Local Labor Markets and Human Capital Investments*

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Abstract

I study whether human capital investments are based on local rather than national demand, using three shocks with differential local effects: the dot-com crash, the 2008 financial crisis, and the shock making Delaware a financial headquarters. Event-study analyses show universities more exposed to sectoral shocks experience greater changes in sector-relevant majors. Using students' home and university locations and nearest-neighbor matching, I develop a test for whether information frictions explain this local elasticity, separately from migration frictions. Information frictions do not appear to explain the result. Findings are consistent with migration frictions, implying encouraging investments based on national demand may increase mismatch.

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1 Introduction

For the past thirty years, the unemployment rate for young workers has been approximately two to three times larger than the adult unemployment rate in the US, OECD, and Japan (OECD 2010). This is true even among bachelor's degree recipients in the US in the years preceding the Great Recession (National Center for Education Statistics 2015).[1] While a large literature has studied and called attention to high rates of youth joblessness, it concludes that explaining this phenomenon remains a puzzle (Blanchflower and Freeman 2000).[2]

Mismatch between the supply and demand for workers in particular sectors and occupations is a prominent explanation for high aggregate unemployment (Shimer 2007, Sahin et al. 2014), but was not considered in the earlier literature on youth joblessness.[3] This mismatch may be particularly pronounced among young workers, who make investments in sector-specific skills based on very little experience in the labor market. One potentially important source of mismatch is that young individuals may invest in human capital based on local, rather than national, labor demand.

Human capital investment based on local demand could yield mismatch between aggregate supply and demand for sector-specific skills, and thus unemployment, in at least two ways. First, industries are geographically concentrated (Ellison and Glaeser 1997), and the number or size of universities in the concentrated industry's market may be small relative to the industry. A shock to a nationally important, but geographically concentrated, industry may then yield a disproportionate response from students who invest only based on their local market. Second, if large universities are located in smaller labor markets, then a disproportionate number of students may make investment decisions based on this small market. Mismatch may decline over time for these young workers as they learn about the labor market and invest in new

[1] Youth unemployment rates increased in the US during the Great Recession, but the ratio of youth to adult unemployment rates in the US fell slightly and ranged between 1.7 and 2 in 2008 and 2009. While unemployment rates fell by 2015, the ratio of youth to adult unemployment rate increased again above two (National Center for Education Statistics 2015). The ratio of youth to adult unemployment rates have been above three for much of the past decade in North Africa, South Asia, the Middle East, and South East Asia and the Pacific (Pieters 2013).

[2] High aggregate unemployment seems to partially explain high youth joblessness, though the reduction in joblessness in the US in the late 1990s did not restore the position of young workers relative to adults (Blanchflower and Freeman 2000).

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

skills.

This paper makes three important contributions. First, I test whether this particular source of mismatch, human capital investments based on local demand, is empirically relevant. 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 choice). Several recent papers have found important general effects of local shocks on high school completion and college enrollment (Cascio and Narayan 2015, Charles, Hurst, and Notowidigdo 2015). It is possible to directly observe in the data 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 the causal relationship difficult to identify (local demand may respond to, rather than determine, local human capital investments).

Using three 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 students choosing the sector-relevant major. I focus on computer science majors after the post-2000 dot-com crash, and business majors after the 2008 financial crisis. The pre-crisis geographically concentrated growth of these industries may have been driven by universities with relevant specializations. However, I exploit that the timing of the crises was exogenous to the number of majors.

The third shock is 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. There is a growing literature on place-based policies and jurisdictional competition, and these topics are highly relevant for policymakers (local policies to attract or retain firms cost local governments 80 billion dollars per year (Story 2012)). However, there is a lack of evidence on whether these policies affect human capital investments. Including this positive labor demand shock also allows me to analyze whether the local elasticity exists for both positive and negative shocks.

Using event-study analyses, I find strong evidence that college majors respond differentially in areas more exposed to both positive and negative labor demand shocks, with data on completions by university and major from The Integrated Postsecondary Education Data System (IPEDS). I compare the effect at universities more geographically exposed to these shocks, to the effect at universities less exposed to the shocks, but whose students experience the same national shock. The dot-com crash reduced the share of computer science majors by an additional 41% at universities where the MSA computer employment share was higher by ten percentage points. Conditional on the MSA unemployment rate change from 2007-2009, universities experienced an additional 2.8% decrease in business degrees after the financial crisis if the MSA finance employment share was higher by five percentage points. After the finance shock in Wilmington, Delaware the share of business degrees increased by an additional 15% at local universities.

I also evaluate how quickly students respond to these shocks, and whether short-run responses are consistent with long-run changes in labor demand. I find students who were sophomores through seniors do not adjust their major in response to the shocks, presumably because switching majors is costly. This implies potentially very adverse effects for these students.[4] Short-run responses reverse after about five years, consistent with changes in sectoral demand. This suggests students may either overestimate the size or duration of the shock, or they understand poor initial placement can have long-run effects (Kahn 2010, Oreopolous et al. 2012, Oyer 2006 2008). Finally, I generally find that college majors respond to local shocks with a greater lag at nonresearch universities.

The second contribution of the paper is to identify the mechanism explaining any local elasticity, which can motivate current policies aimed at reducing potential mismatch. Students may invest in human capital based on local, rather than national, labor demand because they lack good information on national demand. After the dot-com crash students in Kansas may hear about bankruptcies of technology companies in California less frequently, or with less sensationalism, than students in California. Alternatively, prospective and currently enrolled students may believe (correctly or incorrectly) that post-graduation labor market prospects are determined by local, rather than national, labor demand. Students may also have strong geographic migration frictions, implying local, rather than national, demand is more pertinent.

If students invest in human capital based on local demand, and this is explained by information frictions, policies reducing these frictions could reduce mismatch and youth unemployment rates. If instead migration frictions explain the local elasticity, encouraging students to base human capital investments on national demand may increase mismatch. Recent initiatives to improve labor market outcomes have provided

[4]This is consistent with recent findings that college majors are most strongly related to wages when students were generally freshmen (Long, Goldhaber, and Hungtington-Klein 2015).

information on national demand, while others provide information on local demand.[5] This paper helps evaluate which of these is likely to exacerbate or ameliorate any mismatch.

I develop a test to isolate the role of migration and information frictions using very rich student-level data from The Freshman Survey. The intuition is straightforward. Using a nearest-neighbor matching procedure, I compare geographically mobile students with similar academic and demographic characteristics at the same university, by whether their permanent home is within 100 miles of a computer-industry cluster (San Jose, CA or Austin, TX). If there are no information frictions, these geographically mobile students should be equally likely to major in computer science, regardless of whether they grew up in Silicon Valley, Austin, or an area without any computer employment. However, if students have better information about local than national labor demand, students from computer-industry clusters may respond differently to the dot-com boom and bust than students from areas with little computer employment, even if they are all geographically mobile.

Information frictions among geographically mobile students do not explain the local elasticity. Geographically mobile students who grew up in San Jose and Austin respond similarly to the boom and bust relative to classmates whose permanent home is not in a computer-industry cluster, but who attend the same university in a low-computer employment area. This suggests the muted response to the dot-com crash at less exposed universities is not explained by those students having worse information about the crash.

While it is difficult to attribute the local elasticity to migration frictions, I find evidence consistent with these frictions by implementing two additional tests and matching procedures. Both suggest that students who are less likely to move to San Jose are less likely to respond to the dot-com boom and bust. First, I compare students at the same university in a low-computer employment area, whose choice of college does not imply high levels of geographic mobility. Among these less geograph-

[5] 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 to design programs training workers for jobs highly demanded in the regional economy (White House *Higher Education*). 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).

ically mobile students, those from San Jose respond more to the boom and bust than their counterparts at the same university. Second, I compare geographically mobile students from San Jose to less geographically mobile students at the same university in a low-computer employment area. The less geographically-mobile students respond less to the dot-com shock.

Policies that encourage fields with high national demand shift students to majors not necessarily demanded locally. Given the suggested importance of migration frictions, this may increase mismatch. The local dependence may also affect aggregate productivity if employers cannot hire the most productive individuals for their vacancies.

Finally, I use the exogenous finance shock in Delaware as a setting for identifying the extent and nature of substitution between STEM and business degrees. Not only did Delaware experience a large positive shock to finance, it was also home to a historically important chemicals sector (including DuPont's headquarters). Recruiting and retaining STEM majors has become an important policy objective in the United States, with former President Obama asking higher education institutions for one million additional STEM graduates ("Science, Technology" 2016). Understanding the policy goal's potential impact requires understanding substitution patterns between majors, both the majors people substitute between and who substitutes. This allocation of talent across fields may affect aggregate productivity (Murphy, Shleifer, and Vishny 1991, Boehm and Watzinger 2015).

I contribute to the literature on selection out of STEM and into finance (Boehm, Metzger, and Stromberg 2015, Philippon and Reshef 2012, Shu 2015) using an exogenous shock to finance, and data on all universities in the area surrounding the shock.[6] I find suggestive evidence that Wilmington-area universities experienced differential selection out of science, and that low GPA students left science for business.

The paper also contributes to an established and growing literature on how individuals make human capital investments (see Altonji, Blom, and Meghir 2012 for a review), especially after economic shocks (Blom, Cadena, and Keys (2015), Ersoy (2017), Liu, Sun, and Winters (2017), Long, Goldhaber, and Huntington-Klein (2014)). I contribute to this literature by focusing on three important case studies, exogenous shocks that affect particular sectors, which map very closely to particular

[6] Anelli, Shih, and Williams (2017) and Ransom and Winters (2016) study selection into and out of STEM majors and how this is affected by foreign students and STEM workers.

majors. Further, most studies have focused on college major choice and national labor demand conditions, rather than local labor demand. Given the importance of local labor markets shown in other work (for example Cascio and Narayan 2015, Charles, Hurst, and Notowidigdo 2015, Manning and Petrongolo forthcoming), this is an important extension with significant policy implications. Two recent studies have also analyzed how major choice is affected by local demand. Long, Goldhaber, and Huntington-Klein (2014) find college major choice in the state of Washington is more responsive to local compared to national wages. Ersoy (2017) studies changes in major allocation after the Great Recession based on the local severity of the recession.

Finally, I explore why very salient national shocks affect college major choice differentially across local labor markets, which complements the literature. I present among the first estimates identifying the role of migration frictions, and the role of geographically-driven information frictions in determining college major choice.

2 Sectoral Shocks with Local Labor Market Impacts

2.1 The Dot-Com Crash and the 2008 Financial Crisis

The 1990s was a period of dramatic growth for computer and internet companies. Figure 1 shows that in 1990 approximately three million people were employed in computer-related industries. By 2000, over four million people were employed in these industries. Figure 1 also shows the dramatic rise of the NASDAQ Composite Index from 1990 to 2000. The latter part of this period is often referred to as the dot-com bubble.[7] In March 2000 dot-com stock prices began a very dramatic decline, for reasons arguably unrelated to negative news about internet stock fundamentals (DeLong and Magin 2006, Ofek and Richardson 2001). Dot-com stock prices continued to fall until 2003.[8] Computer employment fell by 15%.

The 2008 financial crisis also represents an important and recent sectoral shock.

[7]The NASDAQ nearly doubled in the year leading up to its peak in the first months of 2000, without positive news about the fundamentals of these stocks to justify this increase (DeLong and Magin 2006). Because the NASDAQ stock exchange contains many technology-related companies, this index is often used to symbolize the dot-com boom and bust.

[8]Wang (2007) contains an overview of theories proposed to explain the dot-com boom and bust, including theories of rational and irrational bubbles, uncertainties in new markets, and innovation that was complementary to traditional technology of brick-and-mortar institutions. Ofek and Richardson (2001) argue the bubble may have burst when lock-up agreements from IPOs expired, increasing the number of sellers in the market.

Panel B of Figure 1 shows the dramatic decline in the Dow Jones Industrial Average starting in 2008. While the crisis significantly affected many industries, it had a clear effect on employment in Finance, Insurance, and Real Estate (FIRE), with employment declining by approximately 8% from 2007 to 2010. Figure 1 shows these national shocks had important effects on the national share of majors in the relevant field.

Figure 2 shows these 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 2a). This was dramatically larger than the decrease nationally, which represented only .13% of total employment.

Similarly, from 2008 to 2009, finance employment fell considerably in Manhattan, with the one-year employment loss in finance representing over 1% of total county employment. Nationally, this effect was much smaller, representing only .3% of total employment.

I use differential local exposure to national shocks to identify whether college major composition is affected by local, or national, economic conditions. I argue that the dot-com crash and the 2008 financial crisis are exogenous shocks to labor demand. Identification requires the very plausible assumption that a drop in majors at universities in MSAs with high industry share does not cause these events, more so than a drop in majors at universities in MSAs with low industry share.

2.2 Delaware Transformed into a Financial Headquarters

Jurisdictional competition and firm relocation represent an alternative source of local labor demand shocks. Due to the prevalence and policy importance of these shocks, I supplement the analysis by studying one such exogenous shock that was internationally prominent.

Prior to 1978, state usury laws determined the interest rate that credit card companies could charge residents of the state. 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.

Delaware, which had historically provided a favorable business climate, was looking to diversify its economy from the automotive and chemical industry.[9] After the *Marquette* ruling, the state recognized the opportunity to attract the finance industry.[10] In 1981, Delaware eliminated its usury laws, with the passage of the Financial Center Development Act (FCDA). This legislation formally allowed out-of-state bank holding companies to acquire a bank in Delaware, and provided an incentive to do so. In addition to eliminating ceilings on interest rates for most kinds of loans, the FCDA reduced other industry regulation and introduced a regressive tax structure for banks.[11]

As a result, many companies moved their finance or credit operations to Delaware, starting with J.P. Morgan in 1981. Weinstein (2017) analyzes labor market adjustment to this shock, and shows the policy resulted in higher FIRE growth in Delaware through 2000. Figure 1 Panel C, reproduced from Weinstein (2017), shows that around the time of the policy there were clear increases in the share of Delaware's employment in FIRE.

The Supreme Court ruling in *Marquette*, followed by Delaware legislation, resulted in an arguably exogenous increase in finance labor demand in Delaware. I study the shock's effect on college majors. I further identify the degree to which these effects were local, which would be consistent with the extent to which these firms became involved with Delaware's universities. Prime examples include the Lerner College of Business and Economics at The University of Delaware (Lerner was the chairman and CEO of the credit card company MBNA),[12] the MBNA American building at Delaware State University, and the MBNA School of Professional Studies at Wesley College in Dover, Delaware (Beso 2005). MBNA was also very active in recruiting new hires on local college campuses (Agulnick 1999). As discussed in the appendix, the change in majors is unlikely directly due to increased corporate funding of the sector-relevant departments, since this funding did not occur immediately after the

[9]Delaware had historically been a favored location for business incorporation, due to its corporation law, Court of Chancery (corporations court), and a government that has traditionally been friendly to business (Black 2007).

[10]The description of the FCDA is based on Moulton (1983).

[11]There capitalization and employment requirements for these acquired banks. Other provisions of the FCDA include allowing borrowers and lenders to negotiate terms without interference from regulators, and banks to charge certain kinds of fees for credit accounts.

[12]MBNA was one of the world's largest credit card companies before being acquired by Bank of America in 2006. It was headquartered in Delaware, and spun out of one of the original firms moving to Delaware following the FCDA.

shock.

3 Data

To study the impact of these shocks, I obtain university-level data on Bachelor's degrees awarded by academic discipline. I include only Research, Doctoral, Master's, and Baccalaureate universities as ranked in the 1994 Carnegie rankings. For the dot-com crash and the Great Recession, I obtain data from 1990-2013 from IPEDS and use two-digit CIP codes to classify majors.[13]

Studying the impact of Delaware's finance labor demand shock requires data on college majors from an earlier period. I obtain university-level data on Bachelor's degrees awarded by 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 (NSF).[14]

To determine the exposure of the university's local labor market to the dot-com crash and Great Recession, 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.[15] I include the FIRE industries, excluding insurance and real estate, as finance-related industries.[16] Using the person weights, I obtain the weighted sum of individuals by industry and metropolitan area.[17] I merge the data on share employed in computers and finance to the university-level data using the 2013 MSA.

Many universities are not located in MSAs, and among those that are in MSAs these may not be represented in the Census. In the principal results, for both of these

[13] The CIP codes pertaining to these majors are listed in the appendix.

[14] I use the academic discipline broad (standardized) classifications, and the NCES population of institutions. Prior to 1996, the sample includes all universities accredited at the college level by an agency recognized by the US Department of Education. Starting in 1996, the sample includes only universities that are eligible for Title IV federal financial aid.

[15] I use the BLS definition of high-technology industries from Hecker (2005). This classifies industries using 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.

[16] This includes Banking; Savings institutions, including credit unions; credit agencies, n.e.c; security, commodity brokerage, and investment companies.

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

categories, I assume percent employed in computers or finance is zero. For robustness, I exclude these universities from the sample.

To determine the exposure of the university's local labor market 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.[18] 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. There are six universities within 15 miles of Wilmington, 34 within 15 to 50 miles, and approximately 170 more than 50 miles away (but within the nearby states).

Figure 2c shows a large proportion of US computer science degrees are awarded by universities in areas with low computer employment share. If all computer science degrees were awarded by universities in high computer employment share areas, a larger differential response in these areas would be mechanical. Similarly, Figure 2d shows a large proportion of business degrees are awarded by universities in areas with low finance employment share.

4 Identifying Local Shocks' Effects on Majors

To identify the shocks' effects, I use an event-study framework similar to LaFortune, Rothstein, and Schanzenbach (2017), which allows the effects to be dynamic. This is important for two reasons. First, these were not one-time shocks. Their magnitude changed over time, and may have also changed perceptions about the persistence of the shock. For example, the dot-com crash began in 2000, but dot-com stock prices continued falling until 2003. Second, these specifications allow me to identify how quickly degree completions respond to the initial shock. I test whether the shock affected enrolled students, or only those enrolling after the shock's onset.

I start with a less parametric specification that does not constrain the phase-in effects to be linear. I estimate year-specific effects using the following regression:

[18] I use the IPEDS 2013 data to obtain latitude and longitude for each university. The NSF IPEDS data do not contain the IPEDS ID of the university. I make a crosswalk between the FICE code (the only identifier in the NSF IPEDS data) and IPEDS code, and then use this to merge with the latitude and longitude data. I manually input latitude and longitude for universities which were no longer in existence in 2013. I calculate the distance between each university and Wilmington, Delaware using the Vincenty formula for calculating distance between two points on the surface of the Earth, assuming it is an ellipse.

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

The variable $Share(Majors_{cmt})$ denotes the share of relevant majors at university c in metropolitan area m in year t (computer science for the dot-com crash, and business for the Great Recession and Delaware finance shock). The variable $Exposure$ denotes the extent to which university j is exposed to the shock. For the national dot-com crash this is the share of metropolitan area $m's$ employment in the computer sector in 2000.

For the Great Recession, using only the MSA finance employment share in 2000 would be problematic for several reasons. The Great Recession was a broad shock affecting many sectors, many of which likely hire business majors into managerial roles. Even in low-finance-share areas, business majors may fall because of reduced demand among nonfinance companies. Nonetheless, the Great Recession did significantly reduce finance employment, with some areas more exposed to finance than others.

I identify the impact of this differential local shock to finance on business majors. Specifically, I compare MSAs similarly affected by the Great Recession, but with different finance employment shares. This helps control for reduced demand for business majors from nonfinance companies, and isolates reduced demand from finance. Similar to Yagan (2017), I use the change in the MSA's unemployment rate from 2007 to 2009 to measure the local impact of the Great Recession. I then define $Exposure$ as an interaction between MSA finance employment share in 2000 and the change in the MSA's unemployment rate from 2007 to 2009. Regression (1) also includes the relevant lower-level interaction terms.

To capture exposure to the localized finance shock in Delaware, $Exposure$ equals one for universities within 15 miles of Wilmington, Delaware.

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 $k_{min} < 0$. These are estimated relative to the year (t^*) in which the graduating students were freshmen at the onset of the shock (2003 for the dot-com shock, 2011 for the finance shock, and 1985 for the Delaware shock).[19]

The variable $TotDegrees_{cmt}$ denotes the total number of Bachelor's degrees awarded by university c in year t. I do not include $Exposure$ uninteracted since this would be perfectly collinear with the university fixed effects (γ_c). I weight the observations by $TotDegrees_{cmt}$, which ensures that changes at larger universities are given more weight than those at smaller universities. I cluster standard errors at the university level.

Second, I estimate more parametric regressions constraining the phase-in and prior trends to be linear:

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

I test whether the shock's initial effect on majors at a university depends on local exposure to the industry ($\beta_{jumpdiff}$) and whether this changes with years from the shock's onset ($\beta_{phaseindiff}$). To best capture the immediate effects of the shock, 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 ($t - t^*$) at -5 (as in Lafortune, Rothstein, and Schanzenbach 2017). In the case of the Great Recession, the ten years preceding the shock includes another recession and recovery. To best capture the boom immediately preceding the shock, I limit the sample to the five years preceding t^*.

I again weight by $TotDegrees$ and cluster standard errors at the university level.

The coefficients $\beta_{trenddiff}$ reflect whether areas more exposed to the industry experienced greater increases in sector-specific majors in the periods preceding these shocks. In studying Delaware's finance shock, this coefficient represents a falsification test. If business majors were differentially increasing in Delaware in the years

[19]Graduates in 2003 were freshmen in 1999-2000, and as a result experienced the initial crash in their freshman year. While Delaware's legislation was passed in February 1981, the first acquisition under this policy was not approved until November 1981 (Erdevig 1988).

preceding the legislation, this would suggest any post-policy effects may be part of a longer-run trend.

In studying the dot-com crash and the Great Recession, the periods preceding the shock were growth periods for the computer and finance industry respectively. Differential effects in more exposed areas during these periods would also imply a relationship between local labor markets 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 crash period since these shocks are more clearly exogenous. It is unlikely that more jobs left high computer employment MSAs because of a greater decrease in computer science majors.

Based on the coefficients in (2), I estimate the differences-in-differences effects for each shock. For universities where MSA computer employment share is higher by 10 percentage points, the differential impact of the dot-com crash (2008 relative to 2002) is: $.1(\beta_{jumpdiff} + 5\beta_{phaseindiff} + 6\beta_{trenddiff})$. For universities in MSAs experiencing equivalent changes in the unemployment rate from 2007-2009, if one is in an MSA with finance employment share higher by 5 percentage points , the differential impact of the Great Recession (2013 relative to 2010) is: $.05(\beta_{jumpdiff} + 2\beta_{phaseindiff} + 3\beta_{trenddiff})$.[20] For Wilmington-area universities, the differential impact of Delaware's legislation (1990 relative to 1984) is: $(\beta_{jumpdiff} + 5\beta_{phaseindiff} + 6\beta_{trenddiff})$.

For policymakers, it is important to know whether certain types of students or universities are more responsive to local demand. This would help identify who may benefit most from policy interventions. I test for heterogeneity by whether the university has a 1994 Carnegie classification as a research/doctoral university or master's/baccalaureate university. If research universities attract students who are more geographically mobile, or who have better information about national demand, then the university's local exposure to the shock may be less important. In the second part of the paper, I use student-level data to more formally test mechanisms explaining elasticity of majors to local demand.

[20] There are no MSAs in the sample with 2000 finance employment share greater than 10%.

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 effects are relative to the year (t^*) in which the graduating students were freshmen at the shock's onset. The parametric and nonparametric results closely match, and each shows changes in sector-specific majors starting approximately with graduates who were freshmen at the shock's onset.

The differential effect on computer science 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 effects are not particularly large and not statistically significant among the graduates who were freshmen at the shock's onset (row 2).

The difference-in-difference is 1.1 percentage points, statistically significant at the 1% level. In 2008, on average 1.6% of degrees awarded are in computer science, among universities where MSA computer employment share is at least .1 (author's calculation). Thus, universities in areas where MSA computer employment share is higher by 10 percentage points experience an additional $1.1/(1.6+1.1) = 41\%$ decline in computer science degrees awarded.

Table 1, column 2 shows a very significant jump effect for the Great Recession, that does not change with years from the shock. The difference-in-difference is .5 percentage points, but not statistically significant. In 2013, on average 17.5% of degrees awarded are in business, among universities where MSA finance employment share is at least .05 (author's calculation). Thus, conditional on the change in unemployment rate from 2007-2009, universities in areas where MSA finance employment share is higher by 5 percentage points experience an additional $.5/(17.5+.5) = 2.8\%$ decline in business degrees awarded.[21]

Table 1, column 3 shows that as years from the legislation increase, Wilmington-area universities experienced a differential 1.9 percentage point increase in the share of business degrees awarded (row 3). This phase-in effect is statistically significant at the 1% level. There is no differential effect on share of business degrees for freshmen in the year of Delaware's legislation (row 2). The difference-in-difference is 5.9 percentage points. In 1990, on average 31.5% of degrees awarded are in business, among universities within 15 miles of Wilmington, Delaware (author's calculation). Thus, univer-

[21] Appendix Table A12 shows the coefficient estimates for all the interactions from this regression.

sities within 15 miles of Wilmington experience an additional $5.9/(31.5 - 5.9) = 23\%$ increase in business degrees awarded.

Figure 3c shows no evidence that Wilmington-area universities had experienced greater increases in business majors before the policy. In fact, in the years preceding the legislation Wilmington-area universities experienced smaller changes in the share of business degrees awarded. This mitigates concerns the post-policy effects are part of a longer-run trend.

Timing

There are several policy-relevant issues related to timing of the effects. First, how quickly do students respond to the shock? Second, are students' responses to short-run changes in demand consistent with long-run changes in demand? Do students seem to be overresponding in the short run?

Students who were sophomores through seniors at the time of the shock's onset do not appear to adjust their majors differentially in exposed areas (see Figure 3 coefficients between the vertical dashed and solid lines), or nationally (Figure 1). Initial investments in college major presumably make switching majors costly. However, this implies potentially very adverse effects for students entering during boom periods, but graduating during a bust. In the case of a positive shock like Delaware's, it may mean students miss entering an industry at a particularly advantageous time.

To study whether responses to short-run changes in demand are consistent with long-run changes in demand, I focus on the dot-com crash and Delaware's finance shock, since the post-period for the Great Recession is too short. In both of these shocks, the short-run response differs from the medium- to longer-run response.

The differentially negative effects of the dot-com crash on computer science majors start to reverse after about five years (2010) (Figure 3), several years after renewed growth in computer employment (Figure 1a). This may suggest students immediately after the crash overestimated the size or duration of the shock. Given the importance of computer science skills for careers in computers, shifting away from computer science majors in the short-run may have had negative long-run career implications since the industry later recovered. 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).[22]

The positive effects of Delaware's legislation on local business majors also start to reverse after about five years (1991), approximately consistent with the timing of the 1990-1991 recession. The magnitude of the effects increase again after the recession, but never quite reach the initial effects. Again, students may have overestimated the size of the shock, or understood that there were positive effects from being an early entrant.

Differences at Research Universities

For each of the shocks, the effects at research universities differ in magnitude and persistence from those at nonresearch universities. The response to the dot-com crash operates with more of a lag at nonresearch universities. Only in the year 2000 do nonresearch universities in higher computer employment areas start experiencing differential increases in computer science majors. Among research universities, these differential increases are part of a trend starting as early as 1990. Immediately following the onset of the dot-com crash (between 2000 and 2003) there appear to be small differential increases in computer science at research universities. However, these differential increases are large among nonresearch universities. Differential decreases in computer science degrees at nonresearch universities in high computer employment areas begin only in 2005, compared to 2004 among research universities.

Finally, the differentially negative effect of the dot-com crash on computer science degrees at exposed universities appears much more persistent at nonresearch universities. Unlike for research universities, there is no reversal in these differentially negative effects as the industry rebounds.[23]

The differential negative effect of the Great Recession on business majors at exposed universities is only evident among nonresearch universities. In the specification including only research universities, the coefficients on the uninteracted year fixed effects fall considerably, from .197 in 2010 to .169 in 2013 (not shown in table). This, combined with the absence of differential effects at exposed research universities,

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

[23]Appendix Table A12 shows the results from estimating (2) separately for research and nonresearch universities. Given the differences in response time between the university types, the results do not convey the large response at both types of universities (seen in Figure 4).

suggests students at research universities are responding similarly to this shock, regardless of their geographic location. In contrast, students at nonresearch universities are responding less to this finance shock if their university is in an area less exposed to the shock.

Among universities within 15 miles of Wilmington, Delaware, University of Delaware is the only research/doctoral university. However, the positive effect of Delaware's finance shock on local business majors appears much larger, as well as more persistent, at nonresearch universities.

These results suggest students at research and nonresearch universities are making decisions about majors based on different information or different criteria. One possibility is that students at nonresearch universities have lower quality information about industry demand, and so they are slower to change majors in response to changes in industry cycles. I will investigate this further using student-level data.

Robustness

For robustness, I use alternative definitions of *Exposure*. For the dot-com crash and Great Recession, I define exposed universities as those in MSAs at the 90th percentile or above in the relevant employment share (rather than employment share in the relevant sector as a continuous variable). The differences-in-differences are slightly smaller, though statistically significant for the dot-com crash (-.7 percentage points), and smaller though still not statistically significant for the Great Recession (Appendix Table A1, Appendix Figure A3).

For Delaware's finance shock, I define $Exposure_j$ in three different ways: distance between university j and Wilmington, Delaware as a continuous variable, an indicator for being within the state of Delaware, and distance within 15 and 100 miles of Wilmington, Delaware (rather than an indicator for distance within 15 miles of Wilmington). The indicator for being within Delaware includes several Delaware universities farther than 15 miles from Wilmington, for example in Delaware's capital city of Dover, and excludes several universities within 15 miles of Wilmington but outside of Delaware (for example Swarthmore College in Pennsylvania). All three of these robustness specifications show large effects on business majors after Delaware's policy (Appendix Table A3, Appendix Figure A3).[24]

[24] Using the indicator for whether the university is in Delaware, the difference-in-difference is

Finally, I estimate the principal specifications excluding universities which are 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 slightly smaller but still statistically significant effect for the dot-com crash (-.9 percentage points versus -1.1 percentage points in the main specification) (Appendix Table A11). The effect for the Great Recession is no longer negative, but still not statistically significant from zero.

Changes in major composition may be affected by changes in student composition at the university. I test whether total degrees awarded differentially changed at universities in areas more exposed to the shock. Table 2, and Appendix Figure A1, show no differential change in total degrees awarded by university's exposure to the shock.

6 Mechanisms: Information or Migration Frictions

I show universities in areas more exposed to sectoral shocks experience greater changes in sector-relevant majors. This could be explained by information or migration frictions. Students in areas more exposed to sectoral shocks may have different information about demand for sector-specific skills, and adjust their investments accordingly. Alternatively, students in areas more exposed to the shock may experience migration frictions, making local conditions more relevant.

To develop appropriate policy responses, it is necessary to identify whether the result is due to information or migration frictions. If students in non-computer areas do not respond to the dot-com crash because of poor information, policy interventions could improve their outcomes. However, if they do not respond to the crash because they want to live locally after graduation, in an area unaffected by the crash, they are already choosing the individually-optimal investment. Encouraging investments based on national demand may increase mismatch.

The previous section shows the response at nonresearch universities appears to be lagged and more persistent, which may seem consistent with these students having worse information. However, it is difficult to identify student information frictions or

4.6 percentage points. Using the continuous distance to Wilmington, the difference-in-difference is 1.2 percentage points. Excluding the universities more than 100 miles from Wilmington reduces the sample by more than 50%, but the coefficient remains large (.04 relative to .059 in the main specification). This effect is not statistically significant ($p = .118$).

migration frictions using university-level data.

In this section, I use rich, student-level data from The Freshman Survey, to develop a test for the role of information frictions, separating these from migration frictions. The intuition is straightforward. Consider two geographically mobile students at Northwestern University, which is not in a major computer employment city and over 2000 miles from San Jose (Silicon Valley). One of these students is from a major computer employment city (San Jose), while the other is not, but instead from San Diego, California (approximately 460 miles south of San Jose and also over 2000 miles from Northwestern). If students have information on national demand for computer skills, the San Jose and San Diego student at Northwestern should respond to the dot-com boom and bust similarly, since migration frictions are nonexistent for these students. However, if students in San Jose have different information about the dot-com industry because it dominates their local market, the San Jose student should respond differently than the San Diego student to the dot-com boom and bust.

Data

The CIRP Freshman Survey (TFS) is administered by the Higher Education Research Institute at the University of California, Los Angeles. Universities conduct the survey among their incoming freshmen classes, often during orientation ("CIRP" 2017). The survey contains detailed student-level data on major choice, academic, and family background. I use the 1990 through 2011 waves of TFS.

Isolating the role of information frictions from migration frictions requires identifying a group of students who are geographically mobile. Using TFS, I do this in two ways. First, the survey asks students whether they chose their university because they wanted to live near home. I include in my sample only those students who said living near home was not an important reason why they chose the university.[25]

In addition, I include only those students who attend a university at least 350 miles from their home, as this shows an additional lack of geographic migration frictions. Finally, I exclude California (Texas) universities from the sample since San Jose (Austin) students staying within the state of California (Texas) may experience migration frictions, despite attending university more than 350 miles away.[26]

[25]Other choices were a) very important and b) somewhat important.
[26]For robustness, I include these universities as well.

I then ask whether among these mobile students, those from high-computer MSAs respond differently to the dot-com boom and bust than those with homes farther from these centers, conditional on their university and other student characteristics. I focus on the two MSAs with the highest computer employment share, San Jose, CA (.259) and Austin, TX (.125). Conditional on attending the same university, not in one of these city areas, and conditional on the distance between home and university, I compare students originally from these city areas to those not from these areas. I define the city-area as ≤ 100 miles of San Jose or Austin. I use the student's zip code to calculate distance between home location and university, and distance between home location and principal cities of the top 15 computer employment MSAs.[27]

Matching Estimation Strategy

There are likely important differences in observable characteristics between students from the San Jose/Austin areas and their counterparts at the same universities. Because the linearity assumptions of OLS regressions may be problematic, I obtain estimates using the Abadie and Imbens (2011) nearest neighbor matching procedure. I match individuals from the San Jose/Austin area to individuals at the same university who are not from these areas, but who have similar observable characteristics.

To obtain the cleanest identification of information frictions, I compare San Jose/Austin students to students whose home markets are clearly not computer areas. In particular, I exclude from the sample any non-San Jose or non-Austin students whose homes are within 100 miles of the principal city of the top 15 computer employment MSAs (among those which are home MSAs for at least one student).[28] I also include only students at universities more than 100 miles from the principal cities of the top 15 computer employment MSAs. This ensures students only have information on labor demand in computer-area clusters from their home markets, and not from their

[27] Before 2001, the survey asks for the student's address, while starting in 2001 they specify they are asking for their permanent/home address. Sample sizes in Table 4 show that before 2001 there are still a significant number of students who provide the zip code for their permanent/home address (given the number of San Jose/Austin students in the sample who are studying more than 350 miles from home).

[28] These are based on share employed in computers in 2000 and include, with share employed in the computer industry in parentheses: San Jose, CA (.259); Austin, TX (.125); Nashua, NH (.121); Binghamton, NY (.102); Boise, ID (.102); Burlington, VT (.1); Raleigh, NC (.097); Santa Cruz, CA (.096); Colorado Springs, CO (.091); Huntsville, AL (.09); Fort Collins, CO (.084); San Francisco, CA (.078); Boston, MA (.075); Palm Bay, FL (.074); Dallas, TX (.066). This MSA computer employment share is calculated in the same way as described in the first part of the paper.

university markets.

I estimate the average treatment effect on the treated separately for San Jose students and their matches, and Austin students and their matches. For each of these groups, I also estimate the matching procedure separately by year bin, and compare estimates across year groups. I place years in the following groups: preboom (1990-1994), early boom (1995-1998), late boom (1999-2001), bust (2002-2006), postbust (2007-2011). While the NASDAQ fell for the first time in a dramatic way in March 2000, it did not reach its low until Fall 2002, and computer employment did not fall in a dramatic way until 2003. Focusing on the end of the boom and the early years of the bust is particularly interesting as it could highlight that some students had better information that the boom was ending. I drop individuals who attend a university without any San Jose/Austin-area students, or without any non-San Jose or non-Austin students (and thus would not be matched).

I specify exact matching on university, and additionally match on the following covariates: SAT/ACT score (ACT converted to SAT using concordance tables), parental income, year, distance between home and university, and indicators for male, black, hispanic, mother has a bachelor's degree, father has a bachelor's degree, and high school GPA was at least a B+. I adjust the estimates for bias based on imperfect matches in all of these variables, using the Abadie and Imbens (2011) procedures.

Assigning arbitrary values to missing variables, and including an indicator for the value being missing, implies individuals with missing values would be matched to each other. This makes the bias adjustment procedures in Abadie and Imbens (2011) problematic. This will also affect the weighting matrix, determining the weight placed on matching each of the covariates, if the matrix is based on the inverse standard errors of the variables. As a result, I exclude individuals with missing values of any of the covariates.

Information frictions may be lower for San Jose/Austin students because their parents are more likely to work in the computer industry. TFS includes detailed information on parents' occupation, and so I can test whether this mechanism explains most of the results. I estimate the matching procedure including only individuals for whom neither parent is a computer programmer or computer analyst. Information frictions may also be stronger for individuals from lower socioeconomic backgrounds. I estimate the matching procedure separately for students whose parents both have a bachelor's degree, and for students who have at least one parent without a bachelor's degree.

For robustness I estimate an OLS regression including in the sample only matched individuals (similar to Matsa and Miller (2013) and Goldschmidt and Schmieder (forthcoming)), and including each of the matching variables as covariates. I estimate the following regression separately for the matches with San Jose students and separately for the matches with Austin students:

$$\begin{aligned} CSmajor_{ijtg} &= \alpha + X_i\gamma + \kappa_g \\ &\quad +\delta_g Years\_g_t * HomeArea\_m \\ &\quad +u_{ijtg} \end{aligned}$$

The variable $CSmajor_{ijtg}$ is an indicator for whether individual i at university j in year t (within year group g) is planning on a computer science major. The vector X contains the matching variables listed above. The variable $Years\_g_t$ denotes whether year t is within year group g, where the year groups are as listed above. The variable $HomeArea\_m$ is an indicator for whether the individual's home is within a 100 mile radius of city m, where depending on the regression m is either San Jose, CA or Austin, TX.

Summary Statistics

Figure 5 shows the main source of identification. The solid triangles show the universities attended by San Jose students (Panel A) and Austin students (Panel B) in the matching sample. This implies these universities are more than 100 miles from the principal cities of the top 15 computer MSAs, they are more than 350 miles from the student's home, and they have at least one non-San Jose (Panel A) or non-Austin (Panel B) student.

The light squares are the homes of non-San Jose (Panel A) and non-Austin (Panel B) students in the sample attending these universities, whose home is more than 350 miles from the university. The dark dots are the homes of San Jose (Panel A) and Austin (Panel B) students attending these universities, whose home is more than 350 miles from the university. The empirical strategy compares the major choice of students whose home is located at a dark dot versus his match whose home is located at a light square, where matches are always at the same university.

Table 3 shows the top ten universities with San Jose and Austin students in the matching sample. These top ten universities include several in the Far West region of the United States (in Washington and Oregon), but also universities on the East Coast and Midwest. The top ten universities with Austin students in the sample are geographically distributed across the United States.

At universities outside the San Jose or Austin areas, the students coming from San Jose or Austin (whose university is more than 350 miles from their home) look quite similar to the set of non-San Jose/Austin students who serve as matches (Table 4). Their mothers are similarly likely to have a bachelor's degree, their parental income is roughly the same, their SAT/ACT scores are very similar, and their HS GPA is equally likely to be above a B+. The percent of matched pairs with these covariates matching exactly is near 100% for most variables. Not surprisingly, we see differences in the probability that one of the parents' occupation is a computer programmer or analyst. I test whether this explains the results.

Kernel-weighted local polynomial regressions show that at non-San Jose universities, San Jose students' choice of computer science majors responds quite similarly to the boom and bust as their counterparts at the same set of universities (Figure 6a). This suggests that information frictions are not prevalent among this set of geographically mobile students. Austin students are initially less likely to major in computer science than their counterparts, but they respond more to the boom. By the end of the 1990s, they are more likely to be majoring in computer science than their counterparts. (Figure 7a). These plots are not utilizing within-pair comparisons and do not show confidence intervals, which will be the focus of the matching estimation.

Results

The matching results show that San Jose students appear to respond to the dot-com boom and bust similarly to their matched counterparts at the same university. For the full sample the differential response in each period is not significant from zero, and not statistically significantly different from the difference in the pre-boom period (column 1). Column 2 excludes individuals with at least one parent who is a computer programmer or analyst, which has little effect on the results.

Columns 3 and 4 show suggestive evidence of heterogeneity by whether both parents have a bachelor's degree (Column 3) and whether at least one parent does not have a bachelor's degree (Column 4). Among those with at least one parent without a bachelor's degree, the response to the latter period of the boom is larger in magnitude than for those whose parents both have a bachelor's degree. However, the effect is not significant relative to the pre-boom period, nor significantly different from the effect among students whose parents both have bachelor's degrees. The magnitude suggests information frictions may be more important for those whose parents have fewer years of education. Despite this heterogeneity, there is not strong evidence that information frictions exist during the period of the dot-com boom.

Among those whose parents both have bachelor's degrees, the positive differential responses of San Jose students in the bust and post-bust period are statistically significantly different from the negative pre-boom difference. This suggests their information may prevent them from overreacting to the bust, conditional on being geographically mobile.

The differential response of Austin students during the boom and bust periods are not statistically significant from the pre-boom difference (Panel B). Removing those whose parents work in the computer industry has little effect on the results. Similar to Panel A, the differential effects are larger among those for whom at least one parent does not have a bachelor's degree. Appendix Table A6 shows similar results from OLS regressions among the matched pairs.

In sum, these results suggest little evidence of information frictions among geographically mobile students at universities in non-computer areas. This suggests the muted response to the dot-com crash at these universities is explained by their less geographically mobile students. More specifically, the muted response could be attributed to migration frictions, if the lack of geographically-driven information frictions among mobile students implies the same for less mobile students.

To be concrete, I find that for two geographically mobile students at the same university whose parents have the same education level, and the same income, home distance to San Jose does not affect their likelihood of majoring in computer science, implying it does not affect their information. I think this reasonably implies that for two less mobile students at the same university whose parents both have the same education level, and the same income, home distance to San Jose does not affect their information (though it will affect willingness to move to San Jose). Of course it is possible that the relationship between distance to San Jose and information varies with student characteristics (such as parental education), and these may be correlated with geographic mobility. Isolating the effect of distance on information for less geographically mobile students is difficult, given that for these students distance may affect computer science degrees through both information and migration frictions.

I next compare geographically mobile and less mobile students, continuing to match on variables that control for general information quality. These comparisons do not guarantee identification of migration frictions, for the reasons described above. However, they do provide important evidence on whether the results are consistent with migration frictions, and whether migration frictions may explain muted responses at less-exposed universities.

The Response of Less-Geographically Mobile Students

I develop two alternative tests. First, I compare the geographically mobile students from San Jose/Austin to less geographically mobile students at the same universities. Specifically, I compare students from San Jose/Austin whose home is more than 350 miles from their university to students at the same university whose home is less than or equal to 150 miles from the university.[29] I infer lower levels of geographic mobility if students choose universities closer to home. Appendix Figure A10 shows the home and university locations for individuals in this sample. Because these students are staying closer to home for university, migration frictions may be stronger for them. Because their home is a significant distance from San Jose or Austin, these migration frictions may imply they respond less to the dot-com boom and bust. Appendix Table A8 gives sample sizes by home location and year group.

Figure 6b shows that these less geographically mobile students respond less to the dot-com boom and bust than their geographically mobile counterparts from San Jose at the same set of universities. Figure 7b shows a smaller difference between Austin students and their less geographically mobile counterparts, although the Austin students appear to respond slightly more to the boom and considerably more to the bust. Appendix Table A7 shows this greater response of the San Jose/Austin students is also evident in the matching procedure, and Appendix Table A6 shows similar results based on the regression estimation. However, the difference in these effects relative to the pre-boom period is not statistically significant.

Second, I compare less geographically mobile students from San Jose/Austin to less geographically mobile students from other areas at the same university. Specif-

[29]When analyzing less geographically mobile students I continue to include only those responding that living near home was not an important reason why they chose their university. I identify less geographically mobile students only through the distance of their university from home.

ically, I compare students from San Jose/Austin whose home is 100-350 miles from their university to students at the same university from other areas whose home is also 100-350 miles from the university. Appendix Figure A11 shows the home and university locations for individuals in the sample. Appendix Table 8 gives sample sizes by home location and year group.

If information about demand changes with distance to San Jose/Austin even among students whose homes are more than 100 miles from these cities, information frictions may be lower in this exercise compared to the principal results. This would work in the opposite direction of the migration frictions, and imply a smaller difference between San Jose/Austin students and their counterparts in this exercise.

Figure 6c shows the San Jose students respond much more to the dot-com boom and bust than their counterparts at the same universities. Figure 7c does not show this pattern for Austin students, though the sample sizes are quite small. Appendix Table A7 shows the greater response of the San Jose students in the matching estimation, and Appendix Table A6 shows similar results in the regression estimation, statistically significant relative to the pre-boom period. There is also some evidence of a stronger response of the Austin students to the late boom relative to the early boom (not statistically significant).

Finally, the matching and OLS results using the principal matching sample are robust to including California and Texas universities (Appendix Tables A6 and A7). Consistent with including students who may be less geographically mobile there is some limited evidence of a slightly stronger response to the early years of the boom among San Jose students.

7 Selection out of STEM into Business

Finally, I use the finance shock in Delaware to address the policy-relevant question of selection out of STEM majors and into business. As Delaware is home to a historically important chemicals sector (including DuPont's headquarters), this shock is particularly relevant for studying substitution between STEM and finance. I test whether increases in business majors after Delaware's legislation came at the expense of science majors. Further, I study whether science loses its high- or low-achieving students to business.

There are sharp declines in the share of science majors at Wilmington-area universities after the shock, evident in both the parametric and nonparametric specifications (Appendix Figure A7, Appendix Table A4). Column 2 of Appendix Table A4 shows a differential increase in the share of science degrees for freshmen in the year of the first policy-induced acquisition in Delaware (row 2). However, in each additional year after the legislation, Wilmington-area universities experienced a differential .8 percentage point decrease in the share of science degrees awarded (row 3).

Based on the coefficients in column 2, this difference-in-difference (given by the same formula as in Section 4) is -5 percentage points. In 1990, on average 19% of degrees awarded are in science, among universities within 15 miles of Wilmington, Delaware (author's calculation). Thus, universities within 15 miles of Wilmington experience an additional $5/(19+5) = 21\%$ decrease in science degrees awarded.[30]

Next, I test the nature of the substitution between science and business using student-level data from The Freshman Survey.[31] I refer to students with a high school GPA of at least a B+ as high GPA students. I estimate a specification similar to Shu (2016), identifying whether share of high GPA students in the major increases or decreases as more students shift into the major.[32] Specifically, I estimate separately for science and business majors:

$$\begin{aligned} HighGPA_{cft} &= \alpha + \beta_1 S + \beta_2 S * Post1 + \beta_3 S * Post1 * Exp \\ &\quad + \beta_4 S * Post2 + \beta_5 S * Post2 * Exp + u \end{aligned} \tag{3}$$

Regression (3) also includes all lower-level interaction terms. The variable $HighGPA_{cft}$ denotes the share of students with high school GPA of at least a B+ in major f at university c in year t. The variable S denotes the share of students at university c in major f in year t. The variable $Post1$ is an indicator for the years immediately following the policy, 1981-1984, while $Post2$ indicates years from 1985 through 1987.

[30] Appendix Table A4 and Appendix Figure A7 show regression results for each group of majors.

[31] Appendix Figure A9 shows sample sizes by distance to Wilmington, Delaware for this analysis.

[32] I also study whether the Delaware shock changed overall composition of students at Wilmington-area universities. I find Wilmington-area universities experienced additional increases in the proportion of nonlocal students, and decreases in the likelihood that students had HS GPA $\geq B+$ (Appendix Table A5, Appendix Figure A8).

The variable Exp indicates whether university c is within 15 miles of Wilmington, DE.[33]

The coefficient β_3 indicates whether post-policy increases in business majors at Wilmington-area universities positively or negatively affect share of high GPA students in the major, relative to pre-policy increases in business majors. If increases in business majors result in lower share of high GPA students in the major, this implies that lower GPA students substitute into business after the policy.

In 1982, there is a large one-year drop in the the number of students at Wilmington-area universities responding to The Freshman Survey.[34] Because this may imply sample selection issues, I exclude this year from the sample.

As an alternative specification, I simply compare the change in the share of high GPA students in the major at Wilmington-area universities relative to the five years preceding the policy, and relative to farther universities. Since this specification is not looking at the effect of changes in the share of business majors, but instead measuring changes in the average high GPA share between the pre- and post-policy period, including 1981 as a post-policy year may yield misleading results. It is unlikely that there were any significant changes in business majors in the year of the policy, and so it is less reasonable to include this year in the average. In this alternative specification, I define the post period as 1983-1984. Similarly, since I am comparing averages of the dependent variable, I compare only to the five years preceding the policy (including a separate indicator for years earlier than that).

Following Delaware's legislation, an increase in the share of business majors has a much more negative effect on share of high GPA students in the major at Wilmington-area universities relative to farther universities (Table 6, column 1, row 3). This suggests differential substitution of low GPA students into business majors at Wilmington-area universities immediately after the policy. The magnitude of the coefficient is smaller in the second post-policy period of 1985-1987 (row 5). The negative coefficient on $S * Post1 * Exp$ in column (2) also suggests that following Delaware's legislation, a decrease in the share of science majors has a more positive effect on share of high GPA students in the major at Wilmington area-universities relative to farther universities. This suggests that after the policy, low GPA students are moving

[33] For robustness, I include indicators for an earlier period, so that I estimate differences only relative to the years immediately preceding the policy.

[34] In 1981, there were 3076 respondents, in 1982 there were 1894, and from 1983 to 1987 there were above 3000 respondents.

from science into business at Wilmington-area universities. While the coefficient is not statistically significant, we cannot rule out large effects.[35]

The coefficients in columns (3) and (4), row (8) show that the share of high GPA students in business majors is lower at Wilmington-area universities immediately after the policy, and higher in science majors. The coefficients are not statistically significant, but the magnitudes are nontrivial. Appendix Table A9 shows generally larger effects when including only University of Delaware as the university with $Exp = 1$ (excluding Swarthmore College), and similar effects when estimating the effect of differential changes in S just relative to the years immediately preceding the policy.

In sum, the results suggest that immediately after Delaware's policy, low GPA students left science for business. This is consistent with other findings that science is not losing its brightest students to finance (Boehm, Metzger, and Stromberg 2015; Shu 2016).

8 Conclusion

This paper tests for the empirical relevance of one potential determinant of skills mismatch: human capital investment based on local rather than national demand. Specifically, I test for changing composition of majors at local universities after a sector-specific local labor demand shock. I further test whether the local elasticity is explained by information or migration frictions. I analyze three sector-specific shocks with local effects: the 2000 dot-com crash, the 2008 financial crisis, and the shock making Delaware an international financial headquarters.

Using university-level data on degree completions by academic discipline from 1966 through 2013, event-study analyses show universities in areas more exposed to sectoral shocks experience greater changes in sector-relevant majors. Sophomores through seniors at the shock's onset do not respond to these local shocks, implying potentially very adverse effects for these students. Large immediate responses are reversed by five years after the shock, suggesting students may have overestimated the size or duration of the shock. Alternatively, they may have understood that poor initial placement would have long-run effects. Nonresearch universities respond to these shocks with a greater lag.

[35] Appendix Table A10 show results from these regressions for each major.

Universities in low computer-share areas may be less affected by these shocks because their students experience migration or information frictions. Identifying which of these frictions explains the result is necessary for developing appropriate policy responses. Using rich student-level data from The Freshman Survey, I am able to isolate the impact of information frictions on major choice by focusing on students who do not experience migration frictions. Using a nearest-neighbor matching procedure, I find geographically mobile students from San Jose, CA and Austin, TX respond similarly to the dot-com boom and bust as their matched counterparts at the same university. This suggests that non-San Jose and non-Austin students do not experience information frictions given their home market is not in a computer-industry cluster. I find greater differences in the response to the dot-com boom and bust when comparing less geographically mobile students, consistent with the role of migration frictions.

The results imply investing in human capital based on local labor demand may yield mismatch between aggregate supply of skills and aggregate demand. In addition, this local dependence may affect aggregate productivity if individuals are not matched to the job in which they are most productive. However, given this local dependence is not caused by information, but more likely migration frictions, policies encouraging human capital investments based on national demand may increase mismatch. These policies may cause students to invest in areas not demanded locally, which is their relevant market given migration frictions.

Finally, the case of jurisdictional competition in Delaware provides a unique opportunity to study selection out of STEM majors by student achievement. I find suggestive evidence that immediately after the policy, low GPA students at Wilmington-area universities left science for business.

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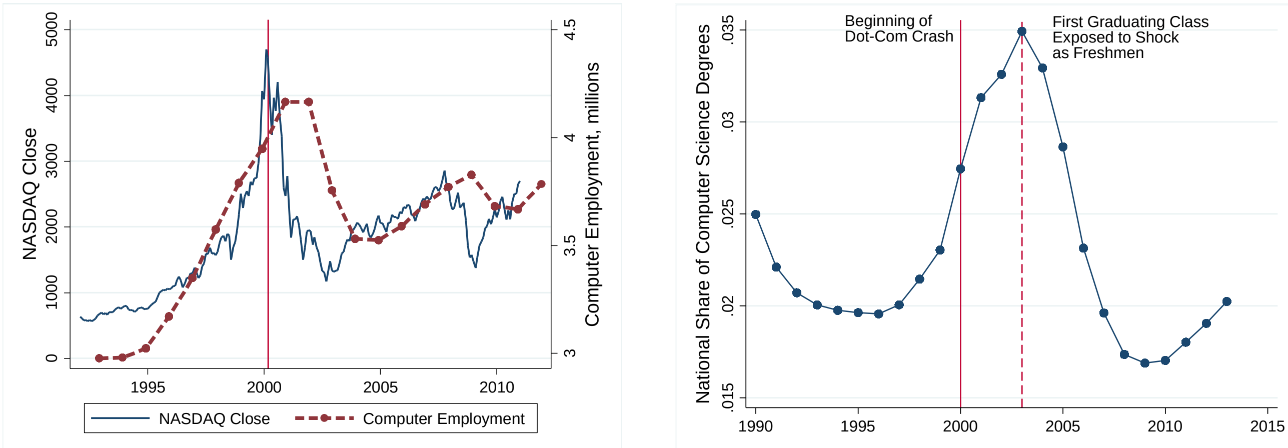
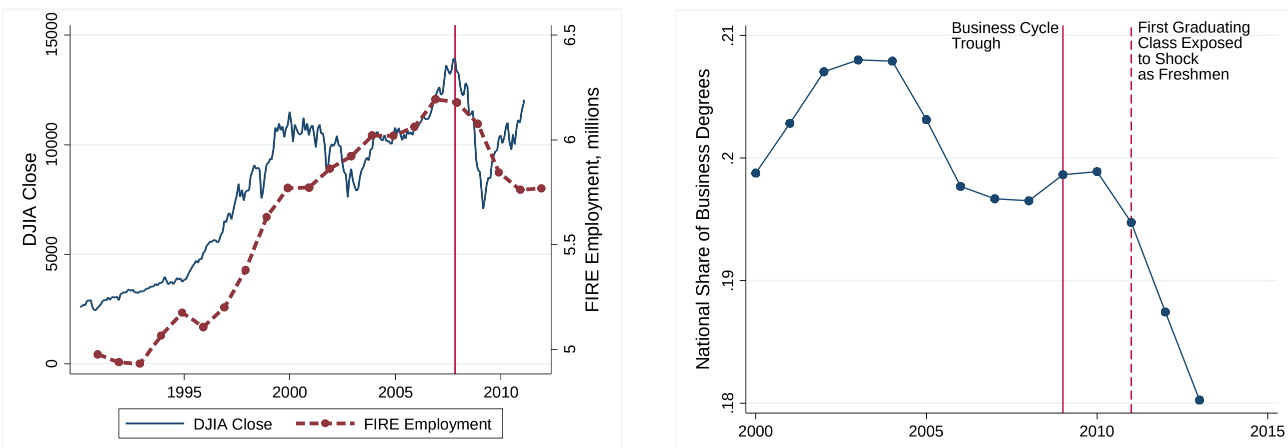
Figure 1: Sector-level Shocks and College Majors in the US

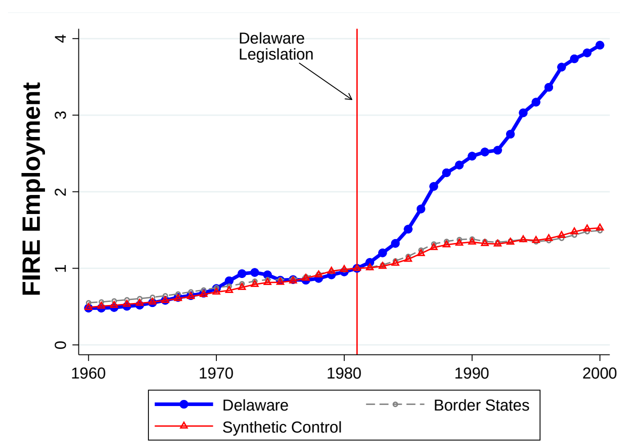
(a) Dot-Com Crash, Computer Employment, and Computer Science Majors



(b) 2008 Financial Crisis, FIRE Employment, and Business Majors



(c) Jurisdictional Competition: Finance Shock in Delaware

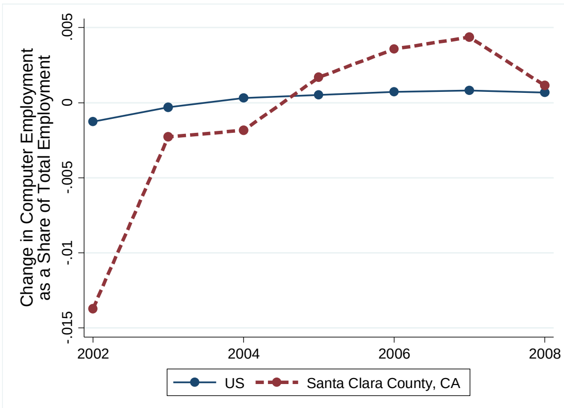


Note: Source for the data on the NASDAQ closing prices: http://www.nasdaq.com/symbol/ixic/interactive-chart, Date accessed: 3/11/2016. Source for DJIA closing prices: https://www.nyse.com/quote/index/!DJI, Date accessed 3/15/2016. Source for national employment data: CES. Computer employment includes employment in the following industries: 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)). Source for plot (c) is Weinstein (2017a). See text for details.

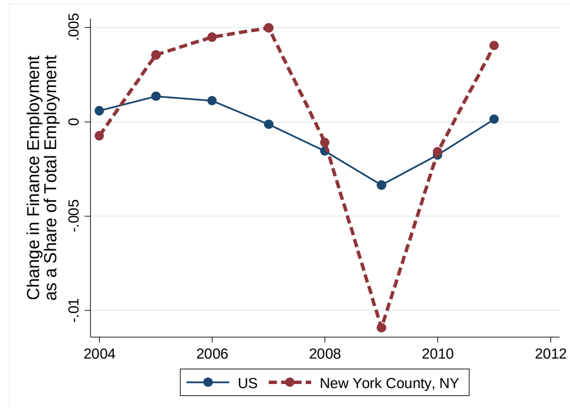
Figure 2: Local Shocks and Local Universities

Differential Local Effects of National Shocks

(a) Dot-Com Crash

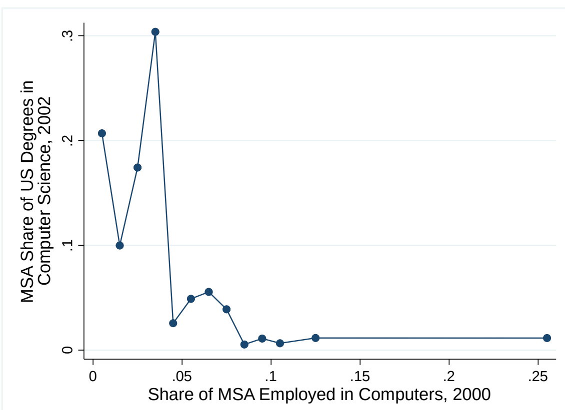


(b) Financial Crisis

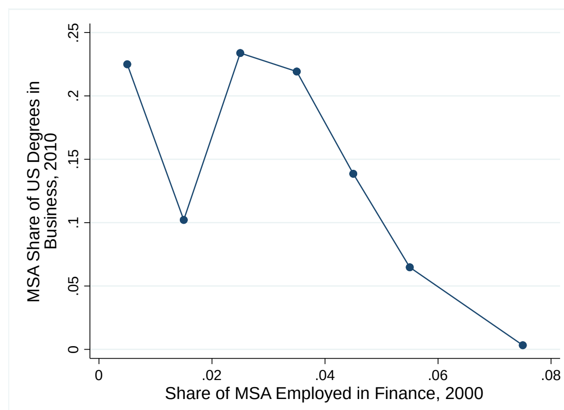


Share of US Degrees in Computer Science and Business, by MSA Employment Share

(c) Computer Science Majors, 2002



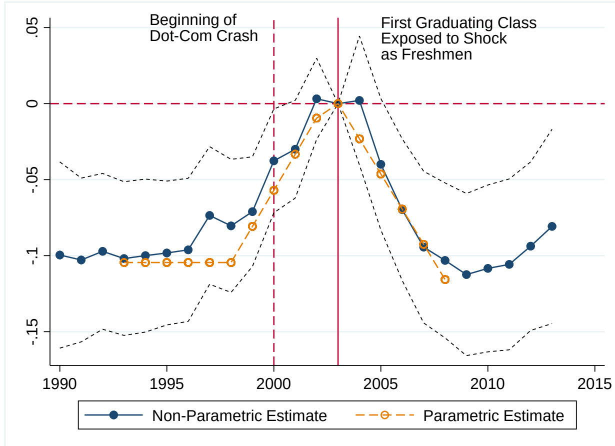
(d) Business Majors, 2010



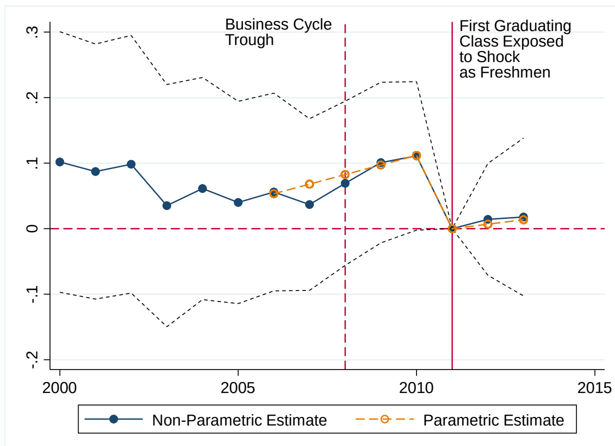
Note: Employment data in Figures 2a and 2b are based on private-sector employment from the Quarterly Census of Employment and Wages. Computer Employment is defined in Figure 2a as "Computer Systems Design and Related Services." Finance employment in Figure 2b is employment in "Financial Activities." Figures 2c and 2d are the total computer (2c) and business (2d) degrees awarded in the MSA group in the year divided by the total of these degrees awarded in the US. Degrees awarded are measured in the year preceding the first year the graduating class were exposed to the shock as freshmen. MSA groups start at zero, and are in intervals of .01. See text for details.

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

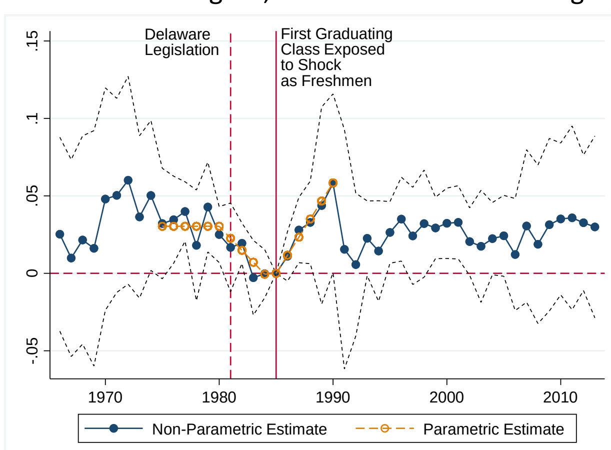
(a) Effect of MSA Computer Employment Share on Share Computer Science Degrees, Relative to 2003



(b) Effect of MSA Finance Employment Share on Share Business Degrees, Relative to 2011



(c) Effect of Being within 15 Miles of Wilmington, DE on Share Business Degrees, Relative to 1985

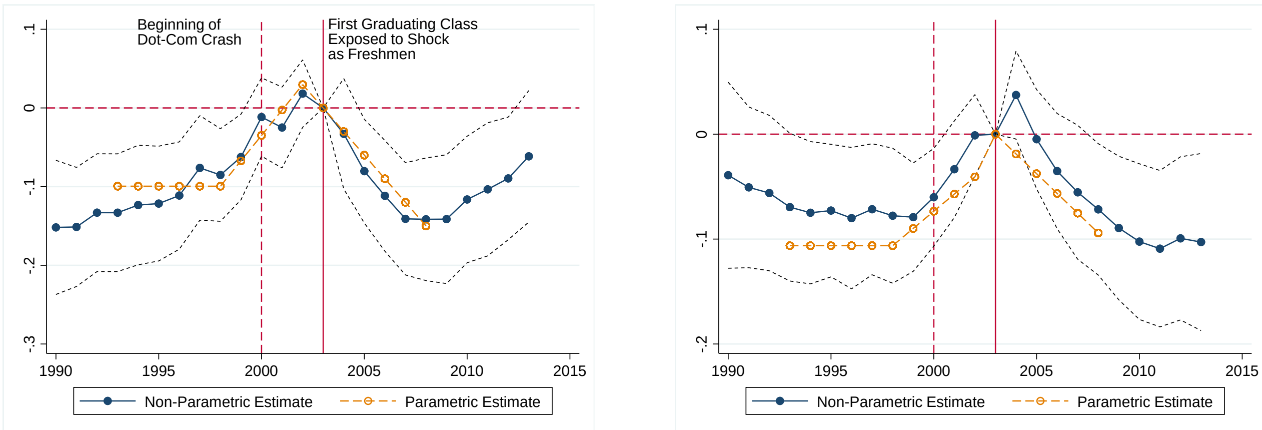


Note: Closed circles show interaction between year fixed effects and university's geographic exposure to the shock (MSA computer employment share in (a), MSA finance employment share*(MSA 2007 unemployment rate – MSA 2009 unemployment rate) in (b), and university within 15 miles of Wilmington, DE in (c)). Dotted lines are 95% confidence intervals for these coefficients. These regressions also include year fixed effects, university fixed effects, total degrees, and lower-level interaction terms. 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). Fitted values are relative to the value in the first treated year. The parametric regressions also include university fixed effects, and the relevant combinations of the interacted variables.

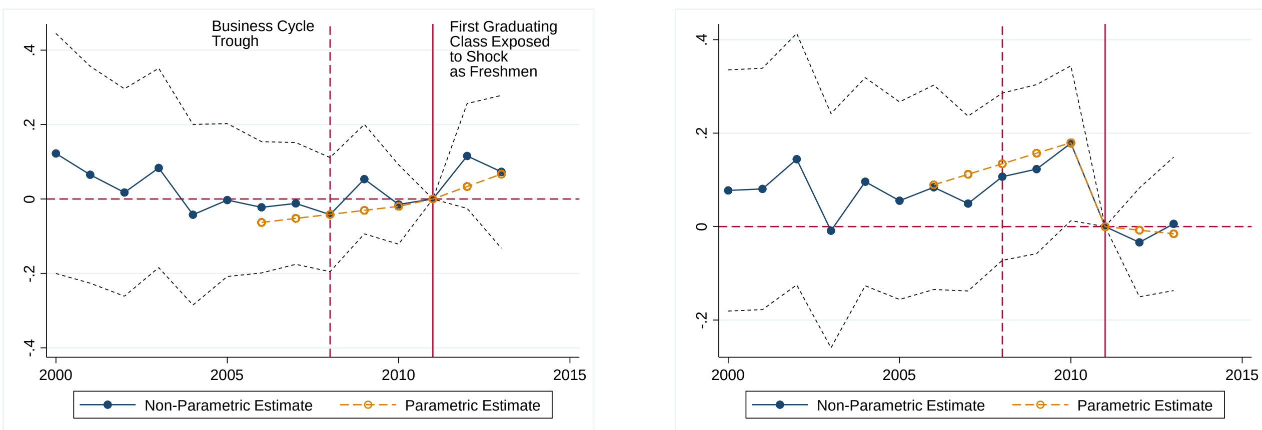
Figure 4: The Effect of Sectoral Shocks on Universities, by Geographic Exposure to the Shock and University Type

Research/Doctoral Universities | Master's/Baccalaureate Universities

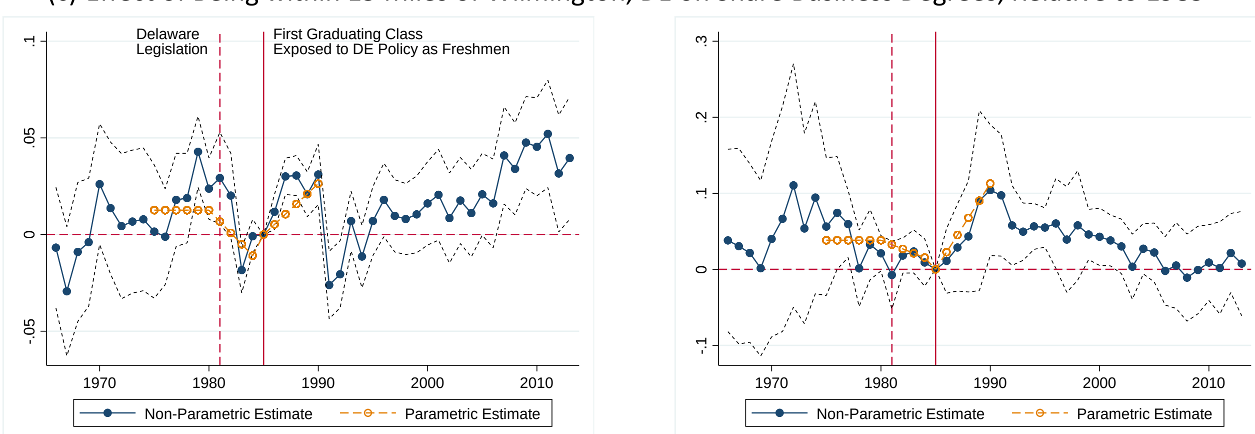
(a) Effect of MSA Computer Employment Share on Share Computer Science Degrees, Relative to 2003



(b) Effect of MSA Finance Employment Share on Share Business Degrees, Relative to 2011



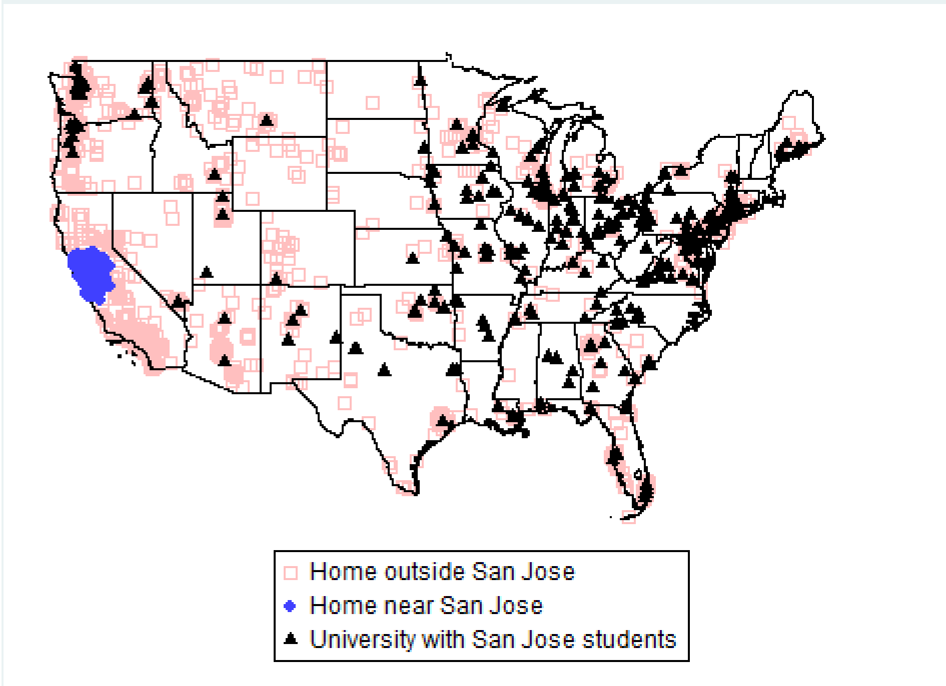
(c) Effect of Being within 15 Miles of Wilmington, DE on Share Business Degrees, Relative to 1985



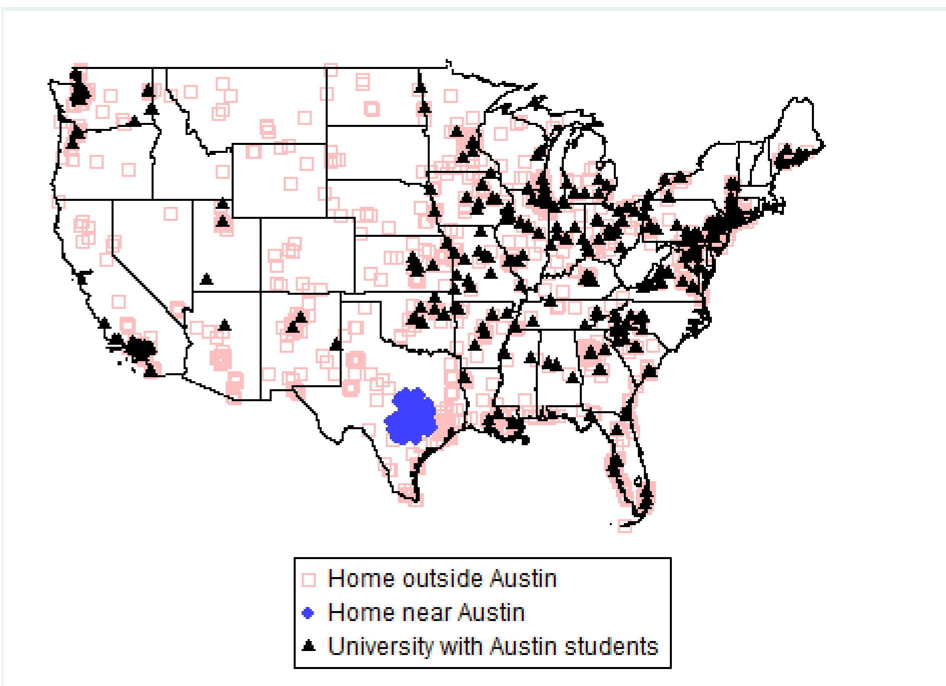
Note: Plots are the same as those described in Figure 3, but with regressions estimated separately for research/doctoral universities and master's/baccalaureate universities. University classifications are based on 1994 Carnegie rating.

Figure 5

Panel A: Home and University Locations of Geographically Mobile San Jose Students and Matched Counterparts

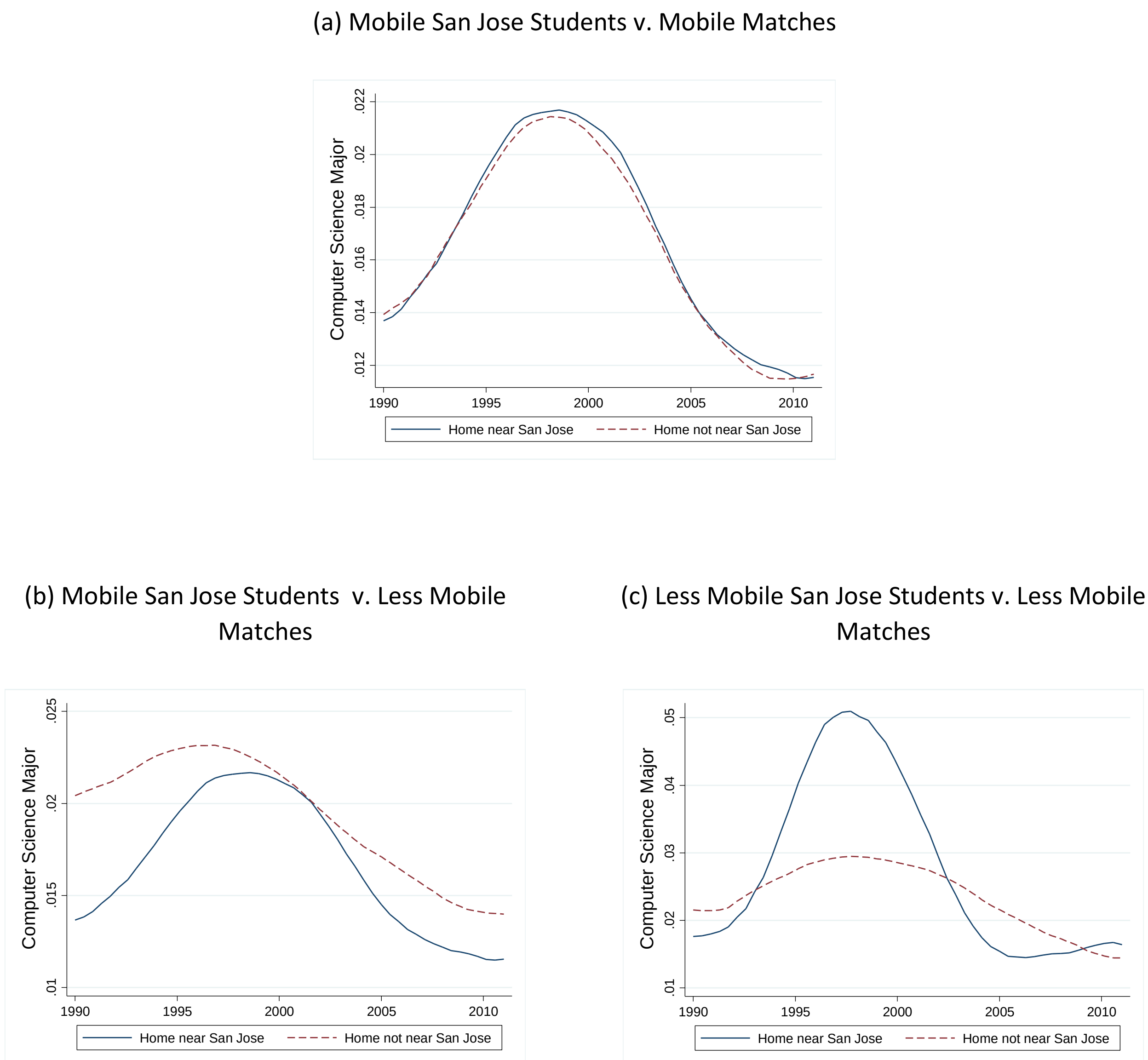


Panel B: Home and University Locations of Geographically Mobile Austin Students and Matched Counterparts



Note: This figure shows the universities (in black triangles) outside California (Panel A) or Texas (Panel B), and outside a 100 mile radius of any of the principal cities of the top 15 computer employment MSAs, with at least one San Jose (Austin) and non-San Jose (non-Austin) student in the matching sample (during the years of the dot-com bust). To be included in the matching sample, both the San Jose (Austin) student and their match must be at the same university, and their homes must be more than 350 miles from the university. The figure also shows the home locations of the San Jose and Austin students in the matching sample, and their matched counterparts. The dark circles represent these students whose homes are less than or equal to 100 miles from San Jose or Austin. The light squares represent these students whose homes are more than 100 miles from San Jose or Austin, and also more than 100 miles from any of the principal cities of the top 15 computer employment MSAs. See text for details.

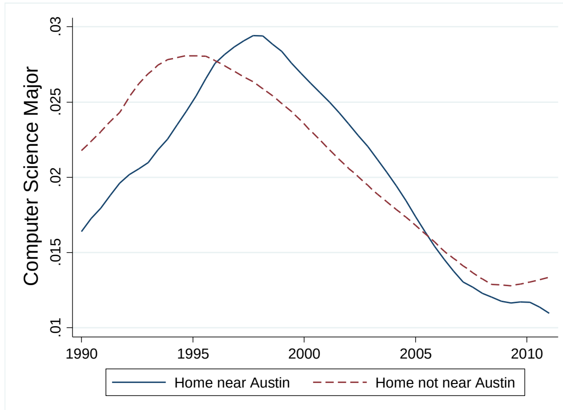
Figure 6 Computer Science Majors and the Dot-Com Boom and Bust, San Jose Students Relative to Matches



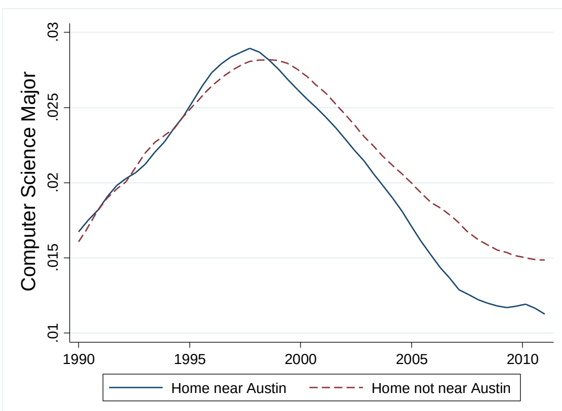
Note: The plots are the result of kernel-weighted local polynomial regressions of whether the student's intended major is computer science on year. I estimate these local polynomial regressions separately for San Jose students and their matches. Figure (a) includes individuals in the main matching sample: students whose home is within 100 miles of San Jose at universities more than 350 miles from their home (and outside California and outside a 100 mile radius of any of the principal cities of the top 15 computer employment MSAs). Matches are students at the same universities, whose home is not within 100 miles of San Jose or any principal city of the top 15 computer employment MSAs, and whose home is also more than 350 miles from the university. Figure (b) includes the San Jose students with the same criteria as for (a), but matches are students at the same universities whose home is ≤ 150 miles from the university. Figure (c) includes students whose home is within 100 miles of San Jose at universities 100-350 miles from their home (but outside a 100 mile radius of San Jose and any of the principal cities of the top 15 computer employment MSAs). Matches are students at the same universities whose home is also 100-350 miles from the university, but outside a 100 mile radius of San Jose or any of the principal cities of the top 15 computer employment MSAs.

Figure 7 Computer Science Majors and the Dot-Com Boom and Bust, Austin Students Relative to Matches

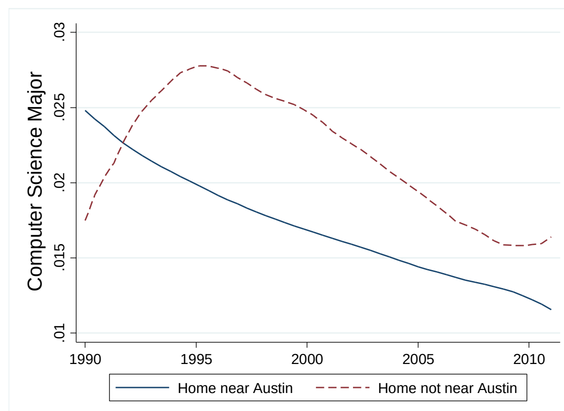
(a) Mobile Austin Students v. Mobile Matches



(b) Mobile Austin Students v. Less Mobile Matches



(c) Less Mobile Austin Students v. Less Mobile Matches



Note: The plots are the result of kernel-weighted local polynomial regressions of whether the student's intended major is computer science on year. I estimate these local polynomial regressions separately for Austin students and their matches. Figure (a) includes individuals in the main matching sample: students whose home is within 100 miles of Austin at universities more than 350 miles from their home (and outside Texas and outside a 100 mile radius of any of the principal cities of the top 15 computer employment MSAs). Matches are students at the same universities, whose home is not within 100 miles of Austin or any principal city of the top 15 computer employment MSAs, and whose home is also more than 350 miles from the university. Figure (b) includes the Austin students with the same criteria as for (a), but matches are students at the same universities whose home is ≤ 150 miles from the university. Figure (c) includes students whose home is within 100 miles of Austin at universities 100-350 miles from their home (but outside a 100 mile radius of Austin and any of the principal cities of the top 15 computer employment MSAs). Matches are students at the same universities whose home is also 100-350 miles from the university, but outside a 100 mile radius of Austin or any of the principal cities of the top 15 computer employment MSAs.

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

		(1)	(2)	(3)
	Y_{cmt}: Share of Majors in	CS	Business	Business
(1)	Post	-0.001	0.006	-0.028***
		(0.001)	(0.008)	(0.005)
(2)	Post*Exposure	-0.014	-0.126*	0.008
		(0.026)	(0.065)	(0.018)
(3)	Post*Exposure*Years Elapsed	-0.047***	-0.008	0.019***
		(0.011)	(0.031)	(0.006)
(4)	Post*Years Elapsed	-0.006***	-0.007*	-0.019***
		(0.000)	(0.004)	(0.002)
(5)	Exposure*Years Elapsed	0.024***	0.015	-0.008*
		(0.006)	(0.014)	(0.004)
(6)	Years Elapsed	0.003***	0.000	0.020***
		(0.000)	(0.001)	(0.002)
(7)	Difference-in-Difference	-0.011***	-0.00491	0.059**
	(Combination of (2), (3), and (5))	(.004)	(.005)	(.025)
	Shock	Dot-Com	Great Recession	Delaware
	Observations	20,988	9,942	3,381
	R-squared	0.745	0.953	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 ≥ year in which graduates were freshmen at the shock's onset (2003 in column 1, 2011 in column 2, and 1985 in column 3). 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 equals the share of the university's MSA employed in finance in 2000 interacted with (2007 MSA Unemployment Rate - 2009 MSA Unemployment Rate). Lower-level interaction terms are also included, and shown in Appendix Table A12. In column 3, 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. In column 1, the difference-in-difference equals $.1(\beta_{Post*Exposure} + 5*\beta_{Post*Exposure*Years\ Elapsed} + 6*\beta_{Exposure*Years\ Elapsed})$. In column 2, $.05(\beta_{Post*Exposure} + 2*\beta_{Post*Exposure*Years\ Elapsed} + 3*\beta_{Exposure*Years\ Elapsed})$. In column 3, $(\beta_{Post*Exposure} + 5*\beta_{Post*Exposure*Years\ Elapsed} + 6*\beta_{Exposure*Years\ Elapsed})$. 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.

Table 2: The Effect of Sectoral Shocks on Total Degrees, by University's Exposure to the Shock

	Y_{cmt}: Total Degrees Awarded	(1)	(2)	(3)
(1)	Post	0.019***	0.022	-0.016*
		(0.006)	(0.018)	(0.009)
(2)	Post*Exposure	0.108	-0.002	-0.078***
		(0.125)	(0.152)	(0.026)
(3)	Post*Exposure*Years Elapsed	0.043	-0.097	-0.023*
		(0.054)	(0.213)	(0.013)
(4)	Post*Years Elapsed	-0.007***	0.026*	0.011**
		(0.003)	(0.014)	(0.005)
(5)	Exposure*Years Elapsed	-0.007	0.025	0.024
		(0.043)	(0.085)	(0.016)
(6)	Years Elapsed	0.030***	0.008	0.005
		(0.002)	(0.006)	(0.004)
(7)	Difference-in-Difference	0.0281	-0.00599	-0.050
	(Combination of (2), (3), and (5))	(.022)	(.019)	(.037)
	Shock	Dot-Com	Great Recession	Delaware
	Observations	20,988	9,942	3,381
	R-squared	0.987	0.992	0.985

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. See notes to Table 1 for definition of variables, and construction of difference-in-difference. 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.

Table 3: Universities in Non-Computer Areas with San Jose or Austin Students

Panel A: Top Ten Universities for San Jose Students

University	City	# San Jose Students	University's Share of the San Jose Students
University of Puget Sound	Tacoma, WA	194	0.04
US Naval Academy	Annapolis, MD	146	0.03
Gonzaga University	Spokane, WA	144	0.03
New York University	New York, NY	143	0.03
Northwestern University	Evanston, IL	136	0.03
Oberlin College	Oberlin, OH	136	0.03
Lewis & Clark College	Portland, OR	134	0.03
University of Pennsylvania	Philadelphia, PA	125	0.03
Carnegie Mellon University	Pittsburgh, PA	116	0.03
Reed College	Portland, OR	104	0.02
University of Notre Dame	South Bend, IN	104	0.02

Panel B: Top Ten Universities for Austin Students

University	City	# Austin Students	University's Share of the Austin Students
University of Notre Dame	Notre Dame, IN	88	0.09
US Naval Academy	Annapolis, MD	77	0.08
Rhodes College	Memphis, TN	57	0.06
Northwestern University	Evanston, IL	39	0.04
Tulane University	New Orleans, LA	35	0.04
University of Southern California	Los Angeles, CA	29	0.03
Pepperdine University	Malibu, CA	29	0.03
New York University	New York, NY	27	0.03
Johns Hopkins University	Baltimore, MD	24	0.02
University of Arkansas	Fayetteville, AR	24	0.02

Note: This table gives the universities with the greatest number of San Jose and Austin area students in the principal matching sample (among students during the years of the dot-com bust). Inclusion in the matching sample implies the student's university is not within 100 miles of the principal city of any of the top 15 MSAs by computer employment share, and not in the state of California (Panel A) or Texas (Panel B). Students in the matching sample must also be attending universities more than 350 miles from their home. The last column gives the university's percent of the San Jose or Austin students in the matching sample.

Table 4: Summary Statistics for Matched Students whose University is > 350 Miles from Home

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	Home in San Jose			Home in Austin		
	No	Yes	% Matching	No	Yes	% Matching
Male	0.43	0.43	97%	0.46	0.47	97%
	[.5]	[.49]		[.5]	[.5]	
Mother has Bachelor's	0.74	0.76	99%	0.74	0.74	98%
	[.44]	[.43]		[.44]	[.44]	
Parental Income	131,674	141,232	81% ≤ 50,000	118,195	119,640	85% ≤ 50,000
	[82,193]	[82,738]	55% ≤ 20,000	[77,514]	[79,810]	57% ≤ 20,000
Parent in Computers	0.05	0.06	N/A	0.03	0.07	N/A
	[.21]	[.23]		[.18]	[.26]	
Black	0.07	0.07	100%	0.05	0.05	100%
	[.25]	[.26]		[.23]	[.23]	
Hispanic	0.03	0.03	100%	0.1	0.12	99%
	[.18]	[.17]		[.31]	[.33]	
Distance Between	1644.67	1826.02	85% ≤ 500	978.57	1075.11	83% ≤ 500
Home, University	[692.74]	[746.78]	65% ≤ 200	[454.82]	[367.84]	47% ≤ 200
HS GPA ≥ B+	0.8	0.79	100%	0.91	0.9	99%
	[.4]	[.4]		0.29	0.3	
SAT/ACT Score	1267.64	1276.01	82% ≤ 100	1257.16	1259.76	83% ≤ 100
	[161.3]	[169.23]		[154.23]	[162.48]	
N	3,581	4,560		1,641	1,748	

Panel B: Number of Matched Students by Home Location and Year Group

	Home in San Jose, CA		Home in Austin, TX	
	No	Yes	No	Yes
Pre Boom (1990-1994)	1,713	2,094	697	741
Early Boom (1995-1998)	2,305	2,861	919	960
Late Boom (1999-2001)	1,949	2,438	923	994
Bust (2002-2006)	3,581	4,560	1,641	1,748
Post-Bust (2007-2011)	3,309	4,383	1,320	1,393

Note: This table contains summary statistics for students in the principal matching sample during the years of the dot-com bust (2002-2006) whose home is ≤ 100 miles from San Jose, CA (Column 1) or Austin, TX (Column 3), and matched students whose home is more than 100 miles from San Jose/Austin and the principal cities of the top 15 computer employment MSAs. The sample is limited to students whose university is more than 350 miles from their home, and who are attending a university outside a 100 mile radius of the principal cities of the top 15 computer employment MSAs. Columns (1) and (2) also exclude students at universities in California, while columns (4) and (5) exclude students at universities in Texas. Columns (3) and (6) give the percent of matched pairs that match perfectly on the given variable, or within a given range. Panel B gives the number of San Jose (Austin) students and their counterparts in the main matching sample. See text for details.

Table 5 The Dot-Com Crash and Computer Science Majors: Differential Effects by Home Location, Matching Estimation

Y = CS Major	(1)	(2)	(3)	(4)
Average Treatment Effect on Treated: Home within 100 miles of San Jose, CA				
Pre Boom (1990-1994)	-0.0005	-0.005	-0.011	0.004
	(.004)	(.005)	(.007)	(.008)
Early Boom (1995-1998)	0.0004	0.002	0.003	0.003
	(.004)	(.004)	(.005)	(.007)
Late Boom (1999-2001)	-0.002	-0.003	-0.01	0.013
	(.005)	(.006)	(.007)	(.009)
Bust (2002-2006)	0.002	0.005	0.008**	-0.001
	(.003)	(.004)	(.005)	(.007)
Post-Bust (2007-2011)	0.001	-0.002	0.006**	-0.015
	(.002)	(.004)	(.004)	(.01)
Average Treatment Effect on Treated: Home within 100 miles of Austin, TX				
Pre Boom (1990-1994)	-0.007	-0.006	-0.003	-0.011
	(.008)	(.008)	(.007)	(.015)
Early Boom (1995-1998)	-0.007	-0.006	-0.012	0.003
	(.008)	(.008)	(.01)	(.012)
Late Boom (1999-2001)	0.004	0.003	0.004	0.007
	(.009)	(.009)	(.011)	(.015)
Bust (2002-2006)	0.003	0.004	0.005	0.001
	(.004)	(.004)	(.005)	(.007)
Post-Bust (2007-2011)	-0.004	-0.006	-0.011	0.005
	(.004)	(.005)	(.005)	(.008)
Parent Occ.	All	≠ CS	≠ CS	≠ CS
Parent Ed.	All	All	Both BA	≤ 1 BA

Note: *** p<0.01, ** p<0.05, * p<0.1. This table presents matching estimates, where the treatment is whether the home is within 100 miles of San Jose, CA (Panel A) or Austin, TX (Panel B). Each coefficient is from a separate estimation, where the outcome is an indicator for whether the student is a computer science major. I limit the sample to individuals with nonmissing values for each of the matching variables, and whose home is greater than 350 miles from the university. Those who have the treatment variable equal to zero must also live outside a 100 mile radius of the principal cities of the top 15 computer employment MSAs. I include only students studying at universities outside a 100 mile radius of the principal cities of the top 15 computer employment MSAs. I also include only non-California universities in Panel A and non-Texas universities in Panel B. I specify exact matching on university. Additional matching variables are SAT/ACT (converted to SAT), parental income (median from provided ranges), year, distance to university from home, and indicators for male, mother has a bachelor's degree, father has a bachelor's degree, black, hispanic, and HS GPA at least a B+ . The bias adjustment from Abadie and Imbens (2011) is used for each matching variable. The mahalanobis matrix is used for weighting. If parent occ. ≠ CS this implies neither parent is a computer programmer or analyst. See Table 4 for sample sizes by year group and home location.

Table 6: Allocation of Talent Between Science and Business Majors After Delaware Legislation

	y = High GPA Share within Major	(1)	(2)	(3)	(4)
(1)	Share in Major	0.241***	0.346***		
		(0.0746)	(0.0610)		
(2)	Share in Major*Post1	-0.233***	0.186***		
		(0.0707)	(0.0372)		
(3)	Share in Major*Post1*Exp	-2.467***	-1.127		
		(0.622)	(1.431)		
(4)	Share in Major*Post2	-0.210***	0.168***		
		(0.0736)	(0.0395)		
(5)	Share in Major*Post2*Exp	-1.738***	-0.618		
		(0.578)	(0.909)		
(6)	Post1	0.0907***	-0.0307**	0.000302	-0.00154
		(0.0185)	(0.0145)	(0.0107)	(0.00751)
(7)	Post2	0.0911***	0.0207	0.00842	0.0150**
		(0.0199)	(0.0143)	(0.00893)	(0.00625)
(8)	Post1*Exp	0.330***	0.441	-0.0168	0.0150
		(0.114)	(0.542)	(0.0385)	(0.0270)
(9)	Post2*Exp	0.179	0.207	0.00459	-0.0258
		(0.113)	(0.288)	(0.0348)	(0.0243)
(10)	Share in Major*Exp	2.534***	0.359		
		(0.643)	(0.394)		
(11)	Early			-0.103***	-0.0941***
				(0.00804)	(0.00561)
(12)	Early*Exp			-0.0360	0.0321
				(0.0313)	(0.0218)
	Major	Business	Science	Business	Science
	Observations	1,393	1,409	1,393	1,409
	R-squared	0.781	0.880	0.799	0.896

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Observations are at the university, major, year level, and all regressions include university fixed effects. The dependent variable is the share of students in the major with at least a B+ GPA in high school. The independent variable *share in major* denotes the share of all students at the university in this major. Post1 is an indicator for 1981 through 1984 in columns 1-2, and an indicator for 1983-1984 in columns 3-4. The year 1982 is excluded from all specifications because of a large drop in response from Wilmington-area universities. Post2 is an indicator for 1985 through 1987. Exp is an indicator for whether the university is within 15 miles of Wilmington, DE. Early is an indicator for year ≤ 1975, and so the omitted category in columns 3-4 is 1976-1981. Observations are weighted by the number of students at the university. Heteroskedasticity-robust standard errors are in parentheses. See text for details.

Local Labor Markets and Human Capital Investments
Appendix: For Online Publication

Russell Weinstein*

October 17, 2017

1 Data

I classify industries as computer-related using a BLS definition of high-technology industries by 1997 NAICS code (Hecker (2005)). I classify as computer-related industries the high-technology industries that are relevant for the computer industry. These include (2000 Census Classification Code in parentheses): "Manufacturing-Computers and Peripheral Equipment (336)", "Manufacturing-Communications, audio, and video equipment (337)", "Manufacturing-Navigational, measuring, electromedical, and control instruments (338)", "Manufacturing-Electronic components and products, n.e.c. (339)", "Software publishing (649)", "Internet publishing and broadcasting (667)", "Other telecommunications services (669)", "Data processing services (679)", "Computer systems design and related services (738)".

Hecker (2005) classifies industries using the 1997 NAICS codes, while I use the 2000 Census Classification Code. These match quite well, with several exceptions. There is no census code for "semiconductor and other electronic component manufacturing", but this industry is probably contained in one of the census codes I have included (possibly "electronic components and products, n.e.c. (339)). There is also no 2000 census industrial classification code for "internet service providers and web search portals." This is also probably included in one of the other codes that I have

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included. Hecker (2005) identifies several industries as "Level-1" in terms of high-technology employment. Of the Level-1 high technology industries, I classify those related to computers as "computer-related" industries.

I classify business majors as business, management, marketing, and related support services. From 2003 through 2013, CIP code 52 refers to this entire group of majors. From 1992 through 2002, CIP code 52 refers to "Business Management and Administrative Services" while CIP code 8 refers to "Marketing Operations/Marketing Distribution". For 1990 and 1991, CIP code 6 refers to "Business and Management", CIP code 7 refers to "Business (Administrative Support)", and CIP code 8 refers to "Marketing Operations/Marketing Distribution". Thus from 2003 through 2013, business majors are defined by CIP code 52, from 1992 through 2002 business majors are defined by CIP codes 52 and 8, and for 1990 and 1991 business majors are defined by CIP codes 6, 7, and 8.

I classify computer science majors as computer and information sciences and support services.[1]

For the analysis of the jurisdictional competition in Delaware, I separate each of the broad academic disciplines into a major group and observe effects on each group. These groups include business and management; economics; communication and librarianship; education; science (engineering; geosciences; interdisciplinary or other Sciences; life sciences; physical sciences; science and engineering technologies); humanities (humanities; religion and theology; arts and music; and architecture and environmental design); services (law; social service professions); math and computer sciences; social sciences (psychology; social sciences excluding economics); and other (vocational studies and home economics; other non-sciences or unknown disciplines).

I convert ACT scores in The Freshman Survey to SAT scores using concordance tables. I use the concordance tables published in 1992 for the college freshmen from 1990 through 1995 (Marco, Abdel-fattah, and Baron 1992). SAT scores were recentered in 1995, so high school juniors in 1994-1995 have newly recentered scores. For college freshmen from 1996 through 2005, I use the concordance tables based on the recentered scores, published in 1999 (Dorans and Schneider 1999). I use the concordance tables published in 2009 (based on test-takers from 2004-2005), starting with

[1] For 2003 through 2013, CIP code 11 refers to this entire group of majors. From 1990 through 2002, CIP code 11 refers to "Computer and information sciences" and there is no separate CIP code referring to support services for computer and information sciences.

college freshmen in 2006 ("ACT and SAT Concordance Tables" 2009).

2 Selection into Major and University After the Finance Shock in Delaware

In this section I present additional tests for changes in the composition of students at Wilmington-area universities after the finance shock. I test whether the shock led to a greater proportion of nonlocal students at Wilmington-area universities, and whether the shock affected HS GPA of students enrolling at Wilmington-area universities.

I code a student as nonlocal if the student's home is more than 50 miles from the university, and estimate regression (2) in the paper. Column 1, row 5 of Appendix Table A5 shows there is a significant preexisting increasing trend in the proportion of nonlocal students at Wilmington-area universities relative to farther universities.[2] The magnitude of the coefficient on $Post * Exposure * YearsElapsed$ suggests that the trend is less positive after the shock, however, the interaction is not statistically significant from zero. Further, the combined effects still suggest an increase in the proportion of nonlocal students after the shock. The difference-in-difference suggests an increase in the proportion nonlocal at Wilmington-area universities of 2 percentage points, which is not statistically significant.

Column 2 shows that Wilmington-area universities experienced an additional 2.2 percentage point decrease in the proportion of students whose HS GPA was at least a B+. Together, these results suggest the policy incentivized nonlocal students to Wilmington-area universities, and students with lower HS GPAs. This would be consistent with these universities attracting high school students interested in business, instead of science, if business students have lower high school GPAs.

2.1 University funding

Following a local demand shock, particular academic programs may experience changes in funding from the university, local/state government, or corporations, and this may

[2] This is consistent with evidence from college guides (Appendix Figure A2). I obtain data on in-state versus out-of-state freshman class enrollment from college guides published by Peterson's and the College Board, as well as from IPEDS. Appendix Figure A2, Panel B, shows the share of out-of-state students increased after the policy, from around 45% to 60%. However, the share also dramatically increases before the policy, from 25% to 45%.

explain the change in majors. Credit card companies eventually supported The University of Delaware's business school, though not immediately, and so cannot explain short-run changes in business majors. The Center for Financial Institutions Research and Education was created at the University of Delaware, expected to be in full operation by the Fall of 1988 (seven years after the initial shock) ("College of Business and Economics" 1987). The business school building at the University of Delaware was named MBNA America Hall in October 1997 (16 years after the shock) ("History" 2016).

Unfortunately the IPEDS Salaries, Tenure, and Fringe Benefits Survey, which contains data on total faculty and faculty salary outlays, does not exist at the department level. As a result, this dataset is not well-suited for studying whether the shock increased resources in the business schools at Wilmington-area universities, and this attracted more students. Further, IPEDS data on university revenue by source is available only starting in 1980. Given Delaware's shock was in 1981, this makes it difficult to identify whether changes are part of a preexisting trend.

References

[1] "ACT and SAT Concordance Tables," *Research Notes (RN-40)*. New York, NY: The College Board, 2009.

[2] "College of Business and Economics Center for Financial Institutions Research and Education, Executive Summary," University of Delaware, 1987.

[3] Dorans, Neil and Dianne Schneider (1999): "Concordance Between SAT I and ACT Scores for Individual Students," *Research Notes (RN-07)*. New York, NY: The College Board.

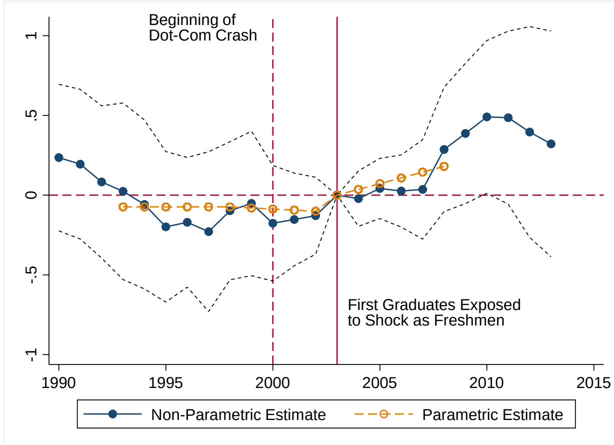
[4] Hecker, Daniel E. (2005): "High-technology employment: a NAICS based update," *Monthly Labor Review*, July.

[5] "History: Alfred Lerner Hall History," University of Delaware, http://lerner.udel.edu/about-us/history, accessed 7/18/2016.

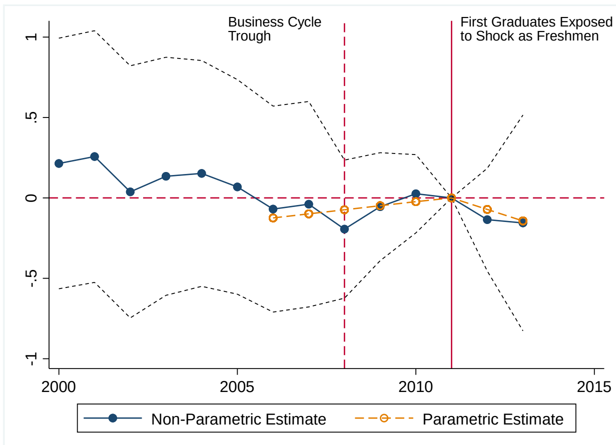
[6] Marco, Gary L., A.A. Abdel-fattah, and Patricia A. Baron (1992): "Methods Used to Establish Score Comparability on the Enhanced ACT Assessment and the SAT," *College Board Report No. 92-3*, New York, NY: College Entrance Examination Board.

Appendix Figure A1 The Effect of Sectoral Shocks on Total Degrees, by University's Geographic Exposure to the Shock

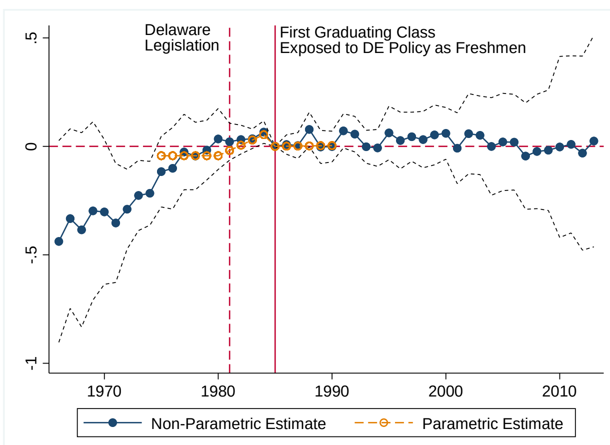
(a) Effect of MSA Computer Employment Share on Total Degrees, Relative to 2003



(b) Effect of MSA Finance Employment Share on Total Degrees, Relative to 2011



(c) Effect of Being within 15 Miles of Wilmington, DE on Total Degrees, Relative to 1985

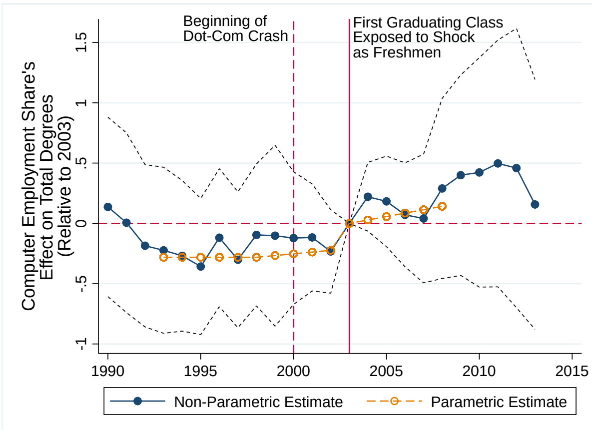


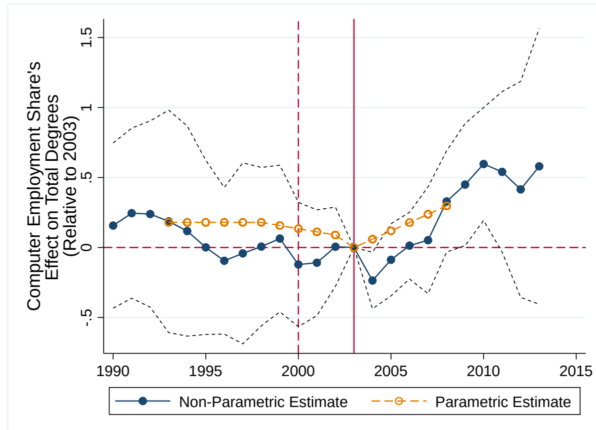
Note: Closed circles show interaction between year fixed effects and university's geographic exposure to the shock (MSA computer employment share in (a), MSA finance employment share*(MSA 2007 unemployment rate – MSA 2009 unemployment rate) in (b), and university within 15 miles of Wilmington, DE in (c)). Dotted lines are 95% confidence intervals for these coefficients. These regressions also include year fixed effects, university fixed effects, total degrees, and lower-level interaction terms. 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). Fitted values are relative to the value in the first treated year. The parametric regressions also include university fixed effects, and the relevant combinations of the interacted variables.

Appendix Figure A2: The Effect of Sectoral Shocks on Total Degrees, by University's Geographic Exposure to Shock and University Classification

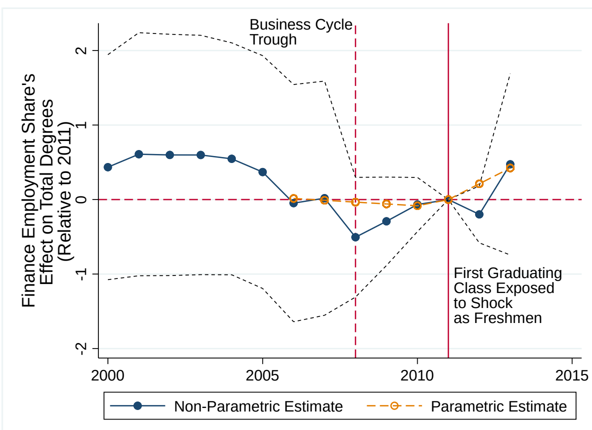
Research/Doctoral Universities | Master's/Baccalaureate Universities

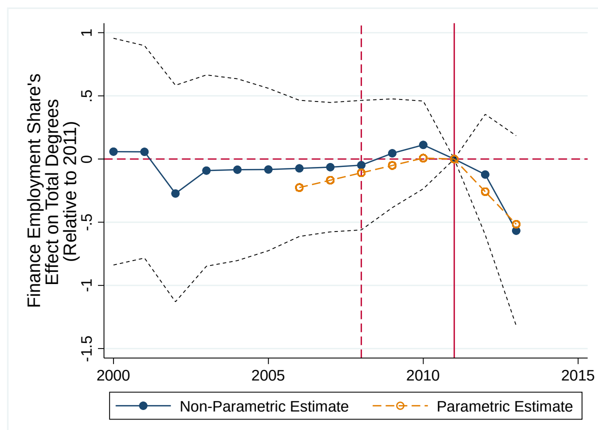
(a) Effect of MSA Computer Employment Share on Total Degrees, Relative to 2003



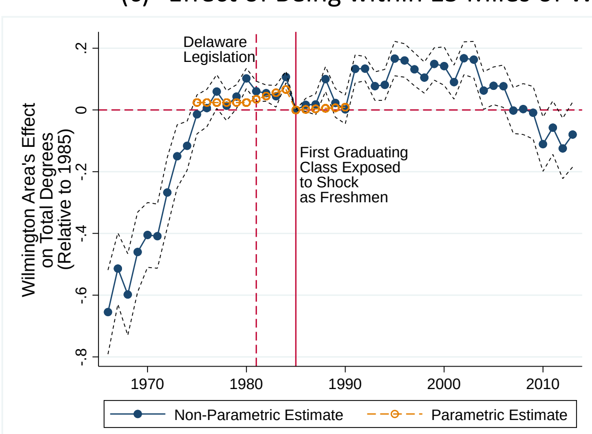


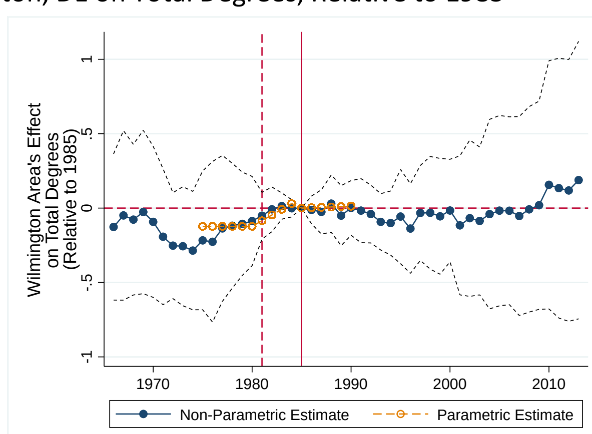
(b) Effect of MSA Finance Employment Share on Total Degrees, Relative to 2011





(c) Effect of Being within 15 Miles of Wilmington, DE on Total Degrees, Relative to 1985

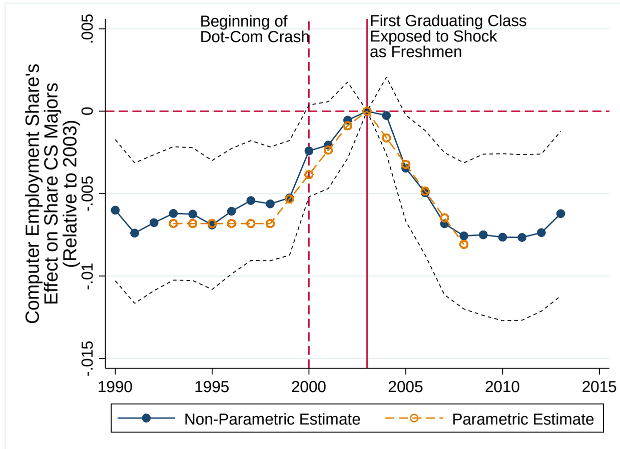




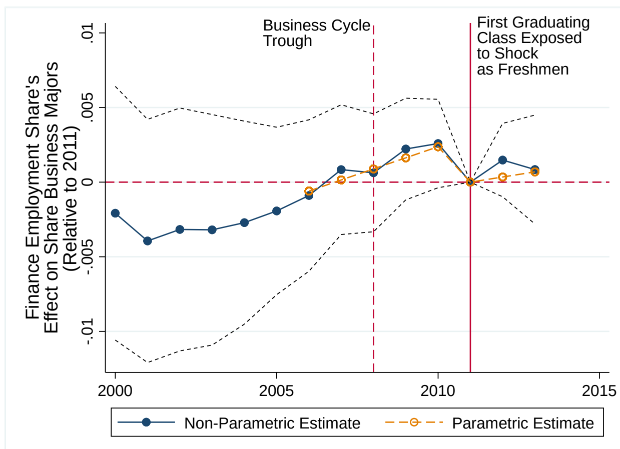
Note: Plots are the same as those described in Appendix Figure A1, but with regressions estimated separately for research/doctoral universities and master's/baccalaureate universities. University classifications are based on 1994 Carnegie rating.

Appendix Figure A3 The Effect of Sectoral Shocks on College Majors, by University's Geographic Exposure to Shock

(a) Effect of MSA Computer Employment Share ≥ 90^{th} percentile on Share CS Degrees, Relative to 2003

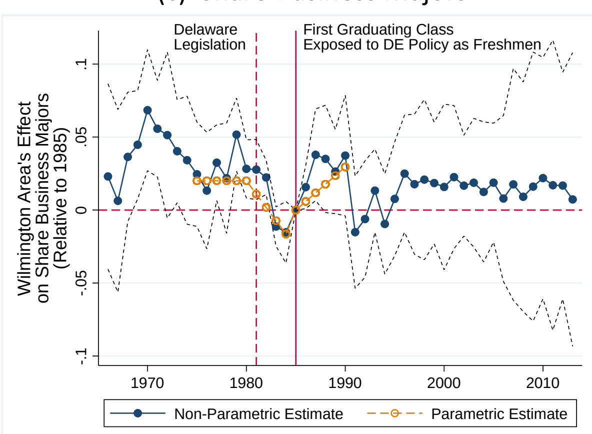


(b) Effect of MSA Finance Employment Share ≥ 90^{th} percentile on Share Business Degrees, Relative to 2011

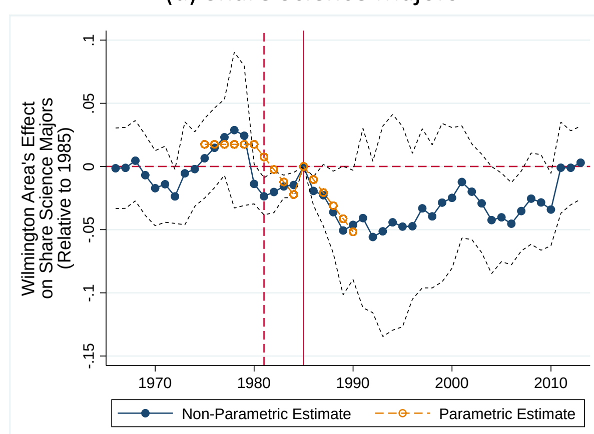


Effect of Being within the State of Delaware, Relative to 1985

(c) Share Business Majors



(d) Share Science Majors

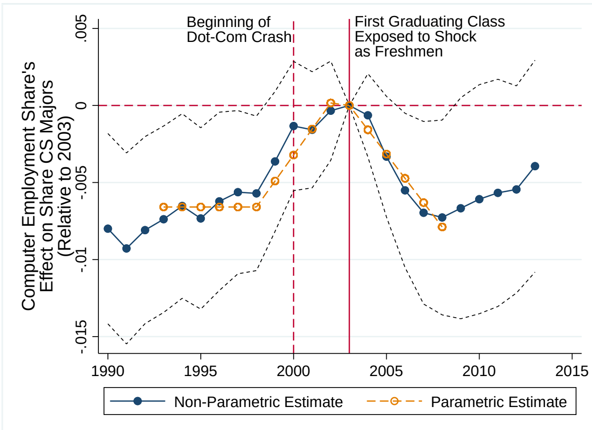


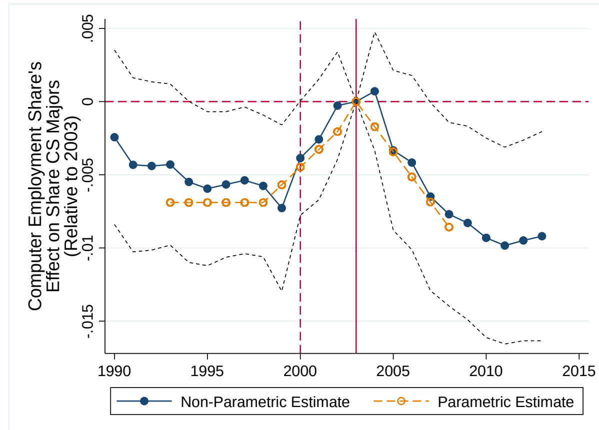
Note: Plots are the same as those described in Appendix Figure A1, but with different definitions of exposure to shock. Closed circles show interaction between year fixed effects and university's geographic exposure to the shock (indicator for MSA computer employment share ≥ 90^{th} percentile in (a), indicator for MSA finance employment share ≥ 90^{th} percentile*(2007 MSA Unemployment Rate – 2009 MSA Unemployment Rate) in (b), and university in the state of Delaware in (c)). Dotted lines are 95% confidence intervals for these coefficients. These regressions also include year fixed effects, university fixed effects, total degrees, and lower-level interaction terms. 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). Fitted values are relative to the value in the first treated year. The parametric regressions also include university fixed effects, and the relevant combinations of the interacted variables.

Appendix Figure A4: The Effect of Sectoral Shocks on College Majors, by Geographic Exposure to Shock and University Classification

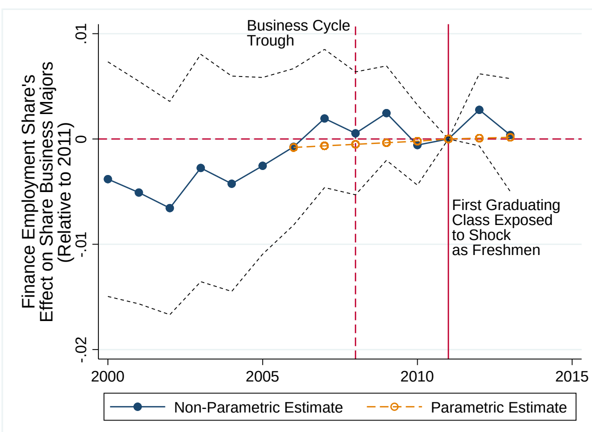
Research/Doctoral Universities | Master's/Baccalaureate Universities

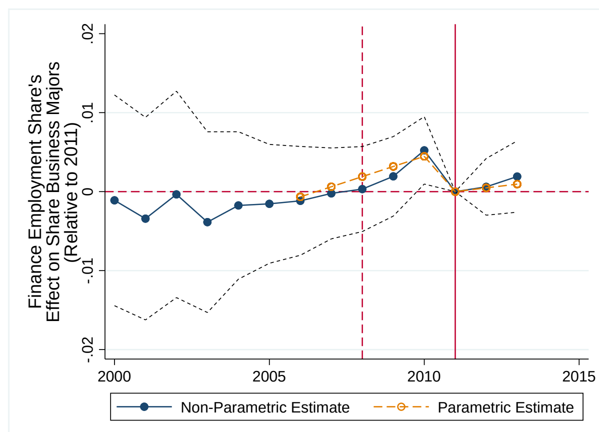
(a) Effect of MSA Computer Employment Share ≥ 90th percentile on Share CS Degrees, Relative to 2003



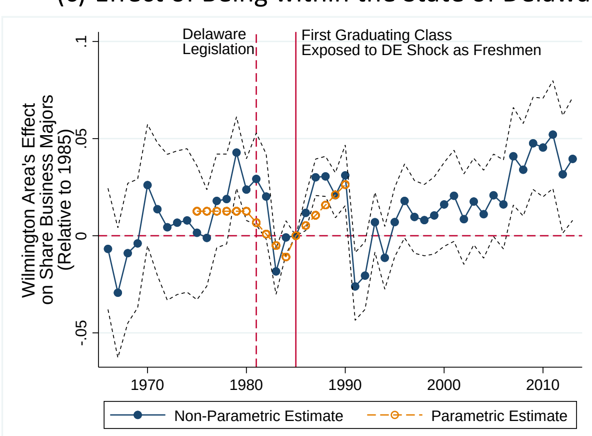


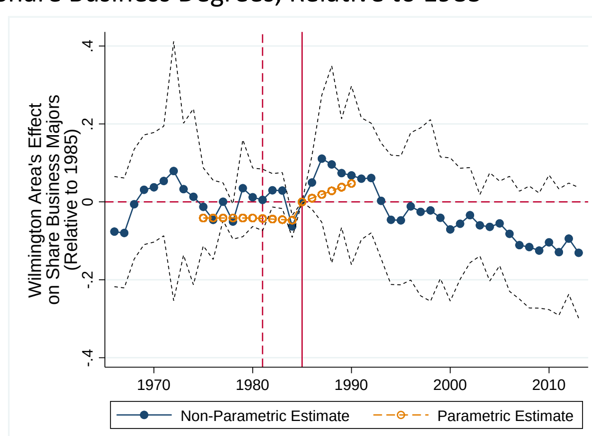
(b) Effect of MSA Finance Employment Share ≥ 90th percentile on Share Business Degrees, Relative to 2011





(c) Effect of Being within the State of Delaware on Share Business Degrees, Relative to 1985

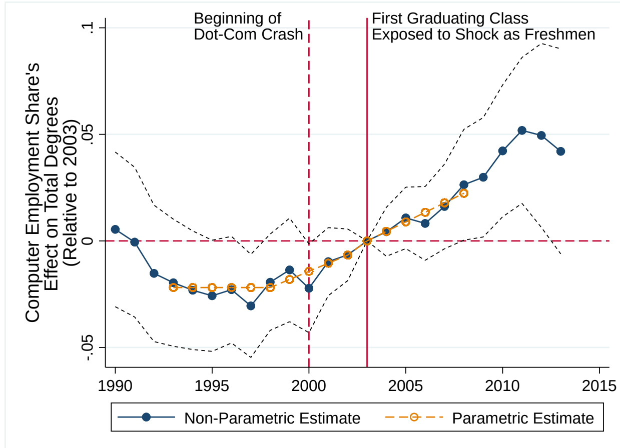




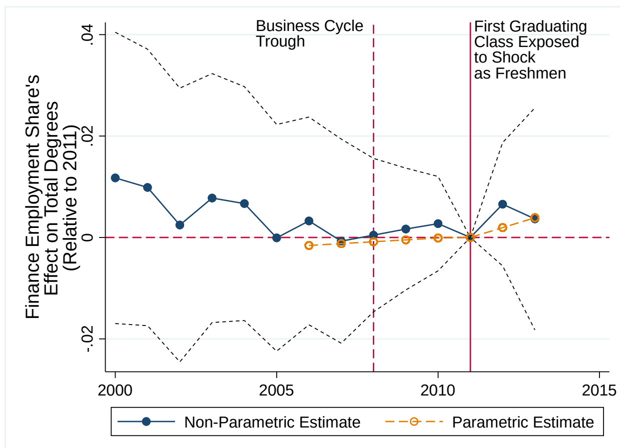
Note: Plots are the same as those described in Appendix Figure A3, but with regressions estimated separately for research/doctoral universities and master's/baccalaureate universities. University classifications are based on 1994 Carnegie rating.

Appendix Figure A5 The Effect of Sectoral Shocks on Total Degrees, by University's Geographic Exposure to the Shock

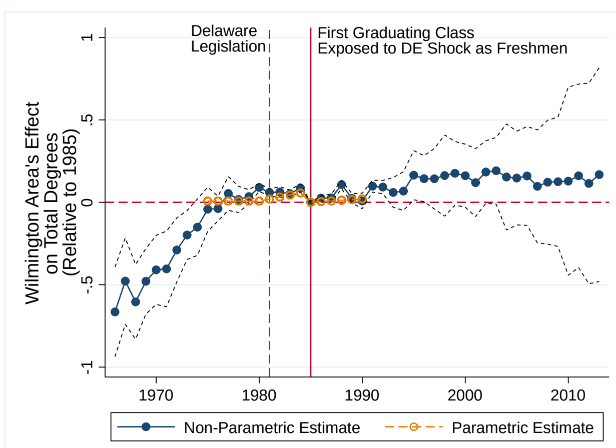
(a) Effect of MSA Computer Employment Share ≥ 90th percentile on Total Degrees, Relative to 2003



(b) Effect of MSA Finance Employment Share ≥ 90th percentile on Total Degrees, Relative to 2011



(c) Effect of Being within the State of Delaware on Total Degrees, Relative to 1985

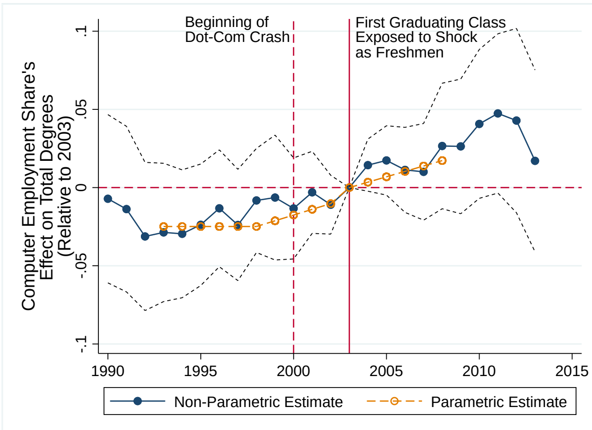


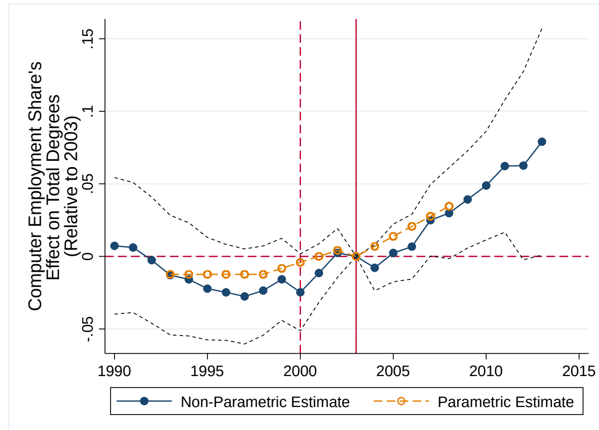
Note: Plots are the same as those described in Appendix Figure A3, but with ln(Total Degrees) as the dependent variable and without total degrees as an independent variable.

Appendix Figure A6: The Effect of Sectoral Shocks on Total Degrees, by Geographic Exposure to the Shock and University Classification

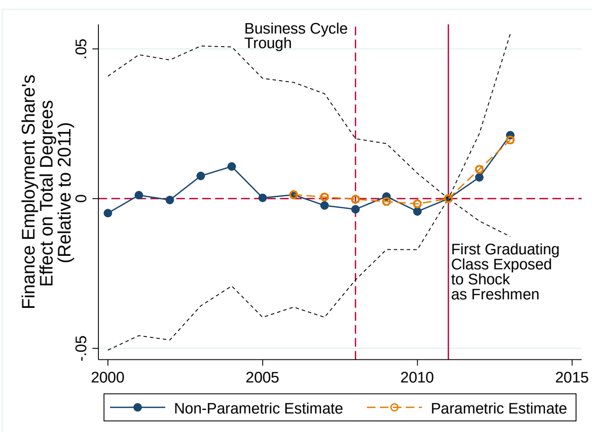
Research/Doctoral Universities | Master's/Baccalaureate Universities

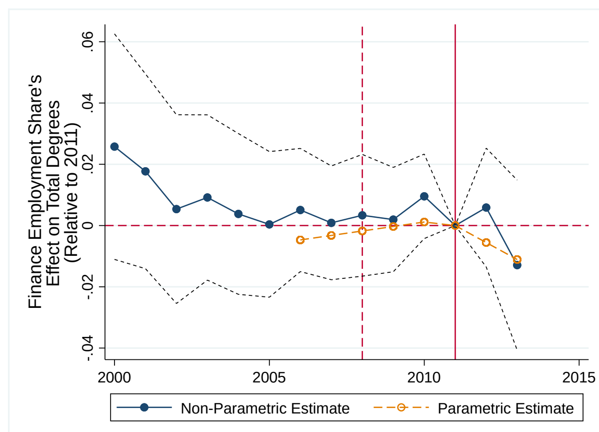
(a) Effect of MSA Computer Employment Share ≥ 90th percentile on Total Degrees, Relative to 2003



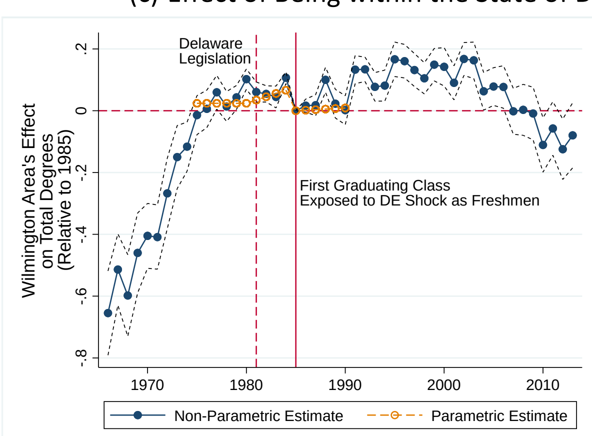


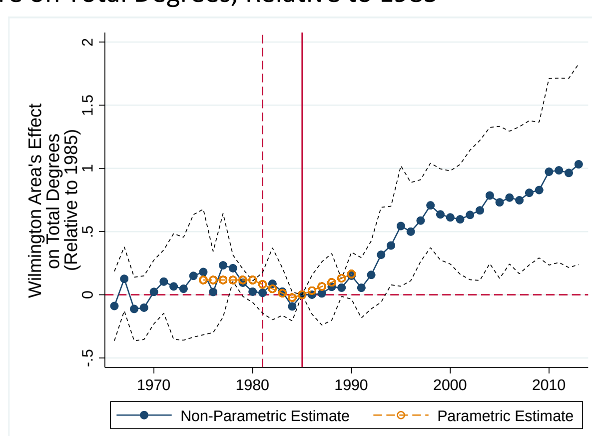
(b) Effect of MSA Finance Employment Share ≥ 90th percentile on Total Degrees, Relative to 2011





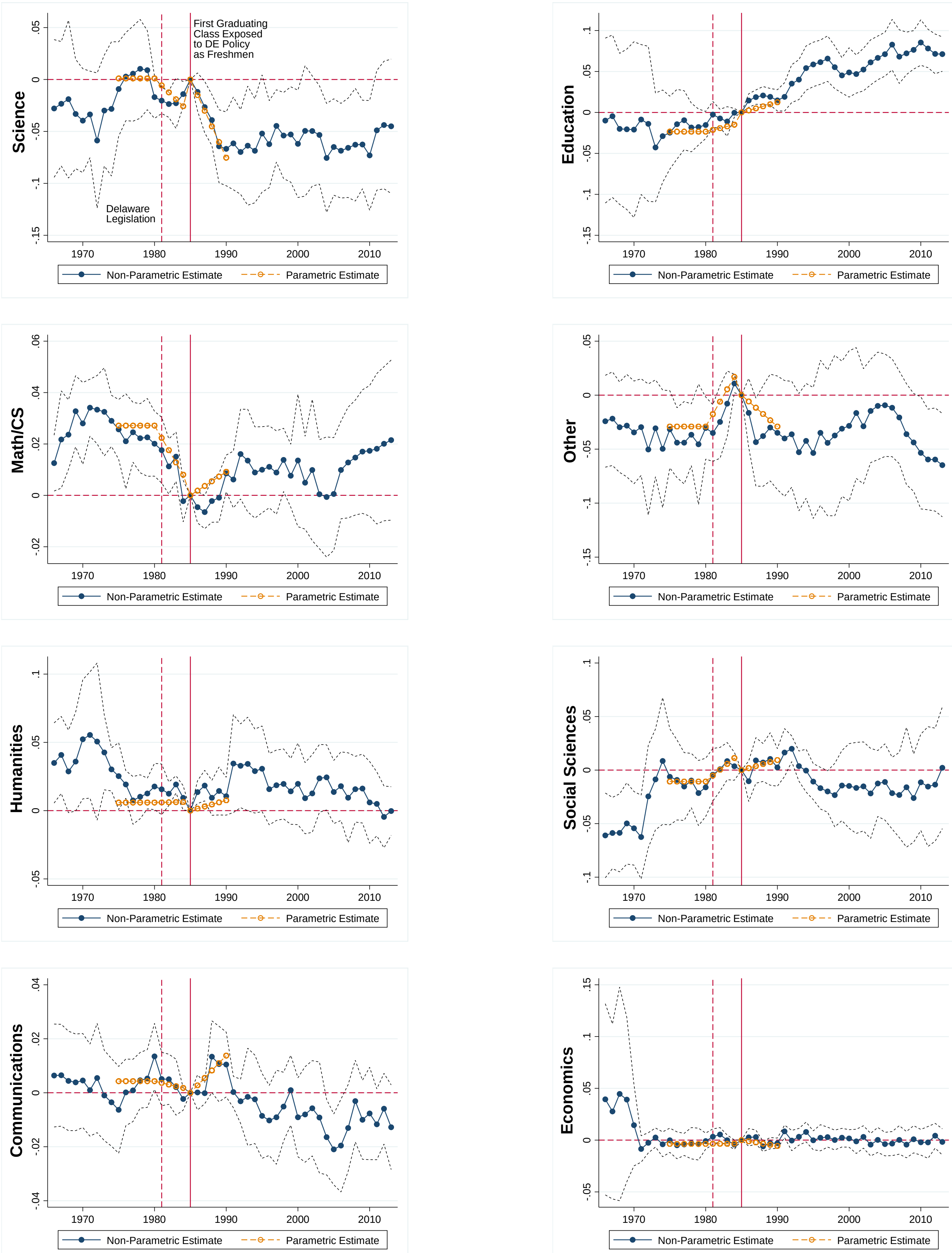
(c) Effect of Being within the State of Delaware on Total Degrees, Relative to 1985

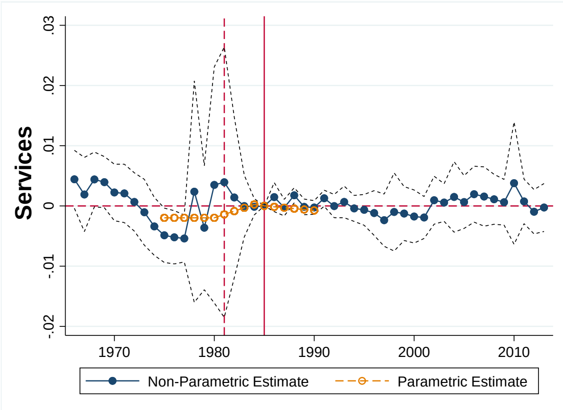




Note: Plots are the same as those described in Appendix Figure A3, but with dependent variable ln(Total Degrees) and without total degrees as an independent variable. Regressions are estimated separately for research/doctoral universities and master's/baccalaureate universities. University classifications are based on 1994 Carnegie rating.

Appendix Figure A7: The Effect of Delaware's Finance Shock on College Majors, Relative to 1985

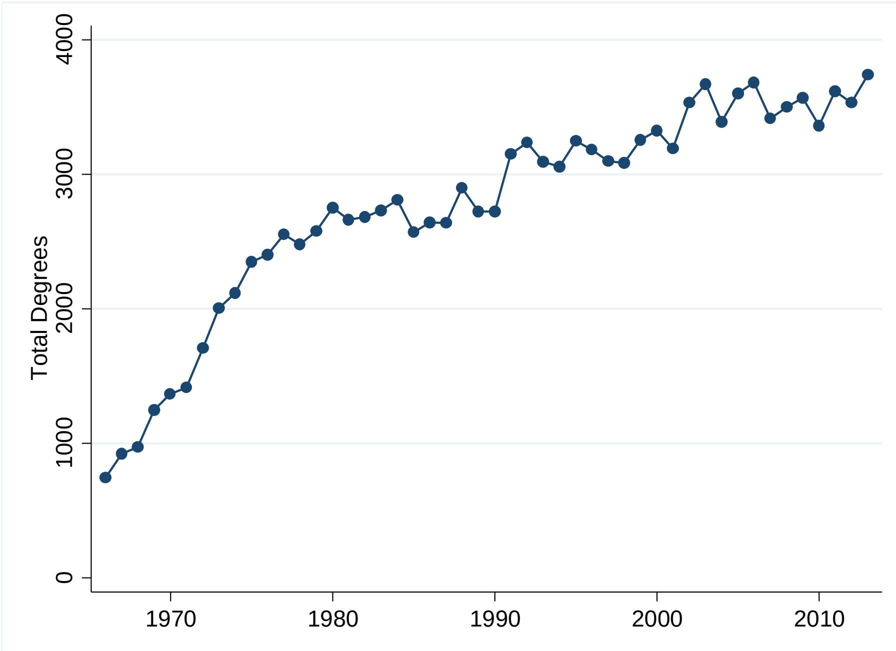




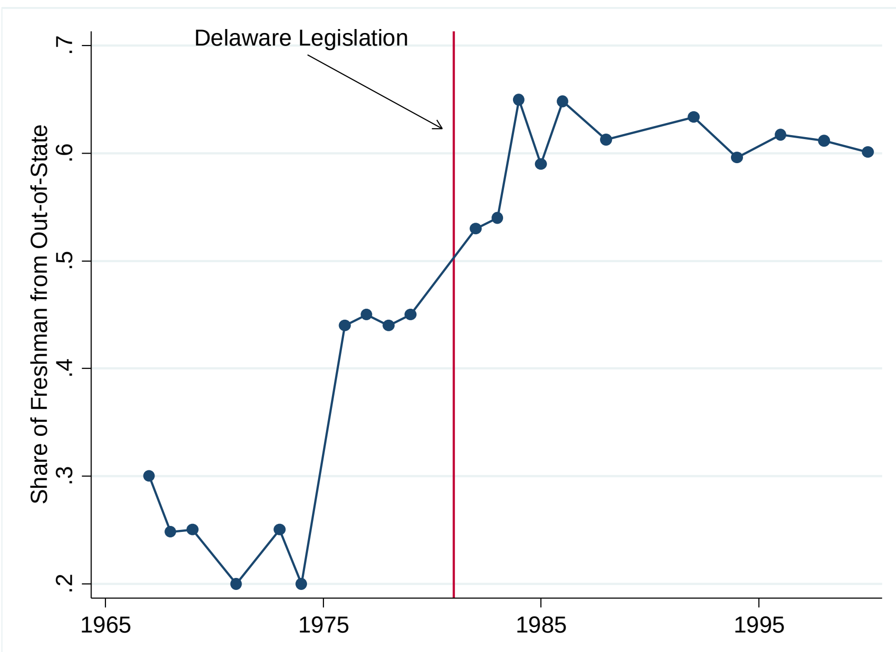
Note: Plots are the same as the plot in Figure 3c, with dependent variable in each plot the share of degrees in each major group at the university.

Appendix Figure A8: Changes in Enrollment at the University of Delaware

(a) Total Bachelor's Degrees Awarded at the University of Delaware



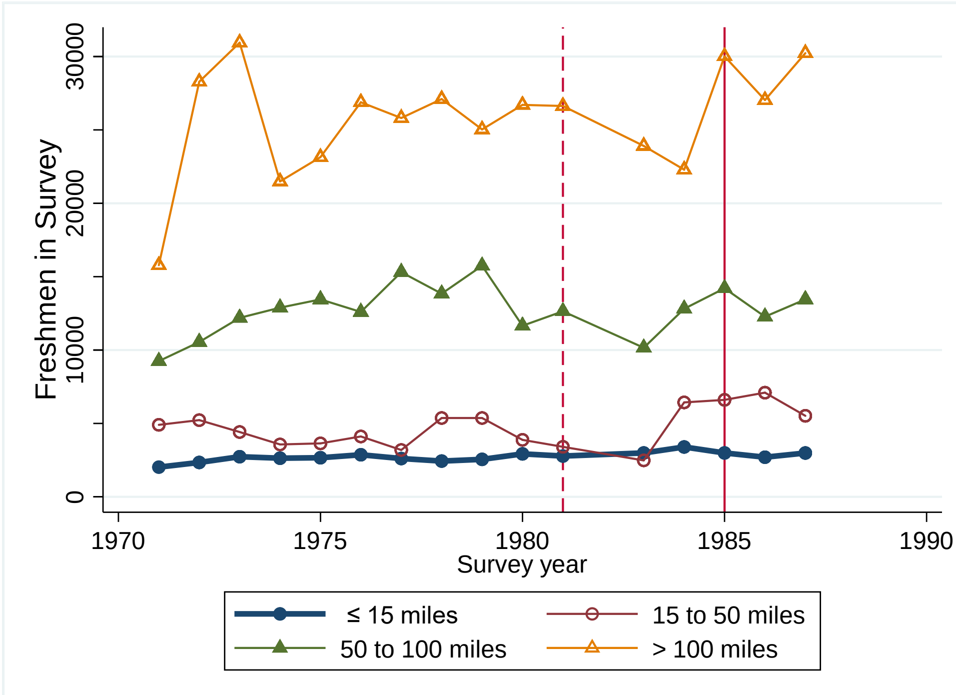
(b) Out-of-State Freshman at the University of Delaware



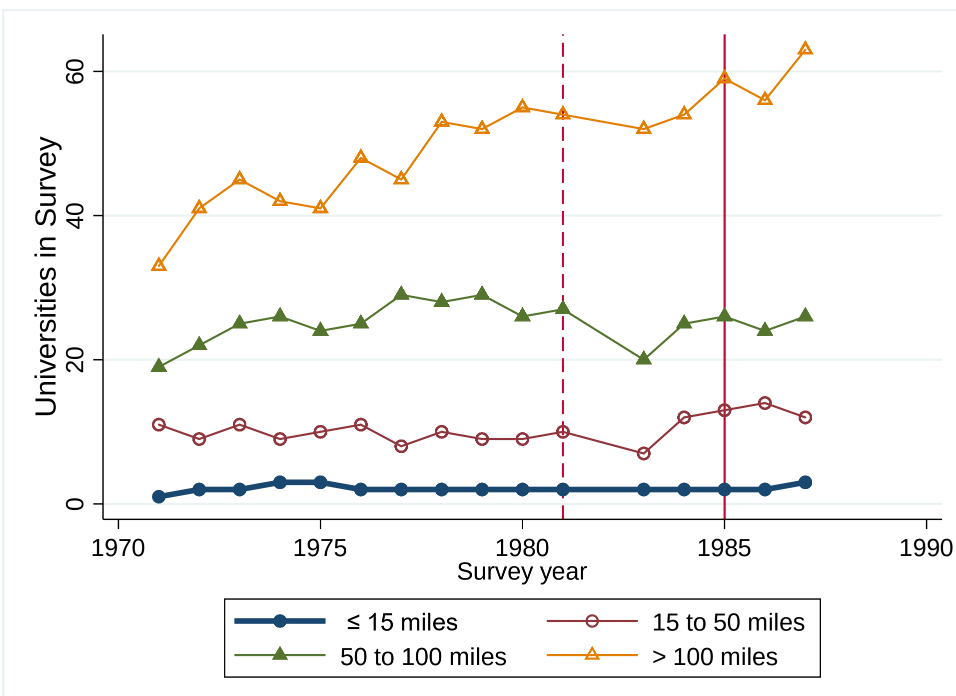
Note: Source for (a) is IPEDS (accessed through the Integrated Science and Engineering Resources Data System of the NSF). Sources for (b) include college guides (Peterson's and the College Board), as well as IPEDS. See text of paper and Online Appendix for details.

Appendix Figure A9: Freshman Survey Sample for Delaware Analysis

(a) Number of Students per Year, by University's Distance to Wilmington, DE



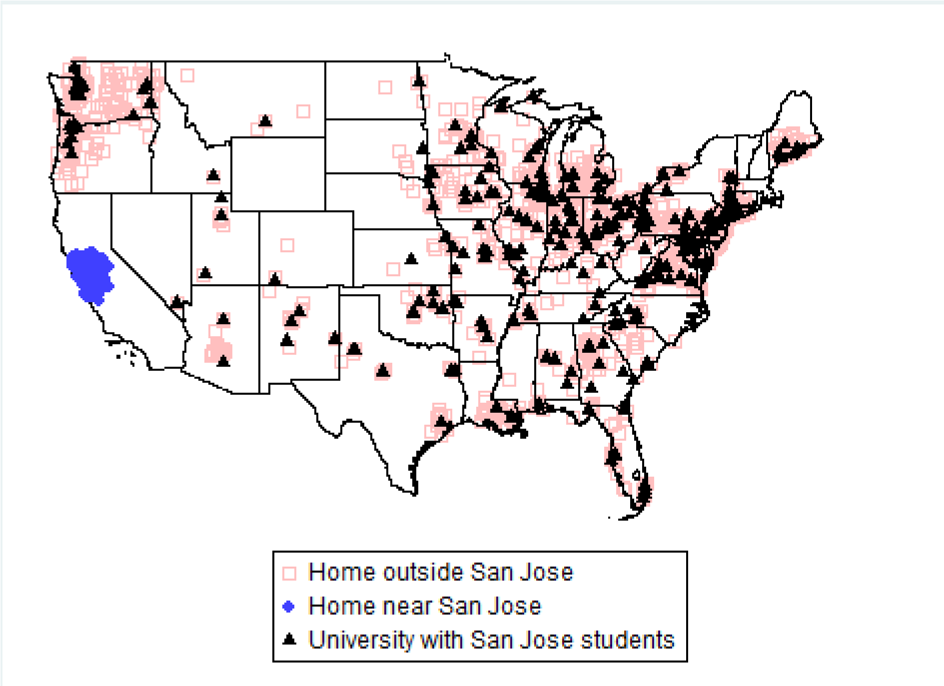
(b) Number of Universities per Year, by Distance to Wilmington, DE



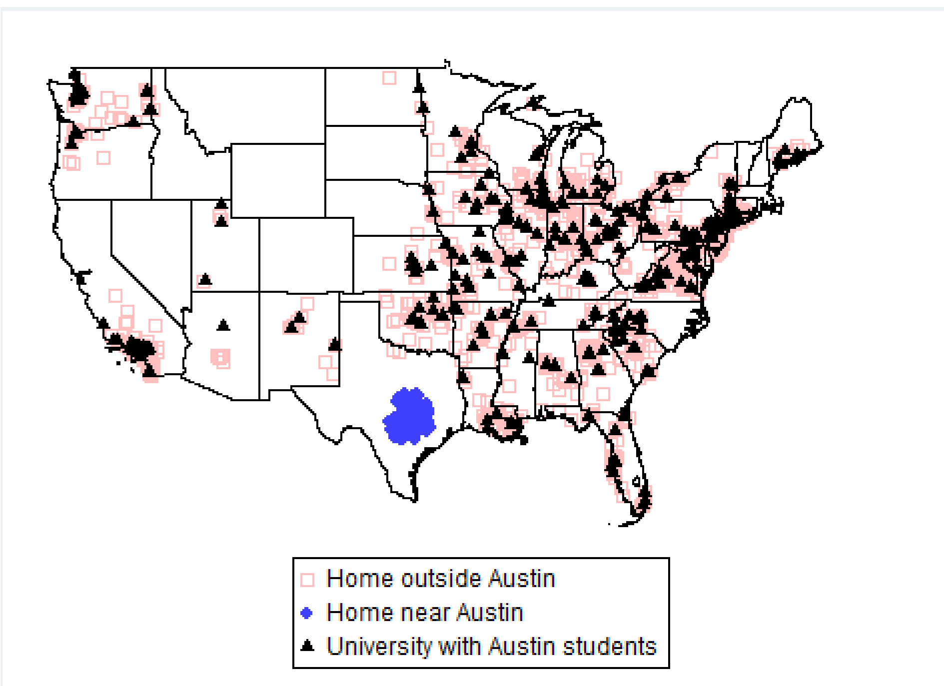
Note: These plots give the number of students and universities per year by distance to Wilmington, DE in The Freshman Survey sample. See text for details.

Appendix Figure A10

Panel A: Non-California Universities with San Jose Students whose Home is > 350 Miles Away, and Home Locations of those Students and Matches whose Home is ≤ 150 Miles from the University



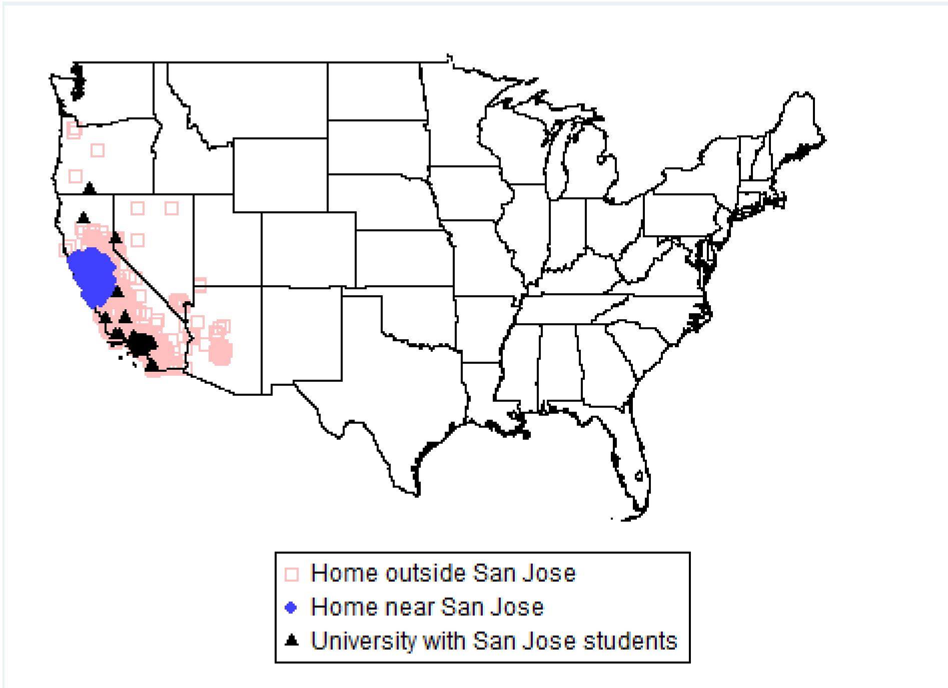
Panel B: Non-Texas Universities with Austin Students whose Home is > 350 Miles Away and Home Locations of those Students and Matches whose Home is ≤ 150 Miles from the University



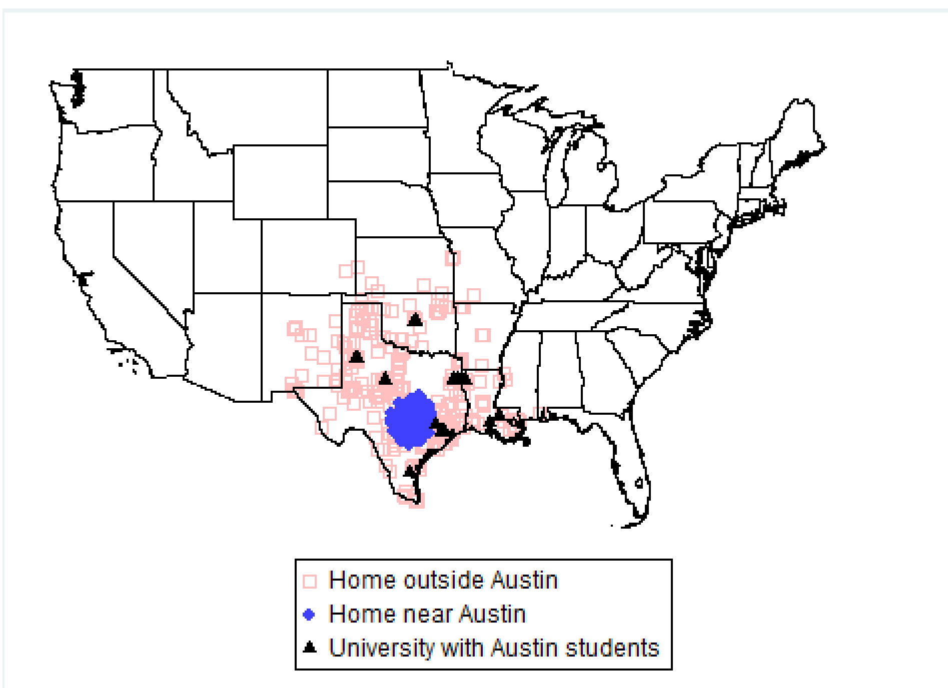
Note: This figure shows the universities (in black triangles) attended by students in the robustness matching sample with mobile San Jose/Austin students and less mobile matches (during the years of the dot-com bust). The criteria for the San Jose/Austin students is the same as in the principal sample, while the matches must be studying ≤ 150 miles from home. The dark circles represent home locations of San Jose and Austin students, whose homes are ≤ 100 miles from San Jose or Austin. The light squares represent their matches, whose homes are > 100 miles from San Jose or Austin, and also > 100 miles from any of the principal cities of the top 15 computer employment MSAs. See text for details.

Appendix Figure A11

Panel A: Universities with San Jose Students whose Home is 100-350 Miles Away, and Home Locations of those Students and Matched Counterparts



Panel B: Universities with Austin Students whose Home is 100-350 Miles Away and Home Locations of those Students and Matched Counterparts



Note: This figure shows the universities (in black triangles) attended by students in the robustness matching sample with less mobile San Jose/Austin students and their less mobile counterparts (during the years of the dot-com bust). To be included in this robustness matching sample, both the San Jose (Austin) student and their match must be at the same university, and their homes must be 100-350 miles from the university. The dark circles represent home locations of San Jose and Austin students, whose homes are less than or equal to 100 miles from San Jose or Austin. The light squares represent home locations of the matches, whose homes are more than 100 miles from San Jose or Austin, and also more than 100 miles from any of the principal cities of the top 15 computer employment MSAs. See text for details.

Appendix Table A1: The Effect of Sectoral Shocks on on College Majors by University's Exposure to the Shock, Alternative Definition of Exposure

		(1)	(2)	(3)	(4)	(5)	(6)
	Y_{cmt}: Share of Majors in		CS			Business	
(1)	Post	-0.001	-0.001	-0.002*	0.000	-0.005	0.004
		(0.001)	(0.001)	(0.001)	(0.005)	(0.004)	(0.009)
(2)	Post*90th pctile	-0.001	-0.002	0.001	-0.011	0.003	-0.025**
		(0.002)	(0.002)	(0.003)	(0.008)	(0.010)	(0.012)
(3)	Post*90th pctile	-0.003***	-0.003**	-0.003**	-0.001	0.001	-0.004
	*Years Elapsed	(0.001)	(0.001)	(0.001)	(0.004)	(0.006)	(0.006)
(4)	Post*90th pctile				-0.003*	0.000	-0.006**
	*Unemp Shock				(0.002)	(0.002)	(0.003)
(5)	Post*90th pctile				-0.000	-0.000	-0.001
	*Unemp Shock*Years Elapsed				(0.001)	(0.001)	(0.001)
(6)	Post*Unemp Shock				0.000	-0.001	0.001
	*Years Elapsed				(0.001)	(0.001)	(0.001)
(7)	Post*Years Elapsed	-0.006***	-0.006***	-0.006***	-0.007***	-0.008***	-0.006
		(0.000)	(0.001)	(0.000)	(0.002)	(0.003)	(0.004)
(8)	Post*Unemp Shock				0.001	-0.000	0.002
					(0.001)	(0.001)	(0.002)
(9)	90th pctile*Years Elapsed	0.001***	0.002**	0.001*	0.003	0.000	0.006
		(0.000)	(0.001)	(0.001)	(0.003)	(0.004)	(0.003)
(10)	Unemp Shock*Years Elapsed				0.000	0.000	-0.000
					(0.000)	(0.000)	(0.000)
(11)	Years Elapsed	0.003***	0.003***	0.003***	0.001	0.001	0.000
		(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
(12)	90th pctile*Unemp Shock*				0.001	0.000	0.001
	Years Elapsed				(0.001)	(0.001)	(0.001)
(13)	Difference-in-Difference	-0.007**	-0.008**	-0.007	-0.002	0.0004	-0.004
		(.003)	(.004)	(.005)	(.003)	(.003)	(.004)
	Shock		Dot-Com			Great Recession	
	Universities	All	Res./Doc.	Mast./Bacc.	All	Res./Doc.	Mast./Bacc.
	Observations	20,988	3,678	17,310	9,942	1,834	8,108
	R-squared	0.745	0.821	0.690	0.953	0.966	0.945

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 ≥ year in which graduates were freshmen at the shock's onset (2003 in columns 1-3, 2011 in columns 4-6). Years elapsed equals the difference between the current year and the first year in which graduates were exposed to the shock as freshmen. The variable *90th pctile* is an indicator for whether the MSA employment share in the relevant sector is ≥ 90th percentile. The variable *Unemp Shock* is the MSA unemployment rate in 2007 minus the rate in 2009. In columns 1-3, the difference-in-difference equals $\beta_{Post*90th\ pctile} + 5*\beta_{Post*90th\ pctile*Years\ Elapsed} + 6*\beta_{90th\ pctile*Years\ Elapsed}$. In columns 4-6, $\beta_{Post*90th\ pctile*Unemp\ Shock} + 2*\beta_{Post*90th\ pctile*Unemp\ Shock*Years\ Elapsed} + 3*\beta_{90th\ pctile*Unemp\ Shock*Years\ Elapsed}$. 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.

Appendix Table A2: The Effect of Sectoral Shocks on Total Degrees by University's Exposure to the Shock, Alternative Definition of Exposure

	Y_{cmt}: Ln(Total Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Post	0.021***	0.032***	0.013**	0.018	0.015	0.018
		(0.005)	(0.009)	(0.005)	(0.013)	(0.016)	(0.021)
(2)	Post*90th pctile	0.003	0.007	-0.008	-0.008	0.007	-0.022
		(0.008)	(0.014)	(0.010)	(0.026)	(0.036)	(0.038)
(3)	Post*90th pctile*Years Elapsed	0.001	-0.000	0.003	-0.001	0.036	-0.037
		(0.004)	(0.006)	(0.005)	(0.027)	(0.046)	(0.030)
(4)	Post*90th pctile*Unemp Shock				-0.000	0.003	-0.003
					(0.006)	(0.008)	(0.008)
(5)	Post*90th pctile				0.002	0.011	-0.007
	*Unemp Shock*Years Elapsed				(0.007)	(0.012)	(0.007)
(6)	Post*Unemp Shock*Years Elapsed				-0.000	-0.001	0.001
					(0.002)	(0.004)	(0.002)
(7)	Post*Years Elapsed	-0.006**	-0.007*	-0.005	0.012	0.004	0.020
		(0.002)	(0.004)	(0.003)	(0.010)	(0.015)	(0.015)
(8)	Post*Unemp Shock				-0.001	-0.002	0.000
					(0.003)	(0.004)	(0.003)
(9)	90th pctile*Years Elapsed	0.004	0.004	0.004	0.008	0.003	0.013
		(0.003)	(0.004)	(0.004)	(0.011)	(0.019)	(0.010)
(10)	Unemp Shock*Years Elapsed				-0.001	-0.002	-0.001
					(0.001)	(0.002)	(0.001)
(11)	Years Elapsed	0.029***	0.028***	0.029***	0.012***	0.009	0.014**
		(0.002)	(0.003)	(0.002)	(0.004)	(0.008)	(0.005)
(12)	90th pctile*Unemp Shock*				0.000	-0.001	0.001
	Years Elapsed				(0.003)	(0.005)	(0.002)
(13)	Difference-in-Difference	0.0290**	0.0275	0.0304*	0.00400	0.0213	-0.0122
		(.015)	(.023)	(.018)	(.013)	(.018)	(.018)
	Shock		Dot-Com			Great Recession	
	Universities	All	Res./Doc.	Mast./Bacc.	All	Res./Doc.	Mast./Bacc.
	Observations	20,988	3,678	17,310	9,942	1,834	8,108
	R-squared	0.987	0.981	0.976	0.992	0.990	0.985

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table presents results from a similar specification as presented in Appendix Table A1. The differences include the different dependent variable, and excluding total degrees as an independent variable in these specifications. See notes to Appendix Table A1 for details.

Appendix Table A3: The Effect of Delaware's Finance Shock on College Majors by University's Exposure to the Shock, Alternative Definitions of Exposure

	Y_{cmt}: Share of Majors in	(1) Business	(2) Science	(3) Business	(4) Science	(4) Business	(5) Science
(1)	Post	-0.028***	-0.010***	-0.017**	-0.003	-0.019***	-0.010**
		(0.005)	(0.003)	(0.008)	(0.005)	(0.007)	(0.004)
(2)	Post*Exposure	0.026***	0.032***	-0.008	-0.005*	-0.005	0.030**
		(0.007)	(0.007)	(0.005)	(0.003)	(0.018)	(0.012)
(3)	Post*Exposure*Years Elapsed	0.015***	-0.000	-0.005**	-0.001	0.012*	-0.010
		(0.006)	(0.009)	(0.002)	(0.002)	(0.007)	(0.008)
(4)	Post*Years Elapsed	-0.019***	-0.016***	-0.012***	-0.014***	-0.012***	-0.014***
		(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)
(5)	Exposure*Years Elapsed	-0.009**	-0.010**	0.003*	0.002	-0.002	-0.006
		(0.004)	(0.004)	(0.002)	(0.001)	(0.004)	(0.004)
(6)	Years Elapsed	0.020***	0.006***	0.015***	0.004	0.016***	0.006***
		(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)
(7)	Difference-in-Difference	0.046**	-0.029	-0.012**	0.000	0.040	-0.053***
	(Combination of (2), (3), and (5))	(.022)	(.026)	(.005)	(.006)	(.025)	(.017)
	Exposure	University in Delaware		Distance to Wilmington		Distance ≤ 15 miles, Nonexposed Distance ≤ 100 miles	
	Observations	3,381	3,381	3,381	3,381	1,536	1,536
	R-squared	0.882	0.926	0.882	0.985	0.920	0.934

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 ≥ year in which graduates were freshmen at the shock's onset (1985). Exposure indicates the degree to which the university was exposed to the shock. In columns 1-2, this is an indicator for whether the university is located in the state of Delaware. In columns 3-4, this is distance to Wilmington, DE in hundreds of miles. In column 5-6, this is an indicator for distance within 15 miles, but including in the regression only those universities within 100 miles of Wilmington, DE. The difference-in-difference is $\beta_{Post*Exposure} + 5*\beta_{Post*Exposure*Years\ Elapsed} + 6*\beta_{Exposure*Years\ Elapsed}$. 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.

Appendix Table A4: The Effect of Delaware's Finance Shock on College Majors by University's Exposure to the Shock

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Y_{cmt}: Share of Majors in	Business	Science	Education	Math/CS	Other	Human-ities	Social Sciences	Commun-ications	Econo-mics	Services
(1)	Post	-0.028***	-0.010***	0.027***	0.011***	-0.006**	0.009***	0.006***	-0.006***	-0.002	-0.001
		(0.005)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
(2)	Post*Exposure	0.008	0.032***	0.013	-0.003	-0.028***	-0.006*	-0.017	-0.001	0.003	-0.001
		(0.018)	(0.012)	(0.011)	(0.004)	(0.008)	(0.004)	(0.011)	(0.004)	(0.002)	(0.002)
(3)	Post*Exposure*Years Elapsed	0.019***	-0.008	0.000	0.007***	-0.017**	0.001	-0.004	0.003**	-0.001	-0.001
		(0.006)	(0.008)	(0.005)	(0.002)	(0.008)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)
(4)	Post*Years Elapsed	-0.019***	-0.016***	0.020***	-0.010***	0.002	0.012***	0.015***	-0.004***	-0.002**	0.001***
		(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
(5)	Exposure*Years Elapsed	-0.008*	-0.007*	0.002	-0.005***	0.012***	0.000	0.006	-0.001	0.000	0.001
		(0.004)	(0.004)	(0.004)	(0.001)	(0.003)	(0.002)	(0.005)	(0.001)	(0.001)	(0.001)
(6)	Years Elapsed	0.020***	0.006***	-0.020***	0.006***	0.000	-0.008***	-0.010***	0.005***	0.002***	-0.001**
		(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
(7)	Difference-in-Difference	0.059**	-0.050***	0.027**	0.001	-0.046*	0.001	-0.002	0.012**	-0.002	-0.001
	(Combination of (2), (3), and (5))	(.025)	(.016)	(.011)	(.004)	(.025)	(.006)	(.01)	(.006)	(.003)	(.003)
	Observations	3,381	3,381	3,381	3,381	3,381	3,381	3,381	3,381	3,381	3,381
	R-squared	0.882	0.926	0.873	0.683	0.943	0.891	0.846	0.809	0.814	0.678

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. See notes to Table 1 for description of regressions. See text of online appendix for details on construction of majors.

Appendix Table A5: The Effect of Delaware's Finance Shock on Student Composition, by University's Exposure to the Shock

		(1)	(2)
		Nonlocal	HS GPA ≥ B+
(1)	Post	-0.026	-0.050***
		(0.024)	(0.018)
(2)	Post*Exposure	-0.067**	0.019
		(0.027)	(0.018)
(3)	Post*Exposure*Years Elapsed	-0.014	0.003
		(0.010)	(0.008)
(4)	Post*Years Elapsed	-0.007	-0.017**
		(0.010)	(0.008)
(5)	Exposure*Years Elapsed	0.026**	-0.010
		(0.012)	(0.008)
(6)	Years Elapsed	0.015	0.019**
		(0.010)	(0.008)
(7)	Difference-in-Difference	0.020	-0.022*
	(Combination of (2), (3), and (5))	(.014)	(.012)
	Shock	Delaware	Delaware
	Observations	736,563	782,102
	R-squared	0.303	0.182

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Observations are at the individual level. Standard errors clustered at the university level in parentheses. Each regression includes university fixed effects. In column 1 the dependent variable is an indicator for whether the student's home is > 50 miles from the university. In column 2, the dependent variable is an indicator for whether the student's HS GPA was ≥ B+. Post is an indicator for whether the year is ≥ the year of the shock's onset (1981). Exposure indicates the degree to which the university was exposed to the shock (an indicator for whether the university is within 15 miles of Wilmington, Delaware). Years elapsed equals the difference between the current year and the year of the shock's onset (1981). The difference-in-difference equals ($\beta_{Post*Exposure}$ + 5*$\beta_{Post*Exposure*Years\ Elapsed}$ + 6*$\beta_{Exposure*Years\ Elapsed}$). Regressions include years through 1987. The variable *Years Elapsed* is censored at -5. I exclude 1982 because of a significant change in sample coverage that year.

Appendix Table A6: The Dot-Com Crash and Computer Science Degrees: Differential Effects by Home Location, OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: CS Major								
Pre Boom	-0.009	-0.014	-0.004	-0.018***	-0.002	-0.036***	-0.012**	-0.014
	(0.006)	(0.010)	(0.004)	(0.007)	(0.008)	(0.007)	(0.005)	(0.010)
Early Boom	-0.005	-0.008	-0.003	-0.010	-0.005	0.001	-0.008**	-0.008
	(0.004)	(0.009)	(0.004)	(0.007)	(0.005)	(0.007)	(0.004)	(0.009)
Bust	-0.013***	-0.025***	-0.014***	-0.016**	-0.015***	-0.018	-0.015***	-0.024***
	(0.004)	(0.008)	(0.003)	(0.006)	(0.005)	(0.013)	(0.003)	(0.008)
Post Bust	-0.015***	-0.023***	-0.014***	-0.021***	-0.018***	-0.008	-0.015***	-0.023***
	(0.004)	(0.008)	(0.004)	(0.007)	(0.006)	(0.015)	(0.004)	(0.008)
Home within 100 miles of San Jose, CA*								
Pre Boom	0.001		-0.007		-0.000		0.002	
	(0.004)		(0.005)		(0.006)		(0.003)	
Early Boom	-0.0002		-0.007		0.021**		0.005	
	(0.004)		(0.005)		(0.006)		(0.004)	
Late Boom	-0.002		-0.004		0.024***		-0.0004	
	(0.005)		(0.005)		(0.008)		(0.004)	
Bust	0.002		-0.002		-0.001		-0.001	
	(0.003)		(0.004)		(0.004)		(0.002)	
Post-Bust	-0.002		-0.007		0.008		-0.003	
	(0.003)		(0.004)		(0.004)		(0.002)	
Home within 100 miles of Austin, TX*								
Pre Boom		-0.002		0.009		0.042		-0.002
		(0.008)		(0.012)		(0.019)		(0.008)
Early Boom		-0.005		0.002		-0.015**		-0.005
		(0.008)		(0.012)		(0.006)		(0.008)
Late Boom		0.002		0.008		-0.004***		0.003
		(0.011)		(0.012)		(0.012)		(0.011)
Bust		0.004		-0.001		-0.003***		0.005
		(0.003)		(0.010)		(0.007)		(0.003)
Post-Bust		-0.004		0.001		-0.020***		-0.004
		(0.004)		(0.010)		(0.012)		(0.004)
Sample	Mobile San Jose v. Mobile Pairs	Mobile Austin v. Mobile Pairs	Mobile San Jose v. Less Mobile Pairs	Mobile Austin v. Less Mobile Pairs	Less Mobile San Jose v. Less Mobile Pairs	Less Mobile Austin v. Less Mobile Pairs	Mobile San Jose v. Mobile Pairs (with CA universities)	Mobile Austin v. Mobile Pairs (with TX universities)
Observations	29,193	11,336	31,491	11,848	26,858	3,456	47,043	11,493
R-squared	0.058	0.075	0.054	0.095	0.037	0.026	0.045	0.074

Note: *** p<0.01, ** p<0.05, * p<0.1. For interaction effects, asterisks denote statistical significance relative to pre boom period. Standard errors clustered at the university level in parentheses. I regress whether the student is a computer science major on university fixed effects, year group fixed effects, and year group fixed effects interacted with an indicator for whether the home is within 100 miles of San Jose (or Austin). I also include as covariates the matching variables listed in Table 4. Columns 1 and 2 present OLS coefficients using the principal matching sample. Columns 3 and 4 present OLS coefficients using the first robustness matching sample, including mobile San Jose/Austin students (home > 350 miles from university) and less mobile pairs (home ≤ 150 miles from university). Columns 5 and 6 present OLS coefficients using the second robustness matching sample, with San Jose/Austin students and matches both of whom study 100-350 miles from home. Columns 7 and 8 present OLS coefficients using the principal matching sample, but also including students at universities in California (7) and Texas (8). All samples include only those students from San Jose (Columns 1, 3, 5, 7) and Austin (Columns 2, 4, 6, 8) and their matched observation/s. See Table 4 for sample sizes by home location and year group for the principal matching sample. See Appendix Table A8 for sample sizes by home location and year group for robustness samples.

Appendix Table A7: The Dot-Com Crash and Computer Science Majors: Differential Effects by Home Location Among Less Mobile Students, Matching Estimation

Y = CS Major	(1)	(2)	(3)
Average Treatment Effect on Treated: Home within 100 miles of San Jose, CA			
Pre Boom	-0.006	0.002	-0.004
	(.004)	(.005)	(.005)
Early Boom	-0.004	0.02**	0.004
	(.004)	(.007)	(.004)
Late Boom	-0.0006	0.024**	-0.003
	(.005)	(.008)	(.006)
Bust	0.001	-0.004	0.004
	(.003)	(.004)	(.004)
Post-Bust	-0.006	0.005	0.001
	(.003)	(.005)	(.004)
Average Treatment Effect on Treated: Home within 100 miles of Austin, TX			
Pre Boom	0.005	0.043	-0.007
	(.007)	(.019)	(.008)
Early Boom	-0.004	-0.008**	-0.007
	(.008)	(.013)	(.008)
Late Boom	0.004	0.005**	0.005
	(.008)	(.014)	(.009)
Bust	-0.003	0.002***	0.005
	(.004)	(.006)	(.004)
Post-Bust	-0.002	-0.012***	-0.004
	(.004)	(.01)	(.004)
Parent Occ.	All	All	All
Parent Ed.	All	All	All
Sample	Mobile San Jose/Austin v. Less Mobile Pairs	Less Mobile San Jose/Austin v. Less Mobile Pairs	Mobile San Jose/Austin v. Mobile Pairs with CA/TX universities

Note: *** p<0.01, ** p<0.05, * p<0.1. This table presents matching estimates, where the treatment is whether the home is within 100 miles of San Jose, CA (Panel A) or Austin, TX (Panel B). Each coefficient is from a separate estimation, where the outcome is an indicator for whether the student is a computer science major. Column 1 presents results using the first robustness sample: mobile San Jose/Austin students (home > 350 miles from university) and less mobile pairs (home ≤ 150 miles from university) whose home is more than 100 miles from any of the principal cities of the top 15 computer employment MSAs. I also include only students whose university is more than 100 miles from any of the principal cities of the top 15 computer employment MSAs, and students at non-California universities in Panel A and non-Texas universities in Panel B. Column 2 presents results using the second robustness sample: less mobile San Jose/Austin students (home 100-350 miles from university) and their less mobile pairs (home 100-350 miles from university), whose home is more than 100 miles from any of the principal cities of the top 15 computer employment MSAs. Column 3 presents results using the principal matching sample, but also including students at universities in California (Panel A) and Texas (Panel B). I limit the sample to individuals with nonmissing values for each of the matching variables (listed in Table 4, though I exclude distance to university from home as a matching variable in columns 1 and 2). The bias adjustment from Abadie and Imbens (2011) is used for each matching variable. The mahalanobis matrix is used for weighting. See Appendix Table A8 for sample sizes by home location and year group.

Appendix Table A8: Sample Sizes for Robustness Samples

Panel A: Mobile San Jose/Austin Students and Less Mobile Pairs

	Home in San Jose, CA		Home in Austin, TX	
	No	Yes	No	Yes
Pre Boom (1990-1994)	1,956	2,096	716	741
Early Boom (1995-1998)	2,684	2,861	969	960
Late Boom (1999-2001)	2,338	2,440	1,000	994
Bust (2002-2006)	4,083	4,561	1,789	1,748
Post-Bust (2007-2011)	4,087	4,385	1,537	1,394

Panel B: Less Mobile San Jose/Austin Students and Less Mobile Pairs

	Home in San Jose, CA		Home in Austin, TX	
	No	Yes	No	Yes
Pre Boom (1990-1994)	1,098	2,646	119	164
Early Boom (1995-1998)	1,586	3,805	297	414
Late Boom (1999-2001)	1,305	3,397	244	380
Bust (2002-2006)	2,310	5,977	478	789
Post-Bust (2007-2011)	1,159	3,575	205	366

Panel C: Principal Sample Including California/Texas Universities

	Home in San Jose, CA		Home in Austin, TX	
	No	Yes	No	Yes
Pre Boom (1990-1994)	2,189	3,180	700	744
Early Boom (1995-1998)	2,966	4,072	924	965
Late Boom (1999-2001)	2,676	4,113	930	1,001
Bust (2002-2006)	4,912	10,347	1,681	1,796
Post-Bust (2007-2011)	4,144	8,444	1,337	1,415

Note: This table gives the number of individuals in the sample by home location for three robustness samples, described in detail in Appendix Table A7.

Appendix Table A9: Allocation of Talent Between Business and Science Majors After Delaware Legislation, Robustness

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Share in Major	0.241***	0.346***			-0.350***	0.296***	-0.350***	0.296***
		(0.0743)	(0.0613)			(0.0845)	(0.0556)	(0.0850)	(0.0553)
(2)	Share in Major*Post1	-0.233***	0.186***			-0.159**	0.116***	-0.159**	0.116***
		(0.0704)	(0.0374)			(0.0705)	(0.0356)	(0.0710)	(0.0354)
(3)	Share in Major*Post1*Exp	-5.350*	-1.884			-2.487	-1.864	-2.791***	-0.949
		(2.773)	(1.636)			(2.853)	(1.829)	(0.676)	(1.372)
(4)	Share in Major*Post2	-0.210***	0.168***			-0.156**	0.0829**	-0.156**	0.0829**
		(0.0732)	(0.0397)			(0.0731)	(0.0379)	(0.0736)	(0.0377)
(5)	Share in Major*Post2*Exp	-2.308	-0.992			0.576	-0.957	-1.922***	-0.408
		(1.979)	(1.060)			(2.195)	(1.456)	(0.654)	(0.964)
(6)	Post1	0.0907***	-0.0307**	0.000302	-0.00154	0.0540***	-0.0441***	0.0540***	-0.0441***
		(0.0184)	(0.0146)	(0.0106)	(0.00756)	(0.0184)	(0.0141)	(0.0185)	(0.0140)
(7)	Post2	0.0911***	0.0207	0.00842	0.0150**	0.0640***	0.00291	0.0640***	0.00291
		(0.0198)	(0.0144)	(0.00881)	(0.00628)	(0.0196)	(0.0140)	(0.0197)	(0.0139)
(8)	Post1*Exp	0.913	0.753	-0.0560	0.0189	0.454	0.768	0.423***	0.387
		(0.557)	(0.623)	(0.0399)	(0.0285)	(0.558)	(0.726)	(0.120)	(0.528)
(9)	Post2*Exp	0.303	0.372	-0.0190	-0.0301	-0.166	0.391	0.257**	0.150
		(0.445)	(0.345)	(0.0361)	(0.0257)	(0.461)	(0.561)	(0.119)	(0.338)
(10)	Share in Major*Exp	2.649***	0.797			0.302	0.898	2.592***	0.274
		(0.664)	(0.511)			(1.329)	(1.199)	(0.872)	(0.637)
(11)	Share in Major*Early					-0.0860	-0.219***	-0.0860	-0.219***
						(0.0732)	(0.0334)	(0.0736)	(0.0332)
(12)	Share in Major*Early*Exp					2.998	-0.423	-1.462*	-0.0584
						(1.992)	(1.321)	(0.815)	(0.692)
(13)	Early			-0.103***	-0.0941***	-0.112***	-0.0148	-0.112***	-0.0148
				(0.00794)	(0.00564)	(0.0143)	(0.0132)	(0.0144)	(0.0132)
(14)	Early*Exp			-0.0606*	0.0265	-0.404	0.230	0.239**	0.0739
				(0.0325)	(0.0232)	(0.282)	(0.553)	(0.104)	(0.284)
	Universities with Exp=1			University of Delaware				University of Delaware, Swarthmore College	
	Major	Business	Science	Business	Science	Business	Science	Business	Science
	Observations	1,375	1,390	1,375	1,390	1,375	1,390	1,393	1,409
	R-squared	0.782	0.878	0.803	0.894	0.809	0.904	0.807	0.905

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. See Table 6 for description of specification and variables. Columns 1-4 are the same as those in Table 6, but exclude Swarthmore College as an exposed university. Columns 5-6 compare the effect of changing share in the major to the five years preceding the shock. Columns 7-8 estimate the same specification as columns 5-6 but also include Swarthmore as an exposed university.

Appendix Table A10: Allocation of Talent Across Majors After Delaware Legislation

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Share in Major	0.241***	0.346***	-0.300**	-0.0484	-0.297	0.0526	-0.102	0.449	1.746	-0.846*	0.683**
		(0.0746)	(0.0610)	(0.143)	(0.320)	(0.361)	(0.102)	(0.154)	(0.404)	(1.885)	(0.494)	(0.287)
(2)	Share in Major*Post1	-0.233***	0.186***	-0.276	0.280	-0.608	-0.131	-0.198	0.121	-2.616	-0.597	-0.522
		(0.0707)	(0.0372)	(0.202)	(0.364)	(1.426)	(0.145)	(0.137)	(0.476)	(1.960)	(0.933)	(0.374)
(3)	Share in Major*Post1*Exp	-2.467***	-1.127	-5.919*	2.673	5.474	0.251	0.861	-1.829	7.588	-1.564	2.828
		(0.622)	(1.431)	(3.164)	(3.709)	(13.68)	(0.600)	(1.149)	(4.768)	(7.315)	(16.25)	(2.318)
(4)	Share in Major*Post2	-0.210***	0.168***	-0.211	-0.413	0.423	-0.0277	-0.0104	0.0156	-3.540*	0.260	-0.937***
		(0.0736)	(0.0395)	(0.178)	(0.437)	(1.279)	(0.128)	(0.122)	(0.454)	(1.807)	(0.806)	(0.318)
(5)	Share in Major*Post2*Exp	-1.738***	-0.618	1.066	-1.983	0.0602	0.667	1.000	-0.655	6.289	-47.40**	2.795
		(0.578)	(0.909)	(2.163)	(4.489)	(21.14)	(0.643)	(0.902)	(3.927)	(10.47)	(19.87)	(1.795)
(6)	Post1	0.0907***	-0.0307**	0.0136	-0.0454*	0.0178	0.0209	0.0349**	-0.0229	0.0577	-0.0203	0.0313
		(0.0185)	(0.0145)	(0.0175)	(0.0236)	(0.0262)	(0.0160)	(0.0152)	(0.0216)	(0.0365)	(0.0231)	(0.0222)
(7)	Post2	0.0911***	0.0207	0.0325*	0.00124	0.0125	0.0167	0.0250*	0.000189	0.127***	-0.0314	0.0740***
		(0.0199)	(0.0143)	(0.0170)	(0.0218)	(0.0250)	(0.0154)	(0.0148)	(0.0218)	(0.0332)	(0.0217)	(0.0218)
(8)	Post1*Exp	0.330***	0.441	0.209	-0.0903	-0.125	-0.0721	-0.137	0.0572	-0.202*	-0.0354	-0.326
		(0.114)	(0.542)	(0.149)	(0.200)	(0.257)	(0.0597)	(0.0995)	(0.174)	(0.109)	(0.248)	(0.212)
(9)	Post2*Exp	0.179	0.207	-0.172	-0.00877	-0.177	-0.119*	-0.135	0.00915	-0.172	0.713**	-0.331
		(0.113)	(0.288)	(0.130)	(0.172)	(0.287)	(0.0661)	(0.0982)	(0.186)	(0.110)	(0.326)	(0.221)
(10)	Share in Major*Exp	2.534***	0.359	-0.667	-3.255	0.814	-0.293	-0.622	-1.827	-7.518	-0.999	-1.495**
		(0.643)	(0.394)	(0.836)	(2.291)	(1.841)	(0.712)	(1.092)	(2.243)	(8.293)	(6.997)	(0.723)
	Major	Business	Science	Education	Math/CS	Other	Human-ities	Social Sciences	Commun-ications	Econo-mics	Services	Un-decided
	Observations	1,393	1,409	1,322	1,360	1,172	1,402	1,362	1,321	949	1,280	1,383
	R-squared	0.781	0.880	0.668	0.707	0.513	0.814	0.830	0.658	0.471	0.599	0.760

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table presents estimates from the same specifications as in Table 6, columns 1-2, but for every major. See notes to Table 6 for details.

Appendix Table A11: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock, Excluding Universities Outside of MSAs, or with MSAs not represented in the Census

		(1)	(2)
	Y_{cmt}: Share of Majors in	CS	Business
(1)	Post	-0.000	-0.001
		(0.001)	(0.011)
(2)	Post*Exposure	-0.026	-0.068
		(0.032)	(0.085)
(3)	Post*Exposure*Years Elapsed	-0.038***	-0.031
		(0.013)	(0.059)
(4)	Post*Years Elapsed	-0.006***	-0.006
		(0.001)	(0.007)
(5)	Exposure*Years Elapsed	0.021***	0.054*
		(0.008)	(0.029)
(6)	Years Elapsed	0.003***	-0.004
		(0.000)	(0.004)
(7)	Difference-in-Difference	-0.00879**	0.00157
	(Combination of (2), (3), and (5))	(.004)	(.005)
	Shock	Dot-Com	Great Recession
	Observations	14,071	7,032
	R-squared	0.747	0.963

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table presents estimates from the same specification as in Table 1, but excluding universities which are not located in MSAs, or the MSA was not represented in the Census. In Table 1, I set the MSA employment share for these universities to zero.

Appendix Table A12: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock and University Classification

		(1)	(2)	(3)	(4)	(5)
	Y_{cmt}: Share of Majors in	CS		Business		
(1)	Post	0.001	-0.002**	0.006	-0.006	0.013
		(0.002)	(0.001)	(0.008)	(0.005)	(0.014)
(2)	Post*Employment Share	-0.062	0.024	-0.463	0.090	-0.838*
		(0.043)	(0.029)	(0.282)	(0.267)	(0.434)
(3)	Post*Employment Share*Years Elapsed	-0.062***	-0.035***	-0.019	0.147	-0.173
		(0.016)	(0.013)	(0.132)	(0.206)	(0.180)
(4)	Post*Employment Share*Unemp Shock			-0.126*	0.009	-0.202**
				(0.065)	(0.070)	(0.094)
(5)	Post*Employment Share			-0.008	0.023	-0.030
	*Unemp Shock*Years Elapsed			(0.031)	(0.054)	(0.039)
(6)	Post*Unemp Shock*Years Elapsed			0.000	-0.001	0.001
				(0.001)	(0.001)	(0.001)
(7)	Post*Years Elapsed	-0.005***	-0.006***	-0.007*	-0.011**	-0.004
		(0.001)	(0.000)	(0.004)	(0.005)	(0.006)
(8)	Post*Unemp Shock			0.003	-0.001	0.005
				(0.002)	(0.001)	(0.003)
(9)	Employment Share*Years Elapsed	0.032***	0.016**	0.048	0.002	0.105
		(0.011)	(0.007)	(0.059)	(0.087)	(0.076)
(10)	Employment Share*Unemp Shock			0.015	0.011	0.023
	*Years Elapsed			(0.014)	(0.021)	(0.018)
(11)	Unemp Shock*Years Elapsed			-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)
(12)	Years Elapsed	0.003***	0.003***	0.000	0.001	-0.000
		(0.000)	(0.000)	(0.001)	(0.002)	(0.001)
(13)	Difference-in-Difference	-0.018***	-0.00535	-0.00491	0.00434	-0.00975
	(Combination of (2), (3), and (5))	(.006)	(.004)	(.005)	(.005)	(.007)
	Shock	Dot-Com		Great Recession		
	Universities	Research/ Doctoral	Master's/ Bacc.	All	Research/ Doctoral	Master's/ Bacc.
	Observations	3,678	17,310	9,942	1,834	8,108
	R-squared	0.821	0.689	0.953	0.966	0.946

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table presents coefficients from the same specifications as those shown in Table 1, but estimated separately for universities that are classified as research/doctoral and master's/baccalaureate. Results in column 3 are the same as those presented in Table 1, column 2. In this table, all coefficients are shown. Standard errors clustered at the university level in parentheses.