Local Labor Markets and Human Capital Investments*

Russell Weinstein†

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Abstract

I study whether human capital investments are based on local rather than national demand, using four shocks with differential local effects: the dot-com crash, the fracking boom, the 2008 financial crisis, and the shock making Delaware a financial headquarters. I find universities in areas more exposed to sectoral shocks experience greater changes in sector-relevant majors. Of the effect on national sector-relevant degrees, differential effects at the most-exposed universities explain 32% (dot-com), 16.5% (fracking), and 43% (financial crisis). I develop a test for whether this local dependence is explained by location preferences, separately from information frictions. Using The Freshman Survey and nearest-neighbor matching based on student home zip codes and choice of college, I find location preferences affect college major choice. With weaker location preferences, students at Silicon Valley universities would have increased computer science intentions 2.1 percentage points (48%) less from pre-boom to bubble.

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†University of Illinois at Urbana-Champaign and IZA. E-mail: weinst@illinois.edu.

1 Introduction

Many college majors represent an investment in sector or occupation-specific skills. Without the relevant major, entry into these sectors or occupations is difficult to impossible. Given wage differentials across sectors and occupations, these decisions may become important for an individual's career and lifetime earnings.[1] These decisions also have important aggregate implications, as they help determine supply of skills in the labor market.

This paper analyzes whether individuals choose sector-specific human capital investments, specifically college major, based on local labor demand, rather than national demand. The relevance of this question is underscored by two facts. First, there are dramatic differences in labor demand across local markets, and substantial geographic concentration of industries. In the US, examples include the computer sector in Silicon Valley, finance in New York, and oil and gas in Texas.[2] Second, geographic mobility is limited and declining even among highly-educated individuals. From 2001 to 2010, annual interstate migration of college-educated individuals was 2.1%, roughly half the rate in the 1980s (Molloy, Smith, and Wozniak 2011).[3] The first fact suggests investments based on local demand may differ significantly from those based on national demand. The second suggests local demand may affect investments, given that college-educated individuals are not very likely to move across markets.

This is the first paper, of which I am aware, studying the impact of local, sector-specific labor demand on local, sector-specific human capital production (college major) across the entire United States. The second contribution of the paper is to study the mechanism explaining the local elasticity. Individuals may make investments based on local rather than national demand because of information frictions, or because of migration frictions. Investments based on local demand may be individually optimal if they are explained by strong location preferences. However, if individuals make investments based on local demand due to information frictions, this suggests an important role for policy improvements. The consequences for the aggregate economy are potentially large if individuals invest based on local demand, regardless of the mechanism.

It is possible to directly observe the correlation between sector-specific human capital investments, local, and national labor demand. However, these correlations alone would not be convincing evidence for this source of mismatch, as endogeneity concerns make causality difficult to establish. Local demand may respond to, not determine, local human capital

[1] Altonji, Blom, and Meghir (2012) document large wage differences across major.

[2] Ellison and Glaeser (1997) show geographic concentration of manufacturing industries.

[3] Related, Manning and Petrongolo (2017) find distance has a strong effect on job search for unemployed workers.

investments.

Using four sector-specific exogenous shocks with differential local effects, I test whether universities in areas more exposed to these shocks experience greater changes in the share of sector-relevant majors. I focus on computer science and computer engineering (CS/CE) majors after the dot-com crash in 2000, geology majors after the boom in oil and gas enabled by hydraulic fracturing (fracking), finance majors after the 2008 financial crisis, and business majors after the creation of an international center for financial services in Delaware in the early 1980s, following a US Supreme Court decision and subsequent state legislation.

While there are clear differences between these shocks, they all had large sector-specific employment effects in some local markets, and smaller or zero effects in others. Investing based on local demand would yield significantly different major choices compared to investing based on national demand. I also exploit that for each shock the timing was exogenous to the number of majors, and there is a close mapping to demand for a particular major.

I find college majors respond differentially in areas more exposed to labor demand shocks, using university-level data on completions by major from The Integrated Postsecondary Education Data System (IPEDS). I compare universities more geographically exposed to these shocks, to less-exposed universities whose students experience the same national shock. I estimate the effect of exposure by year, as well as use a more parametric dynamic specification, enabling identification of preexisting trends.

For graduates five years after the first treated cohort, the dot-com crash reduced the share of CS/CE degrees by an additional 1.6 percentage points, or 41%, at universities in more exposed areas (MSA computer employment share higher by ten percentage points). The fracking boom increased the share of geology degrees by an additional .1 percentage points, or 26%, at universities in more-exposed counties (top quartile nearby new oil and gas production from 2004 to 2014).

The financial crisis reduced the share of finance degrees by an additional .4 percentage points, or 13%, at universities in more exposed areas (MSA finance employment share higher by five percentage points). Unlike the other shocks, this is not significant, while the immediate effect is significant. This may reflect relatively quick recovery of the stock market, or that the shock became very broad based. Delaware's finance shock increased the share of business degrees an additional 5.9 percentage points, or 27%, at local universities.

These differential local effects are important in explaining the shocks' effects on majors nationally. Of the aggregate decline in CS/CE after the dot-com crash, over 30% can be explained by differential impacts on majors in top-quartile exposed areas, as opposed to the shock's national impact on majors affecting all universities equally. Of the overall increase in geology majors after the fracking boom, 16.5% can be explained by differential effects in

top-quartile-exposed counties. Of the national decline in finance degrees after the crisis, over 40% can be explained by differential impacts in top-quartile-exposed MSAs.

The dot-com crash and the 2008 financial crisis were temporary shocks to sectoral employment. Nonetheless, students who were enrolled during these shocks adjusted their majors, arguably long-term investments, based on these temporary shocks. Students may have overestimated the size or duration of the shock, or alternatively they understood poor initial placement can have long-run effects (Kahn 2010, Oreopolous et al. 2012, Oyer 2006 2008).

Second, I explore the mechanisms underlying this local elasticity. I develop a test to isolate the role of information frictions and location preferences using very rich student-level data from The Freshman Survey (TFS). While TFS has surveyed over 15 million students since 1966 ("CIRP" 2018), this is the first Economics paper in the growing literature on college major choice to use the student-level data.[4] The test's intuition is straightforward. Using nearest-neighbor matching, I compare students who grew up in the same commuting zone (CZ), and have similar academic, parental, and university characteristics, but make different choices about attending college in Silicon Valley. Based on this matching, I argue these students have similar information but potentially different preferences for living in Silicon Valley, revealed through their college choice. Because the survey is administered before classes start, students have not yet obtained information from their university's labor market. Using additional data sources, I confirm that college choice is indeed a signal of location preferences.

I argue these different location preferences explain differences in majors between students at Silicon Valley universities and their same-CZ matches attending non-Silicon Valley universities. Conditional on interest and ability in CS, students with strong Silicon Valley preferences should be more likely to increase CS major intentions during the bubble because of differential demand for these skills in their desired geographic market. Students with similar interest and ability in CS, but with weaker Silicon Valley preferences revealed through their choice of university should less dramatically increase their CS intentions. The increase in demand for CS skills was less dramatic in their desired geographic markets. They may instead substitute into other technical disciplines.

I find strong evidence that location preferences affect college major intentions. Before the boom, there is no significant difference in CS major intentions between students at Silicon Valley universities and their same-CZ matches attending non-Silicon Valley universities. This suggests the matching identifies students with similar information, as well as interests and abilities in CS. However, relative to the pre-boom years, students at non-Silicon Valley universities are 2.1 percentage points (48%) less likely to intend on CS majors during the

[4]Previous papers have used the aggregate TFS data, for example Bound, Hershbein, and Long (2009).

bubble relative to same-CZ matches at Silicon Valley universities.

This implies the dramatic increase in CS intentions during the bubble at Silicon Valley universities would have been 48% smaller if students there had weaker location preferences. Further, I show that without these location preferences, Silicon Valley students attending their local university would have been equally likely to increase CS intentions during the bubble as non-Silicon Valley students attending their local university. Information differences do not appear to explain the local elasticity.

There are two main concerns for why this test may not identify the role of migration frictions. First, students staying in Silicon Valley for college may do so because of their interest or ability in CS, rather than migration frictions. Fortuitously, TFS directly asks individuals whether they chose their college because they wanted to live near home. Restricting to the students staying in Silicon Valley for college because of migration frictions and their matches, those staying in Silicon Valley are also much more likely to increase CS intentions during the bubble.

Additionally, I include only matched pairs in which the match at a non-Silicon Valley university attends a technical university (e.g. California Polytechnic State University-San Luis Obispo). The results hold among these students who have revealed interests and skills in science, but may choose a particular STEM field based on demand in their desired market. Similarly, the result is robust to including only students attending universities targeted in the recruiting of top technology firms.

Despite the matching, students choosing Silicon Valley universities may also have different information than same-CZ students choosing universities elsewhere. For robustness, I include only students with parents in technical occupations (e.g. computer programming), where information differences are arguably much smaller, and find similar results.

The paper contributes to an established and growing literature on how individuals make human capital investments (see Altonji, Blom, and Meghir 2012 for a review).[5] Several recent papers study the impact of national business cycles, including the Great Recession, on major choice (Blom, Cadena, and Keys (2015), Ersoy (2017), Liu, Sun, and Winters (2017)). Choi, Lou, and Mukherjee (2016) study how major choice responds to skewness of stock market returns within an industry, and Long, Goldhaber, and Huntington-Klein (2015) study the effect of major-specific wages. Bardhan, Hicks and Jaffee (2013) study whether aggregate increases in demand for specific occupations leads to increased aggregate degree completions related to the occupation.

[5] A related literature shows the return to higher education varies considerably across major (Altonji, Blom, and Meghir 2012 contains a review, Kinsler and Pavan (forthcoming), Lang and Weinstein 2013), and also that the effect of graduating in a recession varies by college major (Altonji, Kahn, and Speer 2016).

I contribute to this literature by focusing on very salient national sectoral shocks, which map closely to majors, and why these salient national shocks differentially affect major choice across local labor markets. I present among the first estimates identifying the role of location preferences in determining college major choice, and more specifically college major responsiveness to economic shocks.

Several recent studies analyze how major choice is affected by local demand. Using data on graduates of eight Washington state public universities from 2007-2012, Long, Goldhaber, and Huntington-Klein (2015) find major choice is more strongly correlated with major-specific wages of recent same-state graduates than with CPS wages in occupations related to the major. I build on and complement their analysis by focusing on exogenous sectoral shocks across the US mapping closely to majors, allowing for identification of causal effects. I also test mechanisms explaining the local elasticity. Ersoy (2017) studies changes in major allocation after the Great Recession based on the local severity of the recession. Foote and Grosz (forthcoming) study the effect of local mass layoffs on enrollment at two-year colleges and field of study for subbaccalaureate degrees, though their analysis does not connect the sector experiencing the mass layoff to field of study.

Two recent papers find important effects of local shocks on the extensive margins of high school completion and college enrollment (Cascio and Narayan 2015, Charles, Hurst, and Notowidigdo forthcoming). Betts and McFarland (1997) find community college enrollments and degrees increase with the unemployment rate in the census region. These reflect individual responses to the opportunity costs of an additional year of schooling. This paper's focus on majors reflects whether individuals tailor those large investments to labor demand.

Investments based on local demand also may help explain why young college-educated individuals have much higher unemployment rates than older individuals (National Center for Education Statistics 2015), a puzzle from an earlier literature (Blanchflower and Freeman 2000). These local investments may yield mismatch between supply and demand for sector-specific skills. Mismatch is a prominent explanation for high aggregate unemployment (Shimer 2007, Sahin et al. 2014), but was not considered in the literature on youth unemployment rates.[6]

The paper also contributes to current policy discussions on CS majors. The current and previous presidential administrations enacted policies to increase access to CS education ("Computer Science for All" 2016, Presidential Memorandum 2017). Further, a recent report requested by the National Science Foundation addressed the current all-time high enrollment in CS, and how universities should respond in the short- and long-run (National Academies

[6]Rothstein (2012) argues there is little evidence that mismatch contributed to the overall unemployment rate after the Great Recession.

2018).[7] Understanding students' decisions to major in CS, and how this is affected by geography and sectoral demand, is crucial for maintaining a strong CS-skilled workforce. While there is a growing literature studying the economic impacts of fracking, this is the first to study whether it affected college majors.

Most generally, I show individuals make investments that enhance their ability to benefit from local shocks. This complements recent work suggesting individuals are affected by local shocks because of low levels of migration (Bartik 2018, Yagan 2018).

2 Sectoral Shocks with Local Labor Market Impacts

I analyze how majors respond to four sector-specific shocks, studying two positive labor demand shocks and two negative shocks. While the shocks affected different sectors, each had differential effects across local labor markets. This implies investments based on local demand will differ from those based on national demand. Below, I briefly describe each shock.

The first shock I study is the dot-com crash, beginning in March 2000 with a steep decline in internet stock prices, for reasons arguably unrelated to negative news about internet stock fundamentals (DeLong and Magin 2006, Ofek and Richardson 2001). Dot-com stock prices continued falling until 2003.[8] Computer employment fell by 15% (Figure 1). The significant crash was preceded by a period of dramatic growth for computer and internet companies, and the late 1990s is often referred to as the dot-com bubble.[9]

For the second shock, I use the dramatic increase in oil and gas production from the introduction of hydraulic fracturing (fracking) and horizontal drilling in the mid-2000s. I show gross natural gas withdrawals increased dramatically, and oil and gas employment more than doubled from 2004 to 2014 (Figure 1, Panel B). The third shock, the 2008 financial crisis and the subsequent Great Recession, affected many industries, but with a clear effect on employment in Finance, Insurance, and Real Estate (FIRE). FIRE employment declined by approximately 8% from 2007 to 2010 (Figure 1, Panel C).

For the fourth shock, I use the creation of an international headquarters for the finance industry created in the state of Delaware, resulting from jurisdictional competition and

[7] In commissioned papers for the National Academies report, Bound and Morales (2018) and Hunt (2018) show CS degrees in the U.S. as a share of total U.S. bachelor's degrees increase in the boom and decrease in the bust.

[8] Wang (2007) summarizes theories explaining the boom and bust, including bubbles, uncertainties in new markets, and innovation complementary to technology of brick-and-mortar institutions. Ofek and Richardson (2001) argue for the role of expiring lock-up agreements from IPOs, increasing sellers in the market.

[9] The NASDAQ nearly doubled in the year leading up to its peak in the first months of 2000, without positive news about stock fundamentals to justify this increase (DeLong and Magin 2006).

firm relocation. Prior to 1978, state usury laws determined the interest rate that credit card companies could charge the state's residents. The US Supreme Court's ruling in *Marquette National Bank of Minneapolis v. First Omaha Service Corp.* allowed a bank to export the highest interest rate allowed by the state in which it is headquartered. In 1981, Delaware eliminated its usury laws, with the passage of the Financial Center Development Act (FCDA). The FCDA also reduced other industry regulation and introduced a regressive tax structure for banks.[10]

As a result, many companies moved their finance or credit operations to Delaware, starting with J.P. Morgan in 1981. Weinstein (2018) analyzes labor market adjustment to this shock, and shows the policy resulted in higher FIRE growth in Delaware through 2000 (also shown in Figure 1 Panel D). While this shock is much more localized than the others, it is valuable given that investments based on local demand would yield very different major choices. Further, this is the first analysis of how human capital investments respond to place-based and local economic development policies, which are very prevalent around the world.[11]

Figure 1 shows the national shocks had important effects on the national share of sector-relevant majors. Figure 2 shows the national sectoral shocks had differential effects on local economies using data from the Quarterly Census of Employment and Wages. From 2001 to 2002, Santa Clara County in California, the home of Silicon Valley, experienced a decrease in "Computer Systems Design and Related Services" employment representing nearly 1.5% of total county employment (Figure 2, Panel A(a)). This was dramatically larger than the decrease nationally, representing only .13% of total employment.

In 2011, the one-year employment gain in natural resources and mining represented nearly 15% of total county employment in McKenzie County, North Dakota, which experienced the greatest cumulative increase in the value of new fossil fuel production from 2004 to 2014. Nationally this employment gain was close to zero. Similarly, from 2008 to 2009 FIRE employment fell considerably in Manhattan, with the one-year employment loss in FIRE representing over 1% of total county employment. Nationally, this effect was much smaller, representing only .3% of total employment. While the increase in FIRE demand in Delaware was very large, if Delaware students made investments based on demand in a larger region the incentives to major in business would be much lower (Figure 1d).

[10]The FCDA had capitalization and employment requirements. Weinstein (2018) lists other provisions. The description of the FCDA is based on Moulton (1983).

[11]Local policies to attract or retain firms cost local governments 80 billion dollars per year in the U.S. (Story 2012).

3 Data

I obtain university-level data on Bachelor's degrees awarded by academic discipline. For the dot-com crash, the fracking boom, and the financial crisis, I obtain total degrees awarded by major using IPEDS data.[12] For the dot-com crash, I classify CS (computer and information sciences and support services) and CE (computer engineering) majors as sector-relevant degrees. For the financial crisis, I classify finance majors as sector-relevant degrees.[13]

For the fracking boom, I classify geology majors as the sector-relevant degrees. I focus on geology for several reasons. First, geology is crucial for understanding where to drill. Given the fracking boom involved innovations in horizontal drilling and hydraulic fracturing, these skills were arguably especially in demand (Vita 2015). Second, geology is offered at universities around the country regardless of their fracking exposure. Excluding petroleum engineering degrees will very likely lead to underestimating the local elasticity. However, these degrees are offered by very few universities, and mostly in fracking-exposed areas.[14] Oil and gas companies certainly demand other more widely-offered engineering degrees, such as chemical, mechanical, and civil engineering. However, these degrees are also demanded by other sectors that may have their own cycles during this period.

Studying Delaware's finance labor demand shock requires earlier university-level data. I obtain Bachelor's degrees awarded by university and academic discipline from 1966 through 2013 from the IPEDS Completions Survey. These data are accessed from the Integrated Science and Engineering Resources Data System of the National Science Foundation. I focus on business and management majors in this part of the analysis as degrees by four-digit CIP codes are not available in these earlier years.[15]

To determine the exposure of the university's local labor market to the dot-com crash and financial crisis, I obtain the share employed in finance and computers using the IPUMS USA 2000 Census 5% sample (Ruggles et al. 2015). I classify as computer-related industries the BLS-defined high-technology industries that are relevant for the computer industry.[16] I include the FIRE industries, excluding insurance and real estate, as finance-related indus-

[12]For these shocks, I limit the sample to universities existing in the 2013 IPEDS data with a 2000 Carnegie code. I include only Doctoral/Research, Master's, Baccalaureate, and Baccalaureate/Associates Colleges as ranked in the 2000 Carnegie rankings. To calculate total degrees by major, I include both first and second majors in the given field, except in 2000 when this distinction is not available. Total degrees awarded at the university also sums all first and second majors.

[13]See appendix for CIP codes, and results using only CS majors. Universities differ in whether they offer CS and CE, or only one. Both CS and CE responded to the dot-com cycle (National Academies 2018).

[14]See appendix.

[15]See appendix for data details.

[16]I use the BLS definition of high-technology industries from Hecker (2005). This uses the 1997 NAICS codes, while I use the 2000 Census Classification Code. These match quite well, with several minor exceptions. These exceptions, as well as the industries I classify as computer-related, are in the appendix.

tries.[17] Using the person weights, I obtain the weighted sum of individuals by industry and metropolitan area.[18] I merge the data on share employed in computers and finance to the university-level data using the 2013 MSA.

Many universities are not in MSAs, and among those that are these may not be represented in the Census. For these categories, the principal results assume percent employed in computers or finance is zero. For robustness, I exclude these universities from the sample.

For fracking exposure, I obtain annual data on the value of oil and gas production from wells drilled for the first time that year (in 2014 dollars), within 200 miles of each county, from Feyrer, Mansur, and Sacerdote (2017).[19] Papers studying the impact of fracking on the local economy often use an instrument for fracking exposure, since the decision of where to frack within the shale may be correlated with local economic characteristics, and trends in the outcome. It is much less likely that the decision of where to frack is correlated with trends in oil and gas related degrees awarded by local universities.[20]

To determine the university's local labor market exposure to Delaware's finance shock, I calculate distance between the university and Wilmington, Delaware (the city where the shock was concentrated) using the university's latitude and longitude.[21] Because this was a Delaware-specific shock, I limit the sample of universities to those in Delaware, New Jersey, Pennsylvania, Maryland, Washington, DC, Virginia, and West Virginia.

If all sector-relevant degrees were awarded by universities in areas with high sectoral employment share, a larger differential response in these areas would be mechanical. Figure 2, Panel B shows a large proportion of CS/CE, geology, and finance degrees in the US are offered by universities in areas not exposed to the dot-com, fracking, or 2008 financial shocks.

4 Identifying Local Shocks' Effects on Majors

I use a dynamic framework to identify the shocks' effects. This is important for two reasons. First, these were not one-time shocks. Their magnitude changed over time, and perceptions

[17] See appendix.

[18] I include individuals 18-65 who worked last year, not living in group quarters, and not in the military.

[19] Production only in the first year a well was drilled is arguably a reasonable proxy for overall production attributed to fracking. Newell, Prest, and Vissing (2016) show that most of the production from a given well occurs within the first 12 months of drilling. Further, Feyrer, Mansur, and Sacerdote (2017) show that most of the gains in mining and natural resources wages and employment, which are relevant for geology majors, are concentrated around the time the well is first drilled.

[20] However, it is of course possible that trends in oil and gas related degrees are correlated with another variable that is correlated with the decision of where to frack.

[21] I use IPEDS 2013 data to obtain universities' latitude and longitude. I make a crosswalk between the FICE code (the only identifier in the NSF IPEDS data) and IPEDS ID, and merge with the location data. I manually input latitude and longitude for universities no longer existing in 2013. I use the Vincenty formula for calculating distance between two points on the surface of the Earth, assuming it is an ellipse.

about the shock's persistence may also have changed. Second, these specifications allow me to identify how quickly degree completions respond to the initial shock.

I do not separately identify dynamic effects from an original shock relative to contemporaneous effects as the shock evolves. However, I will analyze changes in major composition in the years after the shock's onset, and relate those changes to demand.

The empirical strategy identifies changes in major composition within a university. These may be driven by students changing majors, or by changing composition of students. Either suggests local shocks have effects on human capital investment decisions, either where or what to study. Changes in the national proportion of sector-relevant degrees surrounding these shocks suggests significant numbers of students changed majors in response to the shocks, and differential local effects are not explained by students changing universities. The robustness and mechanisms section address selection into universities more directly.

I start by estimating year-specific effects using the following regression:

$$\begin{aligned} Share(Majors_{cmt}) &= \alpha_0 + \gamma_c + \delta_t + \sum_{r=k_{min}}^{k_{max}} Exposure_c * (1(t = t^* + r))\, \beta_r \\ &\quad + \eta TotDegrees_{cmt} + u_{cmt} \end{aligned} \tag{1}$$

The variable $Share(Majors_{cmt})$ denotes the share of relevant majors at university c in area m in year t. The variable $Exposure$ denotes the extent to which university c is exposed to the shock. For the dot-com crash this is the share of metropolitan area $m's$ employment in the computer sector in 2000. For the 2008 financial crisis, I use the share of metropolitan area $m's$ employment in finance in 2000. For the fracking boom, I use whether the county's cumulative value of new oil and gas production from 2004 to 2014 is within the top quartile. For Delaware's shock, $Exposure$ is one for universities within 15 miles of Wilmington, Delaware.[22]

The coefficients β_r identify the differential effect on majors in areas more exposed to the industry in each year, including years before t^* as $k_{min} < 0$. I measure years relative to t^*, in which the graduates were freshmen at the shock's onset (2003 for the dot-com shock, 2009 for the fracking boom, 2011 for the finance shock, and 1985 for the Delaware shock).[23] As a rough measure of the fracking boom onset, I use the year in which fracking success had been publicized in at least 25% of shale plays (2006), using publicity data from Bartik, Currie, Greenstone, and Knittel (forthcoming).

[22]There are six universities within 15 miles of Wilmington

[23]While Delaware's legislation passed in February 1981, the first acquisition was approved in November 1981 (Erdevig 1988). I assume 2007-2008 freshmen were the first exposed to the financial crisis given the bailout of Bear Stearns in March 2008.

The variable $TotDegrees_{cmt}$ denotes the total Bachelor's degrees awarded by university c in year t. $Exposure$ uninteracted is perfectly collinear with the university fixed effects (γ_c). I weight the observations by $TotDegrees_{cmt}$, ensuring changes at larger universities get more weight than those at smaller universities. I cluster standard errors at the university level.[24]

The main identification assumption is that the timing and local exposure to the shocks are not caused by local changes in major, or correlated with other factors differentially affecting majors in exposed areas. Estimating the effects of exposure by year, including before the shock, provides important evidence on the strength of the identification assumption. Figure 1 shows that for the dot-com crash and financial crisis, the period preceding the negative shock was an important boom period for the industry. The period preceding the positive shock in Delaware was a bust period for the industry. This mitigates concerns of preexisting trends in the same direction as in the post-shock period.

Differential effects in more exposed areas during these pre-shock boom or bust periods would also imply a relationship between local demand and human capital investments. This too would be an interesting result, though subject to endogeneity concerns. Job growth may have responded to university specialization, rather than the reverse. I focus on the crashes since these shocks are more clearly exogenous. It is unlikely that more jobs left high computer employment MSAs because of greater decreases in CS/CE majors. Even if universities in high-computer areas experience greater increases in the boom, greater decreases during the crash suggest differential responses to the same economic event.

I also estimate similar regressions constraining the phase-in and prior trends to be linear:

$$\begin{aligned} Share(Majors_{cmt}) &= \alpha_0 + \gamma_c + \delta_t \\ &+1(t \geq t^*)\beta_{jump} + 1(t \geq t^*)(Exposure_j)\beta_{jumpdiff} \\ &+1(t \geq t^*)(t - t^*)\beta_{phasein} + 1(t \geq t^*)(t - t^*)(Exposure_j)\beta_{phaseindiff} \\ &+(t - t^*)\beta_{trend} + (t - t^*)(Exposure_j)\beta_{trenddiff} \\ &+\eta TotDegrees_{cmt} + u_{cmt} \end{aligned} \tag{2}$$

I test if the shock's initial effect on majors depends on the university's local exposure to the industry ($\beta_{jumpdiff}$) and whether this changes with years from the shock's onset ($\beta_{phaseindiff}$). To best capture immediate effects, I include only post-policy years within five years of the shock. I include the ten years preceding the shock, and censor the trend variable

[24]Following Feyrer, Mansur, and Sacerdote (2017), I estimate the fracking regressions clustering at the county year level, to address spatial correlation from including new production in a county for multiple county groups in the regression. These result in smaller standard errors, and so I report those clustered at the university level.

$(t - t^*)$ at -5 (as in Lafortune, Rothstein, and Schanzenbach 2018). The ten years preceding the Great Recession includes another recession and recovery. To best capture the boom immediately preceding the shock, for this shock I include only the five years preceding t^*.

The coefficients $\beta_{trenddiff}$ reflect whether universities in more exposed areas experienced greater changes in sector-specific majors preceding these shocks. In studying the fracking boom and Delaware's finance shock, this coefficient represents a falsification test. If relevant majors were differentially increasing in exposed areas in the years preceding the shock, this would suggest any post-policy effects may be part of a longer-run trend.

Based on the coefficients in (2), I estimate the effect of exposure to these sectoral shocks relative to the year preceding the shocks. I present results showing the effect of exposure for the first graduates exposed as freshmen (t^*), and five years after the first graduates exposed as freshmen ($t^* + 5$). The differential impact of the shock in a more exposed area in year t^* relative to $t^* - 1$ is: $Exposure * (\beta_{jumpdiff} - \beta_{trenddiff})$. The differential impact in year $t^* + 5$ relative to $t^* - 1$ is: $Exposure * (\beta_{jumpdiff} + 5\beta_{phaseindiff} + 6\beta_{trenddiff})$.

I show the differential effect of exposure to the dot-com crash if the MSA computer employment share is higher by .1, and the differential effect of exposure to the 2008 financial crisis if the MSA finance employment share is higher by .05.[25] For the fracking boom and the Delaware shock, I show the differential effect when the exposure indicator is one.

5 The Effect of Local Shocks on Major Composition

For each shock, I find larger effects on sector-specific majors at universities in areas more exposed to these shocks. Figure 3 shows the coefficients from estimating regressions (1) and (2). The omitted interaction is with year t^* in which the graduating students were freshmen at the shock's onset. The nonparametric (equation 1) and parametric (equation 2) results closely match, and each shows differential changes in sector-specific majors starting with graduates who were freshmen at the shock's onset, or with later graduates.

The differential effect on CS/CE majors in high computer employment MSAs increases with years from the shock's onset (Table 1, column 1, row 3), and this is highly significant. The dot-com crash reduced the share of CS/CE majors by an additional 1.6 percentage points at universities in MSAs with computer employment share higher by ten percentage points, for graduates five years after the first graduates exposed as freshmen (row 8). This effect is statistically significant at the 1% level. In 2008, on average 2.3% of degrees awarded are in CS/CE, among universities where MSA computer employment share is at least .1

[25] There are six MSAs with computer employment share $\geq$.1, and 20 universities in those MSAs. There are five MSAs with 2000 finance employment share $\geq$.05, and zero $>$ .1, and 91 universities in those MSAs.

(weighted by total degrees, author's calculation). Thus, universities in areas where MSA computer employment share is higher by 10 percentage points experience an additional $1.6/(2.3 + 1.6) = 41\%$ decline in CS/CE degrees awarded. The effects are not statistically significant among the graduates who were freshmen at the shock's onset (row 7).

The fracking boom increased the share of geology majors an additional .1 percentage points at universities in top-quartile-exposed counties, for graduates five years after the first graduates exposed as freshmen. The effect is significant at the 1% level. In 2014, on average .48% of degrees are awarded in geology at universities in top-quartile-exposed counties. Thus, universities in top-quartile-exposed counties experience an additional $.1/(.48 - .1) = 26\%$ increase in geology degrees awarded. The effect is smaller and less significant for the first-exposed graduates.

The differential effect of the 2008 financial crisis in high finance areas is more immediate, and grows with years from the shock. The 2008 financial crisis reduced the share of finance majors by an additional .2 percentage points at universities in MSAs with finance employment share higher by five percentage points, for the first graduates exposed as freshmen ($p \leq .05$). For graduates five years after the first exposed cohort, the additional decrease was .4 percentage points. While larger in magnitude, this is not statistically significant. In 2013, on average 2.7% of degrees awarded are in finance, among universities where MSA finance employment share is at least .05 (author's calculation). Thus, universities in areas where MSA finance employment share is higher by 5 percentage points experience an additional $.4/(2.7 + .4) = 13\%$ decline in finance degrees awarded.[26]

The absence of a significant effect for graduates five years after the first exposed cohort may be explained by the relatively quick recovery of the stock market after the initial 2008 shock. By the time the first class exposed to the shock as freshmen graduated in 2011, the DJIA had recovered 77% of what it had lost from its peak to its trough.[27] If graduates in high finance employment areas chose finance majors in a way correlated with financial markets, graduates after 2011 would see significantly reduced disincentives to choose finance. Alternatively, because the financial crisis ended up a very broad-based shock affecting many industries, it is possible that by five years after the first affected cohort, disincentives to choose finance were reduced relative to other majors in high finance areas.

Table 1, column 4 shows that with each year from the legislation, Wilmington-area universities experienced a differential 1.9 percentage point increase in the share of business degrees awarded (row 3) ($p \leq .01$). There is no differential effect on share of business de-

[26] Appendix Figure A8 shows no differential effect on business majors, consistent with these demanded by many nonfinance sectors also affected by the recession.

[27] Based on DJIA closing price of 12414.34 on June 1, 2011, and peak of 14164.43 in October 2007 and trough of 6594.44 in March 2009 (Yahoo Finance, Amadeo 2018).

grees for graduates who were freshmen in the year of Delaware's legislation, relative to the preceding year (row 7). However, five years after these first-exposed graduates, Delaware's finance shock increased the share of business majors by an additional 5.9 percentage points at Wilmington-area universities. In 1990, on average 27.9% of degrees awarded are in business, among universities within 15 miles of Wilmington, Delaware (author's calculation). Thus, universities within 15 miles of Wilmington experience an additional $5.9/(27.9 - 5.9) = 27\%$ increase in business degrees awarded.[28]

Figure 3 shows that for each shock, the effect of exposure on sector-relevant majors was not trending in the same direction as in the post-shock period. For three of the shocks (dot-com, financial crisis, and Delaware), in the pre-shock period the trend in the effect of exposure on sector relevant majors was the reverse of the post-shock period. This is consistent with the periods preceding the negative dot-com crash and financial crisis being boom periods for the industry and the period preceding Delaware's positive shock being a bust period for FIRE Employment (Figure 1). These pre-trends mitigate concerns that the identification assumption is violated.

5.1 Local Exposure's Role in Explaining National Changes

I next determine the extent that national changes in CS/CE, geology, and finance degrees are explained by national conditions equally affecting universities, as opposed to differential local exposure to sectoral shocks. I use the coefficients from regression (1) to implement a simple accounting exercise. I do not focus on Delaware's finance shock since this less clearly represented a national increase in demand for business majors.

The year fixed effects, δ_t, from regression (1) identify the impact on share relevant majors experienced by all universities, regardless of their exposure. I multiply $\hat{\delta}_t * TotDegrees$ to obtain the change in relevant degrees at each university attributed to national factors, as predicted by the regression. Summing across all universities, I obtain the national change in relevant degrees attributed to national factors.

Similarly, I multiply $\hat{\beta}_r$ by $Exposure_j * TotDegrees$ to obtain the change in relevant degrees at each university attributed to differential shock exposure. Summing across all universities, I obtain the national change in relevant degrees attributed to differential exposure.

I evaluate the contribution of local exposure to the change from $t^* - 1$ to the year which produces the greatest difference in national majors relative to $t^* - 1$. Of the raw overall decrease of 18,037 CS/CE degrees from 2002 to 2009, approximately 44% is explained by differential impacts in more exposed areas, and 32% by differential exposure in MSAs at the

[28] The appendix shows results for all classifications of majors.

75th percentile or above (MSA computer-employment share greater than about 3.5%).

Of the raw overall decrease of 2,514 finance degrees from 2010 to 2013, approximately 63% is explained by differential impacts in more exposed areas, and 43% by differential exposure in MSAs at the 75th percentile or above (MSA finance-employment share greater than about 3%). Of the raw overall increase of 2440 geology degrees from 2008 to 2014, approximately 16.5% is explained by differential impacts in top-quartile-exposed areas. Because the exposure variable for this shock is an indicator, this underestimates the contribution of local exposure by ignoring areas with exposure less than or equal to the 75th percentile.

Differential effects at universities in top-quartile-exposed areas explain less of the overall change in after the fracking boom relative to the dot-com crash and financial crisis, although the percentage is still important. This may be explained by fewer universities in top-quartile fracking exposed areas (300) than top-quartile dot-com or financial crisis exposed areas (439 and 523 respectively). Total degrees awarded in these areas as a percent of all US degrees is similarly smaller (21% for fracking, 39% for the dot-com crash, and 41% for the financial crisis). Alternatively, using fracking exposure within 200 miles may include universities at which students do not view the shock as local, reducing the estimated effect of differential local exposure.

Timing

The dot-com crash and the financial crisis temporarily affected computer and FIRE employment (Figure 1). Nonetheless, students adjusted majors based on the shock, both nationally and differentially at more exposed universities. Shifting out of these majors in the short run may have negatively affected long-run outcomes since the industries recovered. Students immediately after the crash may have overestimated the size or duration of the shock. Alternatively, these students may have understood poor initial placement would have long-run labor market consequences (Kahn 2010, Oreopolous et al. 2012, Oyer 2006, 2008).

The differentially negative effects of the dot-com crash on CS/CE majors at exposed universities start to reverse by 2010 (Figure 3), lagging renewed growth in computer employment (Figure 1a).[29] The differentially negative effects of the financial crisis on finance majors at exposed universities do not appear to reverse when FIRE employment eventually increases, although the estimates are imprecise.

While oil and gas employment eventually fell, it is more difficult to call the ten-year boom "temporary" and thus less surprising that students adjusted in the short run. It is also not

[29]This is also consistent with a cobweb model of labor supply (Freeman 1975, 1976), though the initial effect on CS/CE degrees is due to the exogenous crash. Later cohorts may invest in CS/CE degrees because fewer students had done so after the shock.

surprising to see the effects increase over time, as the extent to which fracking would increase production also increased over time.

Unlike the dot-com crash and the 2008 financial crisis, Delaware's finance shock had a long-run impact on sectoral employment. Delaware's FIRE employment continued to grow over the twenty years following the policy (Figure 1). If students immediately after the policy understood the long-run employment effects, the effect on business majors may be quite stable over the post-policy period. Figure 3 shows increasing effects for the first treated cohorts followed by remarkably stable and persistent differential impact at Wilmington-area universities. Alternatively, the university may not have expanded capacity for business majors.

Sophomores through seniors at the shock's onset do not appear to adjust their majors differentially in exposed areas (Figure 3), or nationally (Figure 1).[30] The response to the dot-com crash appears to operate with a greater lag. Initial course investments presumably make switching majors costly, and this may be most costly in STEM fields. However, this implies potentially very adverse effects for students entering during a boom, but graduating during a bust. In the case of a positive shock, it may mean students miss entering an industry at an advantageous time.

Robustness

A university's geographic exposure to shocks may also affect students' application and enrollment decisions. Universities' major composition may have changed because of changes in student composition, rather than students changing their major. Total degrees awarded do not vary by university's exposure to the shock (Appendix Figure A1, Appendix Table A10). The students selecting into exposed universities may change after these shocks, and I address this in the next section using student-level data.

Students at more selective universities may have better information about labor demand and may be more geographically mobile. As a result, students at these universities may respond less to local demand. I test whether the university's geographic exposure to shocks has smaller effects at the top 20 US News and World Report-ranked universities (1999 rankings). I do not implement this analysis for Delaware's finance shock given there are no top 20 universities with $Exposure = 1$.

The medium-run effects on CS/CE majors are approximately 44% smaller for the top 20 universities and they are not statistically significant from zero. The effects for the

[30] Similarly Long, Goldhaber, and Huntington-Klein (2015) find majors are most strongly related to wages when students were generally freshmen. Bound and Morales (2018) and Hunt (2018) also show national CS degrees respond to the dot-com crash with a lag.

non-top 20 universities are statistically significantly negative. The coefficients on $(t \geq t^*)(Exposure)(top20)$ and $(t \geq t^*)(t - t^*)(Exposure)(top20)$ are jointly significant from zero, although neither is significant from zero on its own (Appendix Table A12). Only two of the top 20 universities are in the top quartile of fracking exposure. The effect of local exposure is larger for these top 20 universities, but also statistically significant for non-top 20 universities. For the finance regressions, the $Exposure * top20$ interactions are not jointly significant, and only the immediate effect for non-top 20 universities is statistically significant from zero.[31]

The principal results are robust to $Ln(Majors)$ as the dependent variable, and controlling for $Ln(TotDegrees)$. The effects suggest CS/CE degrees decrease an additional 24% at universities in MSAs with 1990 computer-employment share higher by .1, for graduates five years after those first exposed. Geology degrees increase an additional 17% in top-quartile-exposed areas, for graduates five years after the first treated cohort. Finance degrees decrease an additional 6% at universities in MSAs with finance employment share higher by .05, though this is not statistically significant. Estimates suggest an additional 21% increase in business majors at Wilmington-area universities after Delaware's finance shock, for graduates five years after the first treated cohort (Appendix Table A13).[32]

For the dot-com crash and 2008 financial crisis, I alternatively define exposure as location in an MSA at the 90th percentile or above in the relevant employment share. These most exposed universities experienced greater decreases in the relevant majors, though the magnitudes are slightly smaller, and the effects of the financial crisis are not statistically significant.

For the fracking boom, I use the cumulative value of new production within 200 miles of the county's centroid from 2004-2014. This is slightly more complicated when using the parametric specification because of the different timing of new production across shale plays.[33] The confidence intervals are much larger on the year*$Exposure$ interactions, and the parametric and nonparametric specifications are less similar. The fracking boom increased the share of geology majors an additional .04 percentage points (17%) if the cumulative value of exposure was higher by 24.5 billion dollars ($p \leq .01$), the difference between the 90th and 10th percentiles.

For Delaware's finance shock, I alternatively define $Exposure_c$ in three ways: distance

[31]Similarly, local exposure may also matter less at research universities. Interestingly, I still see large effects at research/doctoral universities, though there are differences relative to nonresearch/nondoctoral universities. See Appendix Table A9 and Appendix Figure A7.

[32]The log specifications exclude university/years without sector-relevant degrees.

[33]In later years, the counties being exposed to fracking may be those with slightly lower cumulative values of exposure, which will affect estimation of the effect of exposure with years from the original shock.

between university j and Wilmington, an indicator for being within Delaware, and finally distance within 15 miles of Wilmington but only including universities within 100 miles of Wilmington as controls.

All three show Delaware's policy had large local effects on business majors (Appendix Table A2, Appendix Figure A3), though not significant ($p = .118$) when excluding farther universities. Not surprisingly the effect is smallest when using the continuous distance measure. This assumes the effects increase linearly in distance, and the impact of increasing distance might be quite small for universities not in the Wilmington area.[34]

Finally, I estimate the principal specifications excluding universities not located in an MSA, or whose MSA was not represented in the Census (rather than setting MSA employment share to zero for those universities). The results show a similar, statistically significant effect for the dot-com crash (Appendix Table A8). The effect for the financial crisis is large in magnitude, but unsurprisingly given the drop in sample size, not statistically significant from zero.

6 Mechanisms: Location Preferences or Information

Local exposure to shocks may affect majors because of information or migration frictions. Students may not have good information about national demand. Alternatively, strong location preferences may make local conditions more relevant. In this section I present a test for the role of migration frictions, separately from information frictions.

I focus on explaining the local response to the dot-com cycle and present two comparisons of CS major intentions that each identify the role of location preferences.[35] First, using nearest-neighbor matching I compare students from Silicon Valley who stay for college to matches who leave. Second, I compare students who travel to Silicon Valley for college to matches from the same commuting zone who stay within 100 miles of home. By comparing students from the same CZ with similar academic and parental backgrounds, I argue students in both sets of comparisons have similar interest/ability in CS as well as information on demand for CS degrees given similar personal networks and news sources. However, conditional on home CZ those choosing colleges in Silicon Valley reveal stronger preferences for living in Silicon Valley.

[34] Changes are unlikely due to increased corporate funding of the business departments at Wilmington-area universities, since this did not occur immediately. See appendix.

[35] I cannot identify location preferences' role in the Delaware effects because of insufficient data on students' home locations in pre-policy years. However, I use TFS to study whether Delaware's shock changed student composition at Wilmington-area universities. Wilmington-area universities experienced additional increases in the proportion of nonlocal students, and decreases in the likelihood that students had HS GPA $\geq B+$ (see appendix text, Appendix Table A4, and Appendix Figure A5).

Conditional on interest and ability in CS, students with strong Silicon Valley preferences should be more likely to choose CS majors during the boom and bubble because of the differential demand for CS degrees in their desired market. Students with less strong Silicon Valley preferences, but with similar interest and ability in CS, may be less likely to choose CS because the differential demand for CS degrees in their desired market is not as large. They may instead choose another technical degree. I address that those choosing Silicon Valley universities may have stronger CS interests or different information, despite the matching.

To implement this test, I use The CIRP Freshman Survey (TFS), administered by the Higher Education Research Institute at the University of California, Los Angeles to 15 million students since 1966. Universities conduct the survey among their incoming freshmen, often during orientation ("CIRP" 2018). Fortunately for the empirical strategy, this timing implies students have not obtained information on labor demand from their college market. Their information will be based on that acquired before moving for college. The survey has detailed student-level data on intended college major, academic achievement, and family background. I use the 1990 through 2011 waves of TFS.

I define students from Silicon Valley as those whose permanent home is in either the San Jose or San Francisco commuting zone (referred to as Silicon Valley homes). I define Silicon Valley universities as those within 100 miles of either San Jose, San Francisco, or Santa Cruz (referred to as Silicon Valley universities). I restrict to students at universities in California or bordering states (Arizona, Oregon, or Nevada). I use the student's zip code to calculate home-university distance.[36] I classify as CS majors both "Computer Science" and "Data Processing or Computer Programming".

Matching Estimation Strategy

To attribute differences to location preferences the key assumption is that students staying in Silicon Valley for college are similar to those who leave, except for location preferences. Similarly, students who move to Silicon Valley for college are similar to those who stay closer to home, except for location preferences.

Students staying close to home for college likely differ from students moving farther away. Because the linearity assumptions of OLS regressions may be problematic, I implement three rounds of nearest-neighbor-matching with exact matching on year and commuting zone, and on university in some rounds, and obtain a matched regression sample. For robustness, I use propensity scores to identify the nearest-neighbor match, based on the propensity to attend

[36]Before 2001, TFS asks for the student's address; in 2001 they specify permanent/home address. Table 4 shows that before 2001 a significant number of students provide the zip code for their permanent/home address (given the number from Silicon Valley at non-Silicon Valley universities).

a Silicon Valley university among individuals from the same CZ.

TFS is ideally suited for this exercise, given its rich demographic and achievement data. Using exact matching on year, I additionally match on SAT/ACT score (ACT converted to SAT using concordance tables), self-rating in math ability, TFS-constructed measure of university SAT/ACT in 2011, parental income, and male, black, hispanic, mother has a bachelor's degree, father has a bachelor's degree, high school GPA $\geq$ B+, and three groups of parental occupation (not business or technical, at least one parent in business and neither in a technical occupation, and at least one parent in a technical occupation).[37] Technical occupations include computer programmer or analyst; engineer; scientific researcher, and statistician. I exclude individuals missing any covariates.

Several of these variables are relatively unique to TFS, and are particularly well-suited to address selection concerns. Matching on self-rating in math ability helps address that conditional on SAT and university selectivity, students leaving Silicon Valley for college may be less interested in or feel less well-suited for the computer industry. Matching on parental occupation helps address that conditional on demographics and achievement, students from the same CZ may have different demand information because of their parents' occupations.

First, I match students staying in Silicon Valley for university to those who leave. Next, with exact matching on university, I match the students staying in Silicon Valley for college to those moving to Silicon Valley for college. Finally, with exact matching on CZ, I match the above students moving to Silicon Valley for college to those from the same CZ attending university within 100 miles of their home. In the case of multiple nearest-neighbor matches, I use only the first match.

The final matched sample includes four groups: students from Silicon Valley who stay near home for college and who leave for college, and students from outside Silicon Valley who stay near home for college and who come to Silicon Valley for college. Students may be matches multiple times. To create a balanced sample, I include one observation for each time an individual serves as a match.[38] I estimate additional regressions clustering standard errors at the individual level to address multiple observations per individual.

Universities vary in how often they participate in TFS, and also in the number of re-

[37]The TFS selectivity measure is the sum of the midpoints of the interquartile ranges of the SAT math and verbal scores (or ACT composite converted to SAT), based on test scores of the 2011 entering class. IPEDS only begins reporting universities' SAT or ACT scores in 2001, also after most of the sample was at the university. Regressions and summary statistics use parental income in 1999 dollars, and convert SAT scores to recentered SAT scores for those taking the test before the recentering. See appendix for occupations classified as business, and for details on variable construction.

[38]A Non-Silicon Valley student at a Silicon Valley university may be a match for several Silicon Valley students. I include an equal number of observations for the non-Silicon Valley student staying close to home matched to this non-Silicon Valley student moving to Silicon Valley.

sponses by year. As a result, I include in the regressions institution-pair fixed effects, for example a fixed effect for the "treated" student in the match attending University of California, Santa-Cruz, and the match attending California Polytechnic State University-San Luis Obispo. Including universities with few years of data will decrease power, reducing matches at universities with more coverage. I identify three sets of years for which many universities report data in each year of the year set. I include students at these universities in any of these three sets of years.[39] The final sample includes years 1992 through 2003, except 1994 and 2001. There is no home zip code data in 1994. Among universities with data in each year of a year set, some are missing 2001. I exclude 2001 to maintain a more balanced sample.

Table 3 describes the matched sample. There are 11,452 students with permanent home in Silicon Valley and who stay for college. They have similar academic achievement, demographics, and parental background as their matches who are also from Silicon Valley, but who leave for college. They also attend universities with similar SAT measure. While the differences are not large, those leaving Silicon Valley have slightly higher SAT (1196 relative to 1185) and attend universities with slightly higher SAT measure (1221 relative to 1200). The quality of the matching suggests these students should have similar information about demand but may have different location preferences given their university choice.

Students moving to Silicon Valley for college look similar to their same-CZ matches staying closer to home. Those staying close to home attend universities with slightly lower SAT measure (1180 relative to 1200), and have slightly lower SAT (1170 relative to 1190), although the differences are not large. This matching also suggests these students have similar information about demand, but different preferences for Silicon Valley and for living close to home. Students with homes outside Silicon Valley also look similar to those with Silicon Valley homes. I will identify the role of location preferences among students similar to those from Silicon Valley who stay near home for college.

Figure 4 and Table 4 show home and university locations of the sample. Outside of Silicon Valley, most students are from Los Angeles, Sacramento, and San Diego. There are 32 universities in the sample, mostly near Silicon Valley or Los Angeles.[40] I estimate:

$$\begin{aligned} CSmajor_{iklt} &= \alpha_k + \eta_l + \kappa_g I(t \in g) + X_i\gamma + \beta_1 NonSVUniv_i \\ &\quad + \delta_g NonSVUniv_i * I(t \in g) + u_{iklt} \end{aligned} \tag{3}$$

[39] Sets are (1) 1992, 1996, 1998, 2000, 2002; (2) 1993, 1995-2000, 2003; (3) 1995-2000, 2003. See appendix.

[40] Many California universities are not in the sample, likely because they do not participate in TFS in each year for one of the year sets. This implies home locations of non-Silicon Valley students at non-Silicon Valley universities will be limited, because of the restriction that they attend university within 100 miles of home.

The dependent variable $CSmajor_{iklt}$ indicates intended major of CS for individual i in year t, whose permanent home is in CZ l, and whose university and whose match's university form university pair k. I include fixed effects for each university pair k, each home CZ l, and each year group g. In the main regressions I include the following year groups g: pre-boom (1992-1993); boom (1995-1998); bubble (1999-2000); and bust (2002-2003). The variable $NonSVUniv_i$ denotes whether individual i attends university outside Silicon Valley. I include in X_i the variables used in the matching procedure.

If location preferences explain greater increases in CS majors at Silicon Valley universities during the dot-com bubble, we would expect negative coefficients on δ_{99-00}. If major choice is determined by information on demand from the individual's home market, we would expect a coefficient of zero on δ_{99-00}.

I report standard errors clustered at the university level. Clustering standard errors at the individual level does not have a meaningful impact.

7 Migration Frictions and Major Choice: Results

Individuals leaving Silicon Valley for college respond less to the dot-com cycle. Figure 5a shows fitted values for those staying in and leaving Silicon Valley for college, relative to the 1992-1993 difference between the groups. These are based on estimating regression (3) but interacting $NonSVUniv$ with whether the permanent home is in Silicon Valley. These fitted values are calculated using only the triple interaction between year group, $NonSVUniv$, and permanent home in Silicon Valley, and lower-level terms associated with this interaction.

Both groups similarly increase likelihood of majoring in CS in 1995-1996. However, in 1997-1998 there are further increases among those staying in Silicon Valley, but not among those leaving. Even more dramatically, in 1999-2000 (the bubble), there is a dramatic increase in CS among those staying in Silicon Valley but a decrease among those leaving. Interestingly, among students from outside Silicon Valley, those moving to Silicon Valley for college respond similarly to the bubble as same-CZ students staying near home, and only slightly less than students staying in Silicon Valley for college (Figure 5c).

For presentation, I show results from the simpler specification, equation (3). In the early 1990s, students from the same CZ who attend a non-Silicon Valley university are .6 percentage points more likely to major in CS, though this is not significant from zero ($\beta_{Non-Silicon\,Valley\,University}$, Table 5). This suggests the matching identifies students with similar information, and interest/ability in CS. During the boom, students at non-Silicon Valley universities become slightly though not statistically significantly less likely (.1 percentage points) to major in CS relative to pre-boom years.

During the bubble, students attending non-Silicon Valley universities were 2.1 percentage points less likely to major in CS relative to same-CZ matches attending Silicon Valley universities, relative to pre-boom years. From 1992-1993 to 1999-2000, CS intentions increased 4.1 percentage points among students in the regression sample at Silicon Valley universities (β_{Bubble}). The coefficient suggests the increase for students at non-Silicon Valley universities was 48% smaller. If students at Silicon Valley universities had weaker preferences for living in Silicon Valley, their response to the bubble would have been 48% smaller.

During the bust, CS intentions of students at Silicon Valley universities return to pre-boom levels (β_{Bust} is near zero), as does the difference relative to matches at non-Silicon Valley universities ($\beta_{NonSVUniv*Bust}$ is not significant). This implies a larger drop among students at Silicon Valley universities, although magnitudes suggest they are still .5 percentage points more likely to major in CS during the bust than matches at non-Silicon Valley universities, relative to pre-boom years.[41] Based on the increase in CS intentions from pre-boom to bust among students at Silicon Valley universities ($\beta_{Bust} = .003$), a differential effect of .5 percentage points is large. Despite the crash, demand for CS skills is likely still higher in Silicon Valley. Thus, this result, although imprecisely estimated, is consistent with students at Silicon Valley universities still having stronger location preferences for Silicon Valley.

In sum, during the bubble students at Silicon Valley universities differentially increase CS intentions relative to similar same-CZ matches attending non-Silicon Valley universities. In this period demand for CS skills was differentially stronger in Silicon Valley, and students with weaker Silicon Valley preferences respond less to the local demand increase.[42] The results suggest the local elasticity identified in the paper's first section would be smaller if location preferences were weaker. Next, I show suggestive evidence on the degree to which these preferences may explain the overall local elasticity.

Larger Response at Exposed Universities: Role of Location Preferences Most US students attend colleges close to home.[43] Thus, focusing on students attending their local university is important for understanding the overall local elasticity. Using the regression coefficients, I identify the differential response of students staying in Silicon Valley for college relative to those attending their local university outside Silicon Valley. I then quantify the

[41] The 1.6 percentage point larger response from bubble to bust among students at Silicon Valley universities ($\beta_{NonSVUniv*Bubble} - \beta_{NonSVUniv*Bust}$) is statistically significant at the 10% level.

[42] This differential is much more pronounced for those with Silicon Valley homes (though the difference relative to those from outside Silicon Valley is not statistically significant) (Appendix Table A6 and Figure 5).

[43] Among 1 million SAT-takers, the median home-university distance was 94 miles (Mattern and Wyatt 2009)).

extent that location preferences explain this differential. An important caveat in relating this exercise to the overall elasticity is that it is based only on the sample of students similar to those who are from Silicon Valley and stay near home for college.

From 1992-1993 to 1999-2000, the coefficients suggest an additional .8 percentage point increase in CS intentions among students staying in Silicon Valley, relative to non-Silicon Valley students staying near home, though this is imprecisely estimated (Appendix Table A6, $\beta_{Bubble*Home\_SV} - \beta_{NonSVUniv*Bubble}$). In 1999-2000, the raw gap in CS intentions between these groups was 1.7 percentage points, and so the gap increased an additional $.8/(1.7-.8)$, or nearly 90%.

After removing the Silicon Valley location preferences of the students from Silicon Valley (using their same-CZ matches at non-Silicon Valley universities), non-Silicon Valley students staying close to home actually respond more positively to the bubble, though not significantly ($\beta_{Bubble*HomeSV} + \beta_{NonSVUniv*Bubble*HomeSV} < 0$). This suggests that among students with weaker Silicon Valley preferences, students whose home is outside Silicon Valley have information causing them to increase investments in CS more than students from Silicon Valley. This may be explained by worse information on the possibility of a bubble.[44]

The first part of the paper showed larger responses to the dot-com cycle among universities more geographically exposed to the computer industry. These results suggest the gap would have been much smaller, or nonexistent, if location preferences were weaker.

Migration Frictions and Major Choice: Robustness

I start by providing support for the assumption that college choice is informative about migration frictions. If not, then students are staying close to home for reasons besides migration frictions, violating the identification assumptions.

Does College Choice Reveal Migration Frictions?

Fortuitously, TFS directly asks respondents if they chose their university because they wanted to live near home. I first show that many students staying in Silicon Valley for college did so to live near home. Students could respond that living near home was a very important reason why they chose the university, somewhat important, or not important. If information

[44] Alternatively, we could assign the non-Silicon Valley students staying close to home the Silicon Valley preferences of their same-CZ matches moving to Silicon Valley. This implies CS intentions of the non-Silicon Valley students staying close to home would be .5 percentage points higher ($\beta_{NonSVUniv*Bubble} = -.005$), although not statistically significantly. Weaker preferences for Silicon Valley among these students explain 62.5% of the response gap of .8 between those staying in Silicon Valley and staying outside Silicon Valley during the bubble.

about labor demand or interest in CS drove the decision to stay in Silicon Valley, we would not expect students to say they chose their university to live near home.

I estimate regression (3), but allow differential effects for those from Silicon Valley, and group years in two. The outcome is an indicator for whether living close to home was at least somewhat important in their college choice. Within matched pairs of students originally from Silicon Valley, those staying in Silicon Valley are 40 to 50 percentage points more likely to report that living close to home was at least somewhat important in their choice (Figure 6, Appendix Table A6). The results are similar among students from outside Silicon Valley. The stability of these preferences over time mitigates concerns that the CS major gap during the bubble reflects changing location preferences.

Further, students graduating from universities outside their home state are 20.5 percentage points less likely to live in their home state one year after graduation, using the US Department of Education's Baccalaureate and Beyond Survey, 2009 (Table 2).[45] Among those graduating outside their home state, and not returning to their home state after graduation, about 48% live in their bachelor's degree institution state. This suggests students who travel for college reveal they have lower migration frictions. This implies they may make human capital investments based on demand outside the market in which they grew up.

Does Choosing a Silicon Valley University Reflect Computer Skills and Interests?

The paper argues that students staying in Silicon Valley for college have strong location preferences for Silicon Valley, and so adjust human capital investments to align with local demand. During the dot-com bubble they are more likely to increase their CS intentions because of greater demand in their desired market. Alternatively, students with strong CS interests may choose to stay in Silicon Valley during the bubble because of its importance to the dot-com sector. Migration frictions do not play a role in this explanation.

I again benefit from TFS's question about choosing a university to stay near home. This allows me to identify those staying in Silicon Valley for college because of a migration friction rather than a career interest. Restricting to the students with migration frictions and their matches, I can rule out that selection into Silicon Valley colleges based on CS interests drives the results. If living near home was at least somewhat important in their college choice, I code students as choosing their college because of a migration friction. These students are about 65% of those staying in Silicon Valley for college.

Students leaving Silicon Valley are 4.6 percentage points less likely to intend on CS during the bubble than their matches who stay in Silicon Valley to be near home, relative to pre-

[45] See appendix for description of Baccalaureate and Beyond sample and further results.

boom years ($p = .01$) (Table 5 column 2).[46] This is larger than the effect in the entire sample of students from Silicon Valley (3.8 percentage points, Appendix Table A6).[47] The students staying in Silicon Valley also respond less negatively to the bust than their matches, and the coefficient is larger in magnitude than in the main sample. These findings suggest the main results are not explained by students selecting into Silicon Valley colleges based on CS interests.

Second, I restrict the sample to students with strong interest and ability in technical fields. Specifically I include only matches where the student at a non-Silicon Valley university attends a technical university, which includes California Institute of Technology, California Polytechnic State University-San Luis Obispo, and California State Polytechnic University-Pomona. As Table 4 shows, many of the matches attend these technical universities, especially California Polytechnic State University-San Luis Obispo. These students arguably have the interest and skills to pursue a CS major, but may choose another science depending on demand in their desired market. Consistent with this, students at these non-Silicon Valley universities are 5.4 percentage points more likely to major in CS than their matches in the pre-boom years (Table 5 column 3).

However, during the bubble this differential decreases, as students at Silicon Valley universities become 3.8 percentage points relatively more likely to have CS intentions (though not statistically significant relative to pre-boom years). Even among students who have revealed an interest and skillset in technical fields, those at non-Silicon Valley universities are less responsive to the dot-com bubble. I argue this is consistent with weaker location preferences for Silicon Valley, where there is differentially stronger demand for CS skills.

Ruling out the interest/skills hypothesis would also be more convicing if students at non-Silicon Valley universities substituted into other STEM majors instead of CS. I show students at non-Silicon Valley universities were more likely to intend on biological sciences during the bubble than same-CZ students at Silicon Valley universities, relative to the pre-boom years (Appendix Table A18).[48]

[46] The effect is large (2.6 percentage points) but less precise (p=.15) restricting to students from Silicon Valley for whom living near home was very important and their matches. This greatly reduces sample size.

[47] Matches at non-Silicon Valley universities may still be negatively selected on CS interest/skills. If during the bubble students with CS interest/skills moved from non-Silicon Valley to Silicon Valley universities, then the Silicon Valley students remaining at non-Silicon Valley universities would be less interested/skilled in CS relative to pre-boom years. This is not likely to be a problem, since removing the threat of positive selection into Silicon Valley universities results in a larger effect. This suggests the main effect is not explained by this positive selection. Since this positive selection would be needed to create a negatively selected control group, negative selection of the matches is also presumably not explaining the effect. I present further results addressing whether students leaving Silicon Valley are those less interested/skilled in CS.

[48] Allowing for heterogeneity by home CZ, students leaving Silicon Valley for college are about 1 percentage point more likely to intend on communications and vocational/other technical majors during the bubble, relative to Silicon Valley students who stay, and relative to pre-boom years. Non-Silicon Valley students

Appendix Table A11 shows the sample's characteristics are fairly stable from the pre-boom period in 1992-1993 to the bubble in 1999-2000. Further, I estimate regression (3), using the characteristics as dependent variables.[49] Relative to the pre-boom period, students at Silicon Valley universities during the bubble do not have significantly different SAT scores (Appendix Table A14, coefficient on *Bubble*). This mitigates concerns that selection into Silicon Valley universities changes during the bubble. This could have explained the gap in majors rather than responses to differential CS demand among individuals with strong (and stable) location preferences.

Some characteristics do change, but it is not clear they suggest Silicon Valley students in the bubble have stronger location preferences or potential interest in CS. Relative to pre-boom years, students at Silicon Valley universities are 7.4 percentage points less likely to have a high self rating in math ability, they are 3.4 percentage points more likely to have a HS GPA $\geq$ B+, they attend slightly less selective universities (SAT lower by 10 points), they are 2.1 percentage points less likely to be male, .8 percentage points less likely to be black, their parents' real incomes are $8,360 (9%) higher, and their mothers are 4.7 percentage points more likely to have a bachelor's degree.

As a further way of ruling out the interest/skills hypothesis, I show that during the bubble students choosing non-Silicon Valley universities were not choosing universities with lower 1990 share of degrees in CS/CE; engineering; or math, relative to pre-boom years (Appendix Table A5). Effects are also large restricting to those with high math self-rating (Appendix Table A20). Finally, there is no differential change during the bubble in how students at non-Silicon Valley universities report competitiveness, drive, or desire to make money, relative to matches in Silicon Valley, and to pre-boom years (Appendix Table A5, columns 4-6).

Does Choosing a Silicon Valley University Reflect Informational Differences?

I estimate regression (3) including only matches where both students have at least one parent in a technical occupation (computer programmer or analyst; engineer; scientific researcher, or statistician). These students are more likely to have similar information on CS demand.

For students with parents in technical occupations, those attending non-Silicon Valley universities are 4.2 percentage points less likely to major in CS during the bubble than their counterparts at Silicon Valley universities, relative to pre-boom years (Table 5, column

staying near home for college are less likely to intend on engineering and communications majors and more likely to intend on biological sciences and to be undecided during the bubble relative to same-CZ students going to Silicon Valley, and relative to pre-boom years (Appendix Table A19).

[49] When using the characteristics as dependent variables in these regressions instead of matching variables, I use an indicator for math rating $\geq$4 of 5 instead of the 1 to 5 variable.

5). The magnitude of this differential is twice as large as in the full sample, although we cannot rule out zero effect. Column 6 shows similar results when including matches where both individuals have at least one parent in a technical or a business occupation. Strong effects among individuals with more similar information mitigates concerns that within-match differentials are due to information, not location preferences.

Technology Firms' On-Campus Recruiting Strategies during the Dot-Com Boom

The location preferences hypothesis suggests students choose majors based on demand in their desired geographic market. This implies students hoping to live in Silicon Valley should attend universities where Silicon Valley firms are recruiting. If Silicon Valley technology firms did not recruit at Silicon Valley universities, access to these companies would be improved by leaving Silicon Valley for college. Differential CS intentions at Silicon Valley universities is then less likely driven by preferences for living locally after graduation.

Using the Internet Archive Wayback Machine, I collect campus recruiting schedules for three large Silicon Valley firms associated with the dot-com bubble: Netscape, Sun Systems, and eBay. While these firms would have been salient to those with CS interests, this is not meant to describe recruiting for the industry.[50] These Silicon Valley companies recruited at local, as well as at farther, universities (Table 6). Choosing a Silicon Valley university does not appear inconsistent with gaining access to important Silicon Valley technology firms.

Technology firms recruiting on campus likely reflects interests and abilities of the university's students. Restricting to campuses attracting these firms also helps mitigate concerns that those leaving Silicon Valley chose less CS-oriented universities. I estimate the principal regression, but limit to pairs in which the Silicon Valley and non-Silicon Valley university in the pair attract one of the firms in Table 6. Students at these non-Silicon Valley universities also respond less to the bubble than their matches (Table 5, column 4). Consistent with these universities reflecting CS interest and ability, response to the bubble at these Silicon Valley universities is greater than at the set of Silicon Valley universities in the main sample.[51]

Matching on Propensity Scores

For further robustness, I identify nearest-neighbor matches using the individual with the closest propensity score. In each year, I first estimate a probit regression to identify the

[50] I present target campuses for one year per firm. When I have multiple years of data, I present Fall recruiting data, since this is generally when recruiting is concentrated, during the boom/bubble. See appendix.

[51] There is no differential response to the bubble among students at Silicon Valley universities relative to non-Silicon Valley universities, among pairs where neither university attracts one of these technology firms (Appendix Table A20).

propensity to attend a Silicon Valley university, among students from Silicon Valley. The explanatory variables are the matching variables listed above.[52] For the second match, I implement the exact match on university described above, without propensity scores, to obtain the non-Silicon Valley students at Silicon Valley universities most similar to the Silicon Valley students. Finally, in each year and for each of the non-Silicon Valley CZs, I estimate a probit regression to identify the propensity to attend a Silicon Valley university.

I form the matched sample with students at Silicon Valley universities and the student with the closest propensity score in the same year and from the same CZ. In cases of tied scores, I use the first match. The third round of matching requires an exact CZ match, so estimating the propensity score requires a large sample from the CZ in each year. To avoid estimating probit regressions on very small samples, I include non-Silicon Valley students only from the Los Angeles or San Diego CZs. These CZs have among the greatest number of non-Silicon Valley students in the main sample.[53] Thus, while the propensity-score matched sample of students with homes in Silicon Valley will be similar to the main sample, those from outside Silicon Valley will be quite different.[54]

Among students from Silicon Valley, those leaving for college increase CS intentions during the bubble 2.1 percentage points less than those staying, although the coefficients are not jointly significant (Appendix Table A17). Silicon Valley students leaving for college are also less likely to major in CS during the boom preceding the bubble, jointly significant at the 5% level. This was less evident in the main specification. Among those from outside Silicon Valley, there is no differential response to the bubble by those choosing Silicon Valley universities.

8 Conclusion

This paper studies whether college majors are influenced by local rather than national labor demand. I test for changing composition of majors at local universities after sector-specific local labor demand shocks. I further test whether the local elasticity is explained by location preferences separately from information frictions. I analyze four sectoral shocks with local effects: the 2000 dot-com crash, the fracking boom, the 2008 financial crisis, and the shock making Delaware a global financial headquarters.

Universities in areas more exposed to these shocks experience greater changes in sector-

[52] I combine the lowest two math self-ratings since very few individuals report the lowest rating, and this could lead to perfectly predicting the treatment variable.

[53] Sacramento also does, but few from this CZ are at universities not within 100 miles of San Francisco.

[54] Non-Silicon Valley students staying close to home largely attend University of California-Los Angeles (Appendix Table A16), in contrast to the main sample.

relevant majors, using university-level data on degree completions by academic discipline from 1966 through 2016. Of the national change in sector-relevant degrees after these shocks, differential effects at the most-exposed universities explain 32% (dot-com), 16.5% (fracking), and 43% (financial crisis). Despite computer and FIRE employment declining for a relatively short period of time, students adjust arguably long-term investments. They may have overestimated the size or duration of the shock. Alternatively, they may have understood that poor initial placement would have long-run effects.

I develop a test for whether the local elasticity is explained by location preferences separately from information frictions. Using nearest-neighbor matching and The Freshman Survey, I compare CS intentions of incoming college freshmen from the same CZ who differ in choosing Silicon Valley colleges. Given the match on home CZ, as well as academic, parental, demographic, and university characteristics, I argue these students have similar information. However, they may have different preferences for living in Silicon Valley, as revealed through their choice of college. I confirm college choice is informative of migration frictions using two datasets.

From pre-boom to bubble, CS intentions increased 2.1 percentage points, or 48%, less among students attending non-Silicon Valley universities relative to same-CZ matches at Silicon Valley universities. There is no difference in their CS intentions during the pre-boom period. The results suggest location preferences play an important role in how students respond to changes in labor demand. Students with stronger location preferences for a market experiencing greater increases in CS demand are more likely to increase CS majors.

Investing in human capital based on local labor demand may yield mismatch between aggregate supply of skills and aggregate demand. This local dependence may also affect aggregate productivity if individuals are not matched to the job in which they are most productive. However, given that location preferences are important in explaining this local dependence, encouraging human capital investments based on national demand may increase mismatch for students with strong preferences. This has important policy implications as some recent initiatives have provided information on national demand to college-going students, while others provide information on local demand.[55]

Most generally, the results show location preferences affect human capital investment decisions, which enhance ability to benefit from local economic shocks.

[55] Carnevale, Strohl, and Melton (2011) provide information on earnings by major nationally. LinkedIn's Training Finder ranks top in-demand careers in local labor markets (LinkedIn *Training Finder*). The Trade Adjustment Community College and Career Training program provided $2 billion in funding for training programs for jobs highly demanded in the regional economy (White House *Higher Education*).

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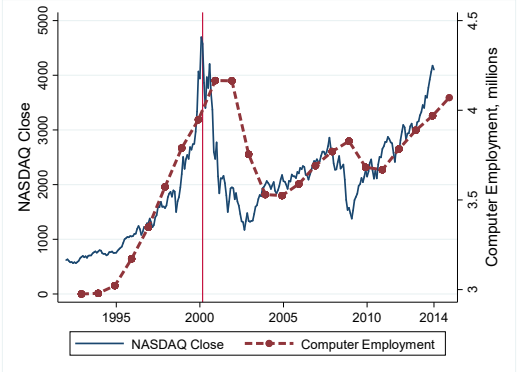
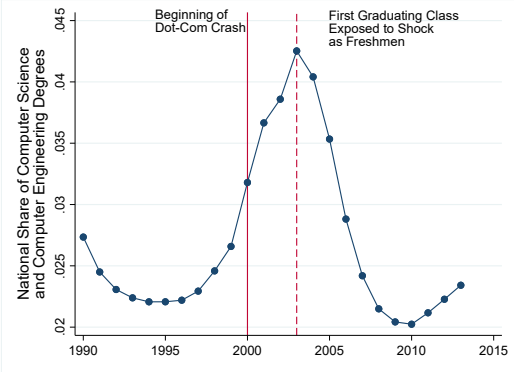
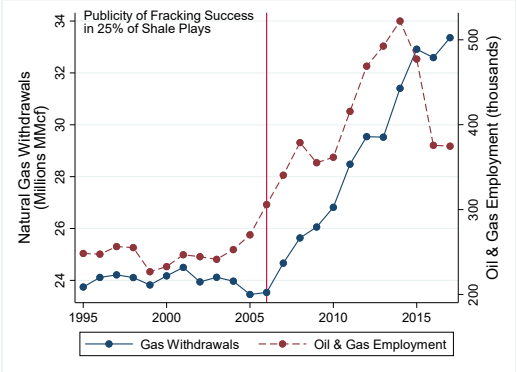
Figure 1: Sectoral Shocks and College Majors in the US

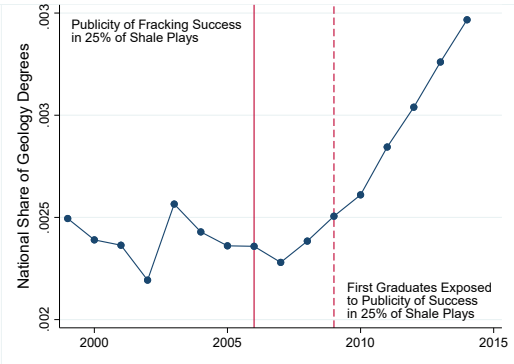
(a) Dot-Com Crash, Computer Employment, and Computer Science/Computer Engineering Majors



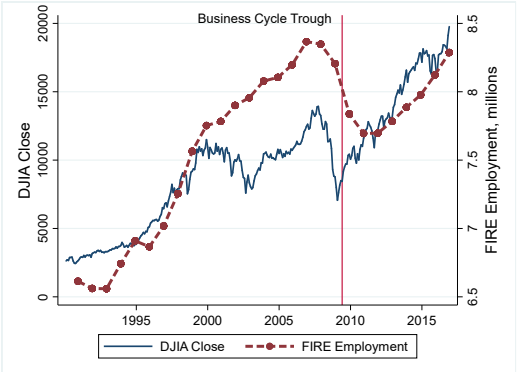


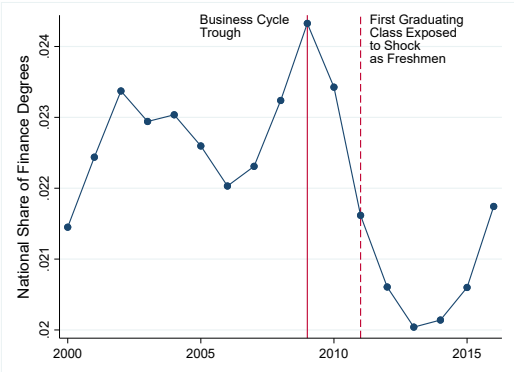
(b) Fracking, Oil and Gas Employment, and Geology Majors



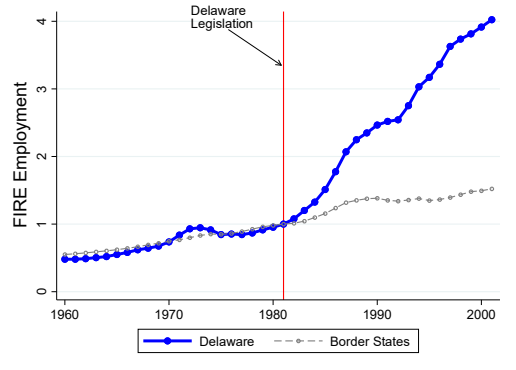


(c) 2008 Financial Crisis, FIRE Employment, and Finance Majors





(d) Jurisdictional Competition: Delaware Becomes a Financial Headquarters

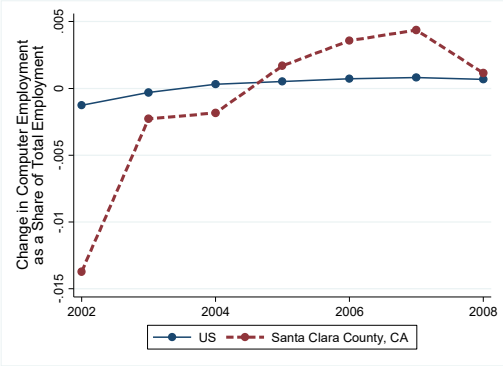


Note: Source for NASDAQ and DJIA monthly closing prices: Yahoo Finance. Source for employment data: CES. Gas withdrawals are Natural Gas Gross Withdrawals from the US Energy Information Administration. Computer employment includes employment in: computer and electronic products; software publishers; data processing, hosting, and related services, computer systems design and related services; and scientific research and development services (based on Hecker (2005)). Oil and gas employment includes oil and gas extraction and support activities for oil and gas operations. FIRE employment includes finance, insurance, and real estate employment. See text for details.

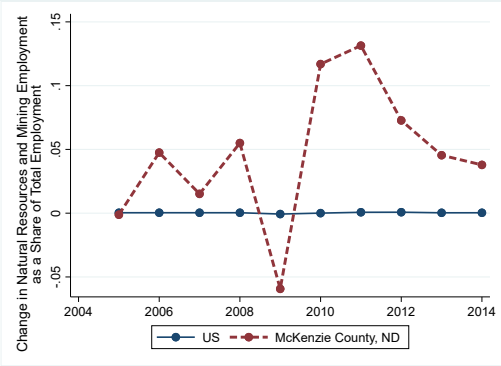
Figure 2: Local Shocks and Local Universities

Panel A: Differential Local Employment Effects of National Shocks

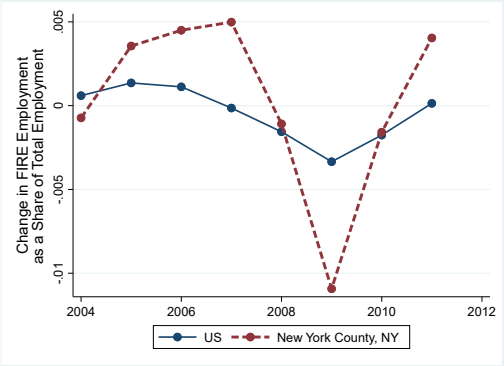
(a) Dot-Com Crash



(b) Fracking

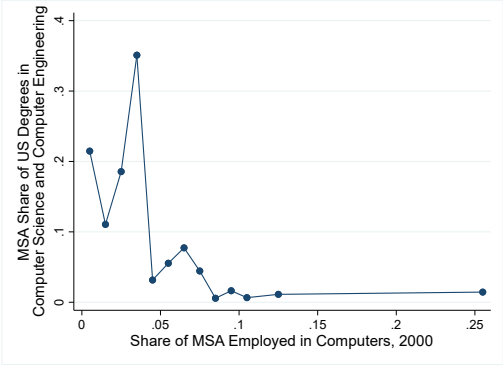


(c) Financial Crisis

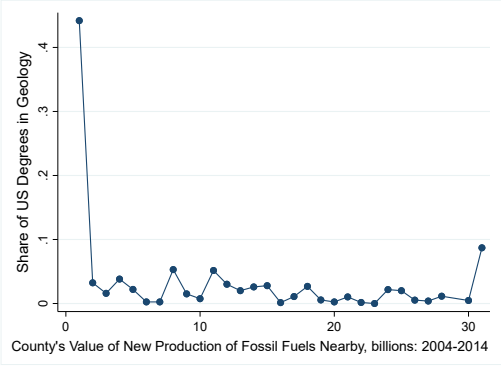


Panel B: Share of US Degrees in Sector-Relevant Fields by Exposure to Sectoral Shocks

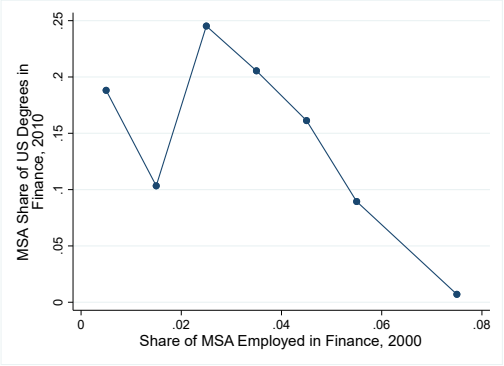
(a) CS/CE Degrees, 2002



(b) Geology Degrees, 2008



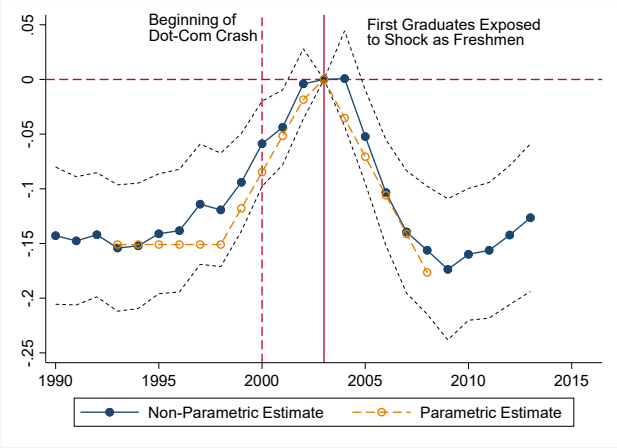
(c) Finance Degrees, 2010



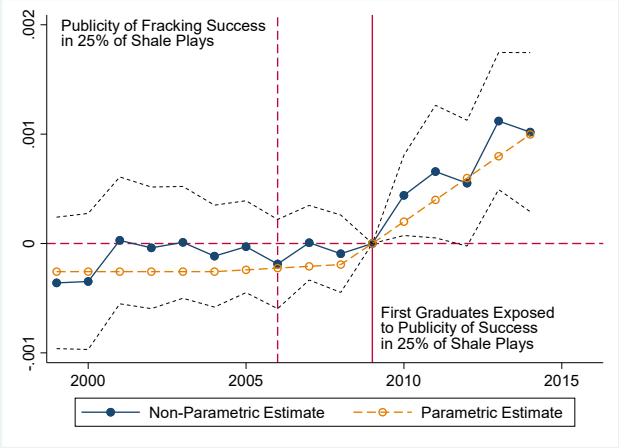
Note: Employment data in Panel A is from the Quarterly Census of Employment and Wages. Computer Employment is defined as "Computer Systems Design and Related Services." FIRE employment in A(c) is employment in "Financial Activities," which includes finance, insurance, and real estate. Plots A(a) and A(c) are based on private employment, while A(b) is based on all ownerships. Panel B(a) and B(c) are the total CS and CE (B(a)) and finance ((B(c)) degrees awarded in the MSA group in the year divided by the total of these degrees awarded in the US. Panel B(b) shows total geology degrees at universities whose cumulative value of new production of fossil fuels from 2004-2014 within 200 miles of their county's centroid is in the given bin. Degrees awarded are measured in the year preceding the first year the graduating class was exposed to the shock as freshmen. MSA groups start at share of MSA employed in the sector equal to zero, and are in intervals of .01. Value of new production of fossil fuel bins start at zero and are in intervals of 1. See text for details.

Figure 3: The Effect of Sectoral Shocks on Universities, by University's Geographic Exposure to the Shock

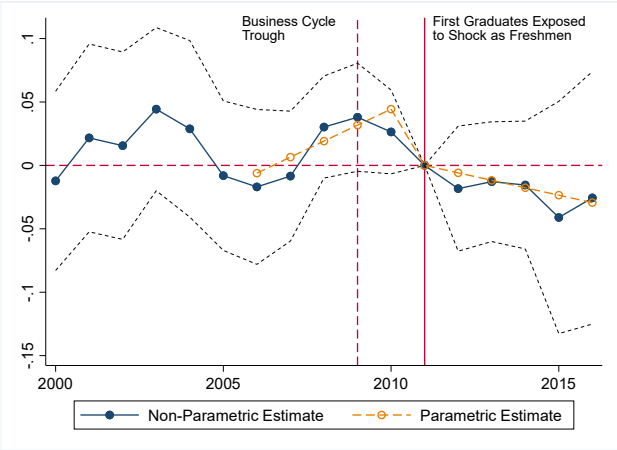
(a) MSA Computer Employment Share and the Effect on Share Computer Science and Computer Engineering Degrees, Relative to 2003



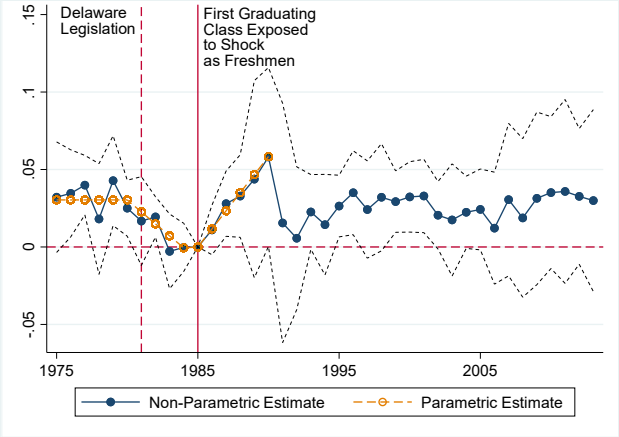
(b) Top Quartile, Cumulative Value of New Fossil Fuel Production within 200 miles, and the Effect on Share Geology Degrees, Relative to 2009



(c) MSA Finance Employment Share and the Effect on Share Finance Degrees, Relative to 2011

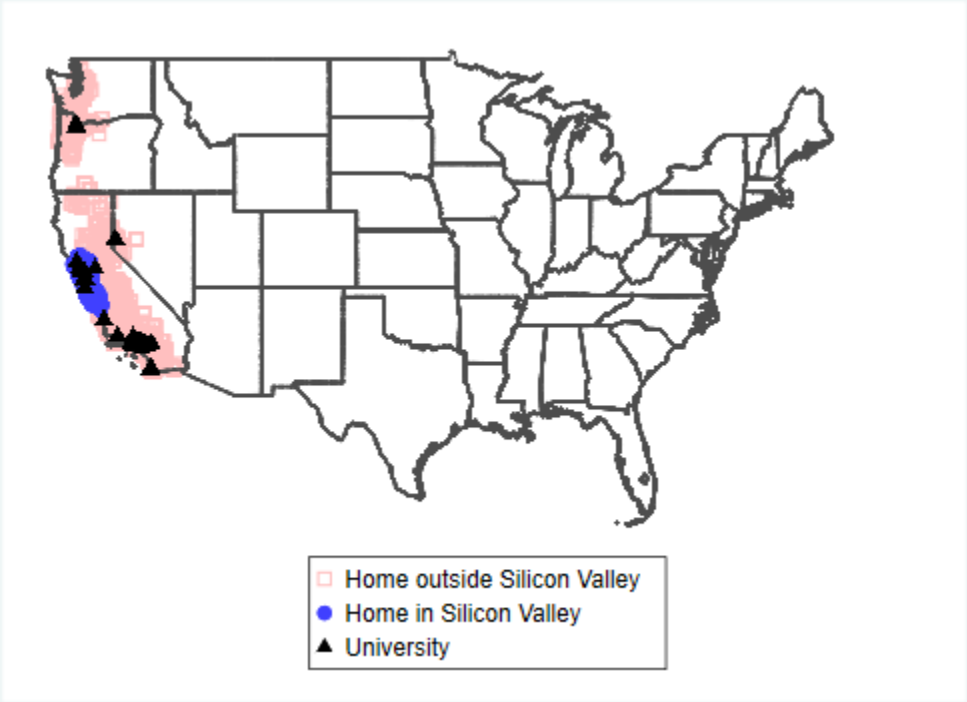


(d) Distance ≤ 15 Miles of Wilmington, DE and the Effect on Share Business Degrees, Relative to 1985



Note: Closed circles show interaction between year fixed effects and university's geographic exposure to the shock (MSA computer employment share in (a), university's county is within the top quartile in terms of cumulative value of new fossil fuel production within 200 miles of the county's centroid from 2004 to 2014 in (b), MSA finance employment share in (c), and university within 15 miles of Wilmington, DE in (d)). Dotted lines are 95% confidence intervals for these coefficients. These regressions also include year fixed effects, university fixed effects, and total degrees. Open circles show fitted values for the effect of university's exposure to the shock, based on coefficients from the parametric regression (interactions between geographic exposure to the shock, indicators for post shock, and years relative to first treated year, when the first graduates were exposed to the shock as freshmen). Fitted values are relative to the value in the first treatment year. The parametric regressions also include university fixed effects, total degrees, and the relevant combinations of the interacted variables. Observations are weighted by total degrees awarded.

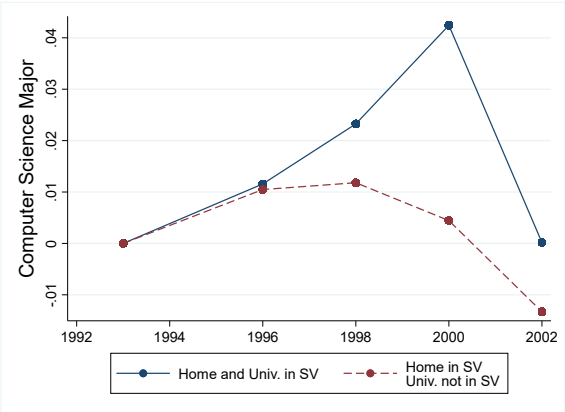
Figure 4: Individuals' Home and University Locations in the Sample for Testing the Role of Location Preferences



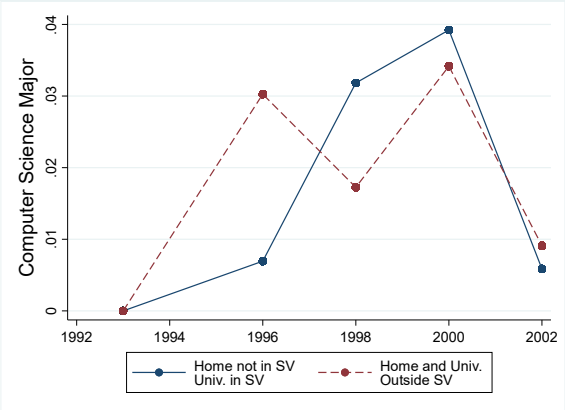
Note: This figure shows the universities (in black triangles) in the matched sample from The Freshman Survey. The figure also shows the home locations of the students from Silicon Valley (dark circles) and from outside Silicon Valley (light squares) attending one of these universities and in the matched sample. The matched sample consists of students with permanent home in Silicon Valley attending Silicon Valley universities matched through a nearest-neighbor matching procedure to students from the same CZ attending non-Silicon Valley universities. The matched sample also contains students with permanent homes outside Silicon Valley attending Silicon Valley universities who are matched to students from the same CZ attending non-Silicon Valley universities within 100 miles of home.

Figure 5: Computer Science Majors by Students' Home and University Locations

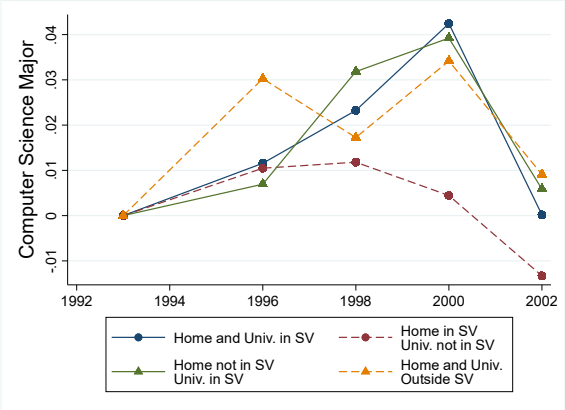
(a) Students whose Permanent Home is in Silicon Valley



(b) Students whose Permanent Home is Outside Silicon Valley

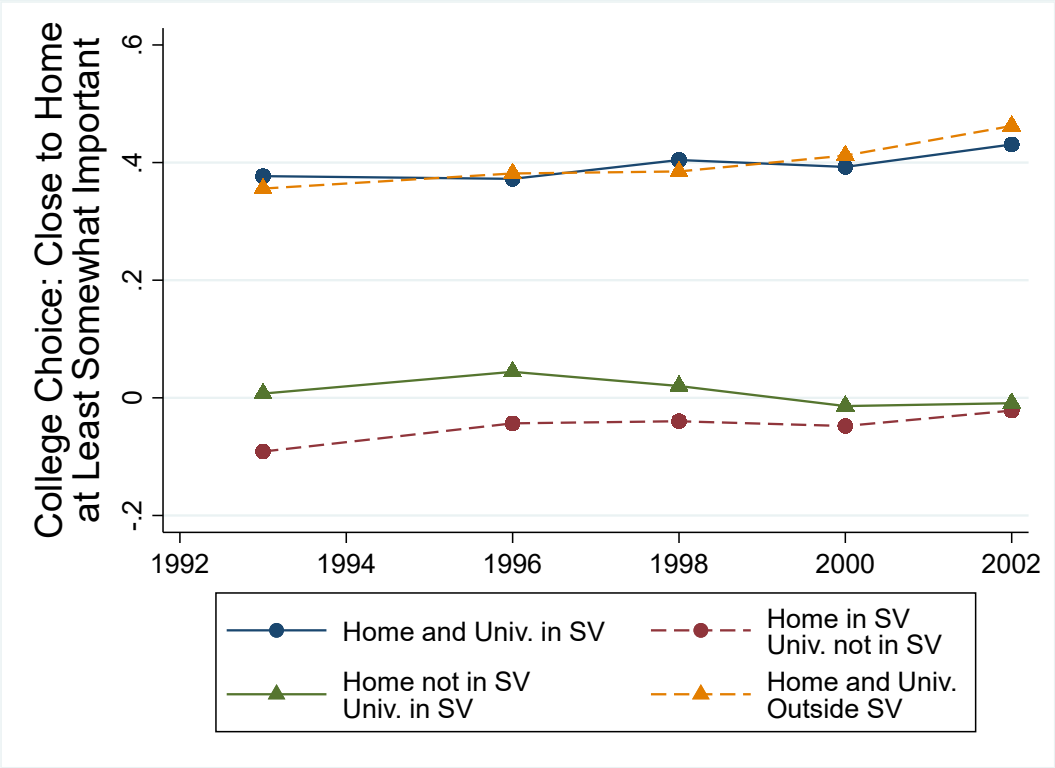


(c) All Students



Note: This figure shows fitted values from a regression with the dependent variable indicating student's intended major is computer science. All figures are from the same regression, but I show the comparisons separately in (a) and (b). Effects are relative to the gap between groups in 1992/1993. In (c), effects are relative to the within-CZ gap in 1992/1993, and the across-CZ gap in 1992/1993. Sample includes individuals and their matches, from a nearest-neighbor matching procedure. Explanatory variables include home CZ fixed effects, institution-pair fixed effects (fixed effect for institution of treated and matched student in the pair), an indicator for whether the student's university is outside of Silicon Valley (further than 100 miles from San Jose, San Francisco, or Santa Cruz), fixed effects for the year groups: 1995-1996, 1997-1998, 1999-2000, 2002-2003 (omitted group is 1992-1993), these interacted with an indicator for the student's university being outside Silicon Valley, interacted with an indicator for whether the student's home CZ is in Silicon Valley, and the triple interaction of the year group, non-Silicon Valley university, and Silicon Valley home. I also include as explanatory variables the variables used in the matching: male, mother has a BA, father has a BA, black, Hispanic, parental income, high school GPA at least a B plus, SAT/ACT score, university SAT/ACT measure (2011), indicators for self-rating in math ability and parental occupation group (at least one parent in a technical occupation, at least one parent in business and neither in a technical occupation, and neither parent in a business or technical occupation). The fitted values are calculated using only the triple interaction between year group, Non-Silicon Valley university, and permanent home in Silicon Valley, and the lower-level terms associated with this interaction.

Figure 6: Importance of Living Close to Home When Selecting College



Note: This figure shows the fitted values from a regression the same as that described in Figure 5. However, the dependent variable is an indicator for whether the student responded that living close to home was at least somewhat important in their choice of college.

Table 1: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock

		(1)	(2)	(3)	(4)
	Y_{cmt}: Share of Majors in	CS/CE	Geology	Finance	Business
(1)	Post	-0.000	0.0001	-0.002***	-0.028***
		(0.001)	(0.0001)	(0.001)	(0.005)
(2)	Post*Exposure	-0.015	0.0002	-0.057**	0.008
		(0.027)	(0.0002)	(0.026)	(0.018)
(3)	Post*Exposure*Years Elapsed	-0.068***	0.0002**	-0.018	0.019***
		(0.012)	(0.0001)	(0.015)	(0.006)
(4)	Post*Years Elapsed	-0.007***	0.0002***	0.000	-0.019***
		(0.000)	(0.0000)	(0.000)	(0.002)
(5)	Exposure*Years Elapsed	0.033***	0.0000	0.013	-0.008*
		(0.007)	(0.0001)	(0.008)	(0.004)
(6)	Years Elapsed	0.003***	-0.0000	0.000	0.020***
		(0.000)	(0.0000)	(0.000)	(0.002)
Differential Impact in Exposed Areas, relative to t*-1					
(7)	Immediate	0.002	0.0002	-0.002**	0.001
		(.002)	(.0002)	(.001)	(.015)
(8)	Medium Run	-0.016***	0.001***	-0.004	0.059**
		(.004)	(.0004)	(.003)	(.025)
	Shock	Dot-Com	Fracking Boom	Financial Crisis	Delaware
	Positive or Negative Shock	Negative	Positive	Negative	Positive
	Exposure	MSA % Computer Employment 2000	Top Quartile New FF Prod. in 200 Miles	MSA % Finance Employment 2000	≤ 15 Miles of Wilm., DE
	Post: Year ≥	2003	2009	2011	1985
	Observations	22,200	22,281	15,289	3,381
	R-squared	0.783	0.7573	0.920	0.882

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Observations are at the university, year level. Standard errors clustered at the university level in parentheses. Each regression includes university fixed effects, and total degrees awarded as a control variable. Post is an indicator for whether the year is greater than or equal to the year in which graduates were freshmen at the shock's onset (2003 in column 1, 2009 in column 2, 2011 in column 3, and 1985 in column 4). Exposure indicates the degree to which the university was exposed to the shock. In column 1, this is the share of the university's MSA employed in computers in 2000. In column 2, exposure is an indicator for whether the cumulative value of new fossil fuel production within 200 miles of the centroid of the university's county is within the top quartile. In column 3, exposure equals the share of the university's MSA employed in finance in 2000. In column 4, exposure is an indicator for whether the university is within 15 miles of Wilmington, Delaware. Years elapsed equals the difference between the current year and the first year in which graduates were exposed to the shock as freshmen. I measure the effect of exposure immediately after the shock (in t*) relative to t*-1 in row (7), and in the medium run in row (8) (in t* + 5 relative to t* -1). Differential impact in exposed areas in t* relative to t*-1 is Exposure*($\beta_{Post*Exposure}$ - (-1*$\beta_{Exposure*Years\ Elapsed}$)). Differential impact in exposed areas in t*+ 5 relative to t*-1 is Exposure*($\beta_{Post*Exposure}$ + 5*$\beta_{Post*Exposure*Years\ Elapsed}$ + 6*$\beta_{Exposure*Years\ Elapsed}$). To obtain the estimates in rows (7) and (8) in column 1 I set Exposure = .1, in column 2 = 1, in column 3 = .05, in column 4 = 1. Observations are weighted by total degrees awarded. Regressions include years preceding the shock only if they are within ten years of *t** , and years following the shock only if they are within five of *t** . The variable *Years Elapsed* is censored at -5. The regression in column 3 includes only the five years preceding *t* * since there is another recession and recovery between *t* *-10 and *t* *-5.

Table 2: Post-Graduation Geographic Mobility, using Baccalaureate & Beyond 2009

Panel A

	Residence After Graduation (2009)		
	Home State	Other State	Total
University in:			
Home State	81.4%	18.6%	9,550
Other State	60.9%	39.1%	1,900

Panel B

	Residence After Graduation (2009) within 50 miles of High School		
	1	0	Total
University within 50 miles of Home:			
1	63.1%	36.9%	5,330
0	45.2%	54.8%	6,120

Note: This table presents the proportion of students living in their home state (Panel A) (or within 50 miles of their high school in Panel B) one year after graduating from college, by whether they attended university in their home state (Panel A) (or within 50 miles of home in Panel B). I use the US Department of Education Baccalaureate & Beyond Survey 2009, and include individuals who were ≤ 25 at the time they received their bachelor's degree and whose home state, bachelor's degree institution state, and state after graduation were one of the 50 US States, or Washington DC.

Table 3: Summary Statistics for Matched TFS Sample, by Home and University Location in Silicon Valley (SV)

	(1)	(2)	(3)	(4)
	Students from SV		Students not from SV	
	University in SV		University in SV	
	Yes	No	Yes	No
Male	0.42	0.43	0.41	0.41
	[.49]	[.49]	[.49]	[.49]
Mother has Bachelor's	0.57	0.57	0.57	0.56
	[.5]	[.5]	[.49]	[.5]
Parental Income	97,347	97,882	95,146	87,392
	[65910]	[62215]	[62529]	[57997]
Black	0.02	0.02	0.02	0.01
	[.15]	[.15]	[.14]	[.11]
Hispanic	0.08	0.08	0.08	0.07
	[.28]	[.28]	[.27]	[.25]
Distance Between	27	299	319	40
Home, University	[25]	[98]	[170]	[33]
HS GPA ≥ B+	0.74	0.75	0.76	0.77
	[.44]	[.44]	[.43]	[.42]
SAT/ACT Score	1185	1196	1190	1170
	[173]	[145]	[160]	[145]
University SAT (2011)	1200	1221	1200	1180
	[131]	[102]	[131]	[113]
Self Math Rating: 1 to 5	3.55	3.58	3.56	3.56
	[.99]	[.9]	[.91]	[.85]
Parental Occupation				
≠ Business or Technical	0.4	0.39	0.4	0.43
	[.49]	[.49]	[.49]	[.5]
≥ 1 Parent in Business,	0.41	0.44	0.46	0.45
Neither in Technical	[.49]	[.5]	[.5]	[.5]
≥ 1 Parent in Technical	0.19	0.18	0.14	0.11
	[.39]	[.38]	[.35]	[.32]
N	11,452	11,452	11,452	11,452

Note: Column 1 contains summary statistics for individuals whose permanent home is in Silicon Valley, and who attend university in Silicon Valley. Column 2 contains summary statistics for their matches, based on a nearest-neighbor matching procedure, also from Silicon Valley but attending university outside Silicon Valley. Column 3 contains summary statistics for individuals whose permanent home is outside Silicon Valley, and who attend university in Silicon Valley. These students are matches to the students in Column 1, with exact matching by university. Column 4 contains summary statistics for individuals who are matches to those in Column 3, from the same home CZ but attending university within 100 miles of their permanent home. Individuals may serve as matches multiple times, and I include an observation for each time the individual is a match. See text for details.

Table 4: Matched University Pairs and Home CZs in the Sample

Panel A: Students with Permanent Home in Silicon Valley: Matching Students at SV Universities (Treated) to Students at non-SV Universities (Match)

Treated Student's University	Match's University	Number	Percent
Santa Clara University	California Polytechnic State University-San Luis Obispo	2,022	8.83
UC Santa Cruz	California Polytechnic State University-San Luis Obispo	1,732	7.56
Santa Clara University	University of California-Los Angeles	1,684	7.35
Stanford University	University of Southern California	1,362	5.95
Sonoma State University	California State Polytechnic University-Pomona	716	3.13

Panel B: Students with Permanent Home Outside Silicon Valley: Matching Students at SV Universities (Treated) to Students at non-SV Universities (Match)

Treated Student's University	Match's University	Number	Percent
Stanford University	University of Southern California	1,288	5.62
Santa Clara University	University of Portland	1,164	5.08
Santa Clara University	University of Nevada-Reno	1,022	4.46
UC Santa Cruz	California State Polytechnic University-Pomona	1,008	4.4
Saint Mary's College California	University of Nevada-Reno	880	3.84

Panel C: Home CZs of Students in the Sample

Home CZ	Students at SV Universities [Unique Individuals]	Students at non-SV Universities [Unique Individuals]
San Francisco, CA	6,283 [6,283]	6,906 [3,067]
San Jose, CA	5,169 [5,169]	4,546 [1,923]
Los Angeles, CA	4,831 [2,249]	4,831 [2,052]
Sacramento, CA	2,169 [1,084]	2,169 [275]
San Diego, CA	1,322 [636]	1,322 [541]
Portland, OR	739 [335]	739 [254]
Seattle, WA	714 [366]	714 [33]
Fresno, CA	577 [274]	577 [63]
Santa Barbara, CA	482 [217]	482 [204]
Eugene, OR	210 [96]	210 [68]

Notes: Panels A and B give the number of observations in the sample for the most prevalent institution pairs in the sample (the institution of the treated individual at the Silicon Valley university and the matched individual at the non-Silicon Valley university). The number presented is the number of treated and matched observations with the given institution pair. Panel C presents the home CZs of the observations in the sample. By design of the matching strategy, the number of observations from a given CZ who attend Silicon Valley universities is equal to the number at non-Silicon Valley universities. The exception is the San Francisco and San Jose CZs, since for the purposes of the matching these are treated as one unit. The sum of observations at Silicon Valley universities and non-Silicon Valley universities across these CZs is the same.

Table 5: Differential Likelihood of CS Major Among Same-CZ Students, by University Location

	(1)	(2)	(3)	(4)	(5)	(6)
Non-Silicon Valley (SV) University	0.006	0.013	0.054**	0.028	0.026	0.013
	(0.004)	(0.011)	(0.021)	(0.016)	(0.020)	(0.008)
Non-SV University*Boom	-0.001	-0.013	-0.005	-0.018	-0.031	-0.016
	(0.007)	(0.010)	(0.023)	(0.020)	(0.026)	(0.011)
Non-SV University*Bubble	-0.021**	-0.046**	-0.038	-0.050**	-0.042	-0.033*
	(0.010)	(0.017)	(0.024)	(0.016)	(0.032)	(0.017)
Non-SV University*Bust	-0.005	-0.017	-0.034*	-0.046*	-0.027	-0.009
	(0.008)	(0.013)	(0.018)	(0.020)	(0.028)	(0.011)
Boom	0.019***	0.017**	0.018	0.035**	0.014	0.021**
	(0.005)	(0.008)	(0.014)	(0.013)	(0.013)	(0.009)
Bubble	0.041***	0.045***	0.050**	0.051***	0.049**	0.047***
	(0.008)	(0.014)	(0.019)	(0.012)	(0.020)	(0.010)
Bust	0.003	0.001	0.007	0.023	-0.010	0.002
	(0.006)	(0.007)	(0.012)	(0.015)	(0.016)	(0.007)
Sample	All	Treated Chose College to be Near Home	Matches at Technical Non-SV University	Univ. with Tech Firm Recruiting	Parent Occ: Technical	Parent Occ Technical/ Business
N	45,808	14,750	12,976	11,574	6,048	24,940
R-Squared	0.047	0.043	0.057	0.040	0.077	0.052

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table shows coefficients from a regression with the dependent variable an indicator for student's intended major is computer science. Sample includes individuals and their matches based on a nearest-neighbor matching procedure. Explanatory variables include home CZ fixed effects, institution-pair fixed effects (fixed effect for institution of treated and matched student in the pair), an indicator for whether the student's university is outside of Silicon Valley (further than 100 miles from San Jose, San Francisco, or Santa Cruz), fixed effects for the following year groups: boom (1995-1998), bubble (1999-2000), bust (2002-2003) (omitted group is 1992-1993), and these interacted with an indicator for whether the student's university is outside of Silicon Valley. I also include as explanatory variables the variables used in the matching: male, mother has a BA, father has a BA, black, Hispanic, parental income, high school GPA at least a B plus, SAT/ACT score, university SAT/ACT (2011), indicators for self-rating in math ability, and parental occupation group (at least one parent in a technical occupation, at least one parent in business and neither in a technical occupation, and neither parent in a business or technical occupation (omitted)). See text for definitions of technical and business occupations. Column 2 includes only students from Silicon Valley who stay in Silicon Valley for college and report that being close to home was at least somewhat important in choosing their college, and includes the same-CZ matches of these students. Column 3 includes only those individuals who are matched with students attending a technical university outside of Silicon Valley (California Institute of Technology, California Polytechnic State University-San Luis Obispo, and California State Polytechnic University-Pomona). Column 4 includes only matches for which both students attend universities targeted for on-campus recruiting by one of the three technology firms listed in Table 6. Column 5 includes pairs where both students in the matched pair have at least one parent in a technical occupation (computer programmer or analyst; engineer; scientific researcher; statistician). Column 6 includes pairs where both students in the matched pair have at least one parent in a technical or a business occupation.

Table 6: Internet and Computer Company Recruiting on College Campuses

	Sun Microsystems (Fall 1996)	Netscape (Fall 1998)	eBay (Fall 2000)
Silicon Valley Universities (within 100 miles of San Francisco, San Jose, or Santa Cruz)			
	UC Berkeley	UC Berkeley	UC Berkeley
	Cal State-Hayward	UC Santa Cruz	UC Santa Cruz
	San Jose State	Stanford	San Jose State
	Santa Clara U.		Santa Clara U.
	Stanford		Stanford
	UC Davis		UC Davis
Non-Silicon Valley Universities in California and Bordering States			
	Arizona State	Caltech	Cal State-Chico
	Cal Poly-San Luis Obispo		Cal Poly
	Cal State-Chico		
	Cal State-Fresno		
	Cal State-Humboldt		
	UC Irvine		
	Cal State-Long Beach		
	Oregon State		
	Portland State		
	UC San Diego		
	UC Santa Barbara		
	UCLA		
	USC		
Total Target Universities Outside California and Bordering States			
	48	5	0

Note: This table lists the campuses targeted for recruiting by Sun Microsystems, Netscape, and eBay in the listed time periods. I collect these data from archived webpages of these companies using the Internet Archive Wayback Machine. I have written the university names as they are written on the company webpages. See text for details.