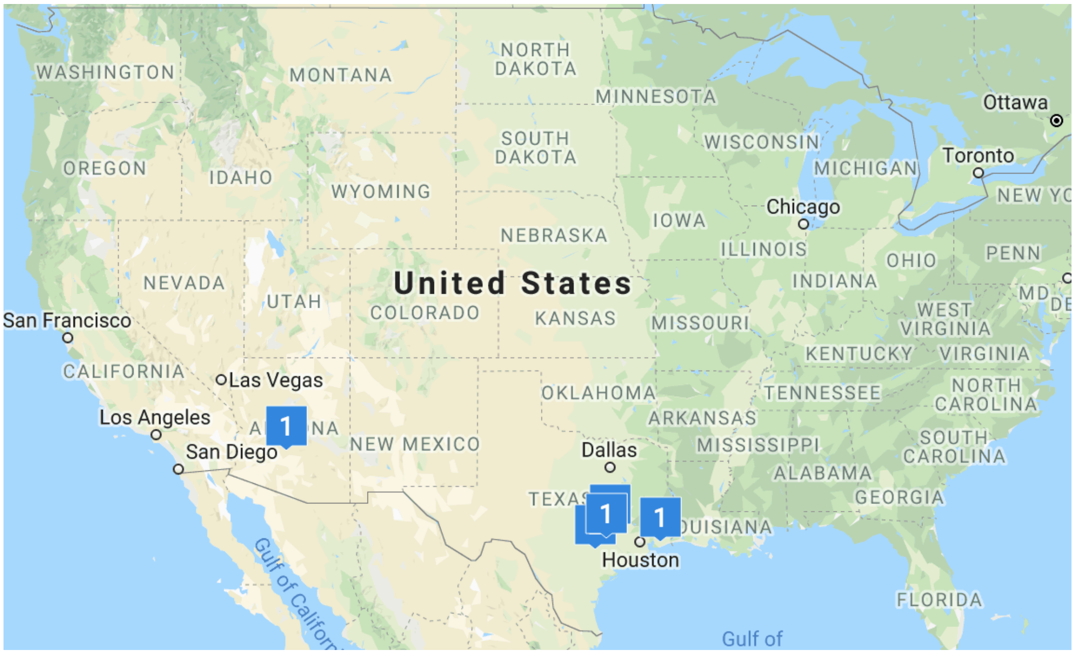

Figure D – University B, Non-Hispanic

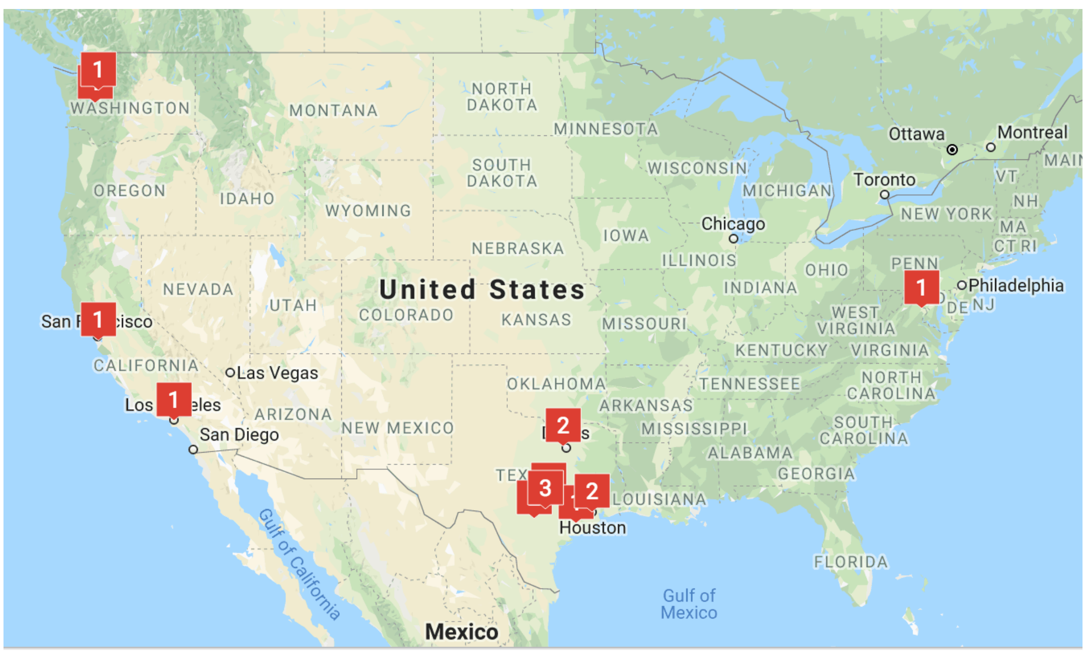

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Figure E – University C, Hispanic

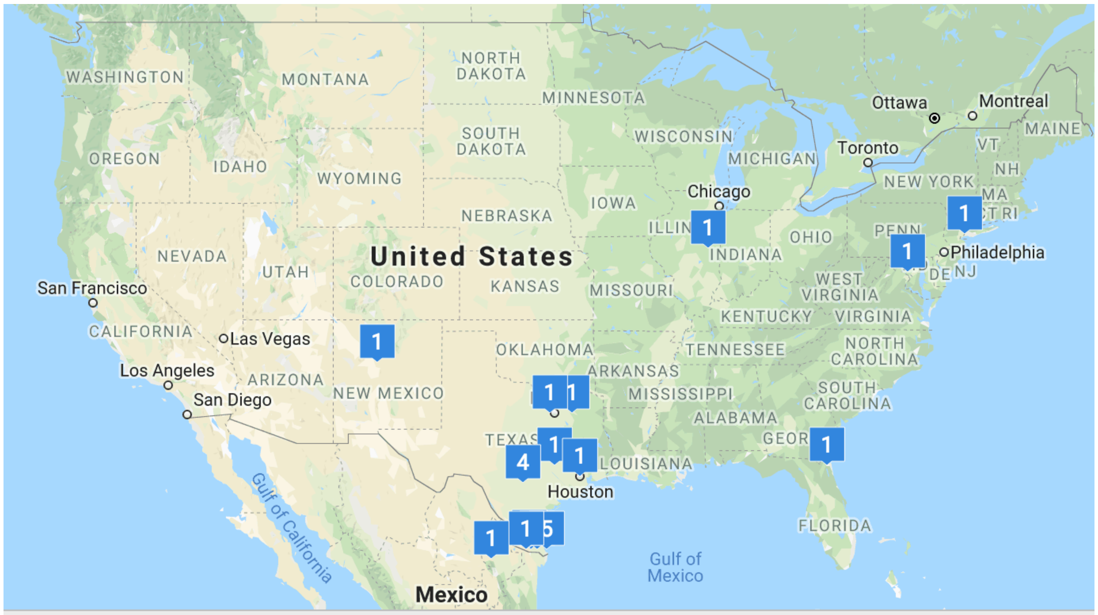

Figure F – University C, Non-Hispanic

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