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IZA DP No. 10598

Local Labor Markets and Human Capital Investments

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ABSTRACT

Local Labor Markets and Human Capital Investments*

I study whether human capital investments are based on local rather than national demand, and whether this is explained by migration or information frictions. I analyze three sector-specific shocks with differential local effects, including the dot-com crash, the 2008 financial crisis, and a shock transforming Delaware into an international financial center. I find universities in areas more exposed to sectoral shocks experience greater changes in sector-relevant majors. Using rich student-level data, I find this is not explained by information frictions, but more likely by migration frictions. The results suggest encouraging human capital investments based on national demand may increase mismatch.

JEL Classification: J24, I20, R12

Keywords: college major choice, local labor markets, migration frictions, information frictions

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* I am grateful to Joe Altonji, Liz Cascio, Josh Goodman, Shawn Kantor, Lisa Kahn, Kevin Lang, Daniele Paserman, Bruce Sacerdote, Johannes Schmieder, Kevin Shih, Ken Simons, Alex Whalley, Yury Yatsynovich, and seminar participants at Rensselaer Polytechnic Institute, Florida State University, the IZA Junior/Senior Workshop, and the Urban Economics Association Meetings for helpful comments and conversations. I thank Lisa Gensel of the University of Delaware Archives and Record Management for providing data and documents. Kunio Kohama provided excellent research assistance.

1 Introduction

The unemployment rate for young workers is approximately two to three times larger than the adult unemployment rate in the US, OECD, and Japan. This has been true for the past thirty years (OECD 2010), and in the US has been true both among bachelor's degree recipients as well as among high school graduates in the years preceding the Great Recession (National Center for Education Statistics 2015).[1] High rates of youth unemployment have adverse effects on young workers, and are costly for social insurance systems. However, high unemployment rates at labor market entry are also known to have long-run career effects (Kahn 2010, Oreopolous et al. 2012, Oyer 2006), magnifying the importance of this phenomenon. 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] There is reason to believe that this mismatch could be particularly pronounced among young workers, who make investments in sector-specific skills based on very little experience in the labor market.

This mismatch may arise for several reasons. One potentially important reason is that young individuals invest in human capital based on local, rather than national, labor demand. This may result in aggregate supply of workers with sector-specific skills not equating with aggregate demand, resulting in higher aggregate unemployment rates for young workers. For example, 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

[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.

workers as they learn about the labor market and invest in new skills.

This paper makes two 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.

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 number 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.

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, then encouraging students to base human capital investments on national demand may increase mismatch. Recent initiatives to improve labor market outcomes have provided information on national demand, while others provide information on local demand.[4] This paper helps evaluate which of these is likely to exacerbate or ameliorate any mismatch.

I am able 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 at the same university, by whether their permanent home is near a computer-industry cluster. I focus on students at universities in areas other than computer-industry clusters. This identification strategy isolates the role of information frictions by comparing students for whom migration frictions are minimal, but who may have access to different industry-relevant information given differences in their permanent home markets. With national information on labor demand, likelihood of majoring in computer science should not depend on whether the student's permanent home is in a computer-industry cluster, given the absence of migration frictions. 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.

I define computer-industry clusters as the two MSAs with the highest share employed in computers in 2000: San Jose, CA (26% employed in computers) and Austin, TX (12.5% employed in computers). For each individual from within 100 miles of San Jose, I identify the closest match at the same university who is not from the San Jose area (or any top 15 computer MSA), based on individual demographic and academic characteristics. To identify geographically mobile students, I include only individuals whose university is not in California, at least 350 miles from their home, and those who say being close to home was not an important determinant of their university choice. I implement the analogous matching procedure for students from Austin.

I find strong evidence that college majors respond to local labor demand conditions. After the dot-com crash, the regression coefficients suggest an 8% decline in computer science degrees at research universities in high computer employment areas

[4]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*).

(MSAs at the 99th percentile of computer employment share). There was no negative effect at research universities in MSAs with low computer employment share. After the financial crisis, the regression coefficients suggest a 13% reduction in business degrees at private universities in high finance employment areas (MSAs at the 99th percentile of finance employment share). In contrast, business degrees decreased by only 4% at private universities in low finance employment areas (MSAs with finance employment share at the 1st percentile). After the finance shock in Wilmington, Delaware the share of business degrees increased by 15% at local universities, and the effect at universities more than 50 miles from Wilmington was 90% smaller.

Using student-level data from the Freshman Survey, the results suggest this finding is driven by migration not information frictions. Geographically mobile students from San Jose and Austin respond similarly to the boom and bust relative to their counterparts at the same university, whose permanent home is not in a computer-industry cluster. Among less geographically mobile students, those from San Jose respond more to the boom and bust than their counterparts at the same university.

The results suggest migration frictions may cause mismatch and higher youth unemployment. This implies encouraging students to study fields with high national demand may be unproductive. This would shift students to major in fields not demanded locally. Given migration frictions, this may increase mismatch.[5] The local dependence may also affect aggregate productivity if employers cannot hire the most productive individuals for their vacancies.

The paper provides new evidence on two additional policy-relevant questions. 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

[5]There is also considerable policy discussion in this area because of the possibility that students are not able to identify majors with the highest return. Recent findings have shown that 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).

and Reshef 2012, Shu 2015) using the exogenous shock to finance in Delaware, and data on all universities in the area surrounding the shock.[6] 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 find suggestive evidence that Wilmington-area universities experienced differential selection out of science, and that low GPA students left science for business and humanities.

The paper also contributes to the literature on how individuals make human capital investments (see Altonji, Blom, and Meghir 2012 for a review), especially after economic shocks. Recent work by Blom, Cadena, and Keys (2015) finds significant reallocation in college majors in response to unemployment rates during schooling years. Long, Goldhaber, and Huntington-Klein (2014) find college majors respond to changes in occupation-specific wages. I contribute to this literature by identifying exogenous shocks that affect particular sectors, which map very closely to particular majors (e.g. the dot-com crash and computer science majors). This allows me to clearly study the effect of sector-specific labor demand on sector-specific human capital investment. Further, most studies have focused on college major choice and national labor demand conditions, rather than local labor demand. An exception is Long, Goldhaber, and Huntington-Klein (2014) which finds college major choice in the state of Washington is more responsive to local compared to national wages.

Finally, these are among the first estimates identifying the role of migration frictions on college major choice, and also the role of information frictions driven by geography.

2 Sector-Specific 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

[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.

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. 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 FIRE, with employment declining by approximately 8% from 2007 to 2010.

Figure 2 shows these national sectoral shocks had differential effects on local economies using data from the Quarterly Census of Employment and Wages. Santa Clara County in California, the home of Silicon Valley, experienced an increase of approximately 45,000 jobs in "Computer Systems Design and Related Services" from 1990 to 2000. This increase represented over 5% of total employment in the county (Figure 2a). By 2002, employment in this industry had fallen from its 2001 peak, with the one-year employment loss representing over 1% of total county employment.

These effects contrast sharply with the shock's effect in Bexar County, Texas, the county where San Antonio is located. From 1990 to 2000, employment in "Computer Systems Design and Related Services" increased by 2,450 jobs. This increase represented .5% of total county employment. After the dot-com crash, employment in this industry increased slightly. The dot-com crash had no negative effects on local employment in this computer industry.

Similarly, finance employment increased more in Manhattan (New York County) than in Leon County, Florida (Tallahassee) during the pre-financial crisis years (Figure 2b). In 2007, the change in finance employment in Manhattan represented about .5%

[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 and uncertainties in new markets. Wang (2007) proposes that the dot-com boom and bust can be explained by innovation that was complementary to traditional technology of brick-and-mortar institutions, giving these firms an eventual advantage over the dot-com companies. Ofek and Richardson (2001) argue that the bubble may have burst when lock-up agreements from IPOs expired, causing an increase in the number of sellers in the market.

of total employment, whereas there were no additional finance jobs in 2007 in Leon County. During the 2008 financial crisis, finance employment fell considerably in Manhattan, with the one-year employment loss representing over 1% of total county employment. This effect was much smaller in Leon County, Florida, representing .3% of county employment.

This paper uses variation in local effects of 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 Creation of an International Financial Center in Delaware

The dot-com crash and financial crisis of 2008 represent national shocks with differential local effects. 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 particularly large.

Prior to 1978, state usury laws determined the interest rate that credit card companies could charge residents of the state.[9] 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.[10] After the *Marquette* ruling, the state recognized the opportunity to attract the finance industry.[11] 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

[9] The exogenous shock to labor demand in Delaware is described in greater detail in Weinstein (2017).

[10] 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).

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

FCDA reduced other industry regulation and introduced a regressive tax structure for banks.[12]

As a result, many companies moved their finance or credit operations to Delaware, starting with J.P. Morgan in 1981. Weinstein (2017) shows the policy resulted in higher levels of Finance, Insurance, and Real Estate (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),[13] 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 shock.

3 Data

3.1 Dot-Com Crash and the 2008 Financial Crisis

To study the impact of the 2000 dot-com crash and the 2008 financial crisis, I obtain university-level data from 1990-2013 on Bachelor's degrees awarded by academic discipline from IPEDS. I classify business majors as business, management, market-

[12] There were several restrictions on these acquired banks, including capitalization and employment requirements. 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.

[13] 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.

ing, and related support services. I classify computer science majors as computer and information sciences and support services.[14] I include only Research, Doctoral, Master's, and Baccalaureate universities as ranked in the 1994 Carnegie rankings.

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.

3.2 Jurisdictional Competition and Firm Relocation

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.[18] These data are accessed from the Integrated Science and Engineering Resources Data System of the National Science Foundation (NSF).[19]

Because this was a Delaware-specific shock, I limit the sample of universities to those located in Delaware, New Jersey, Pennsylvania, Maryland, Washington, DC, Virginia, and West Virginia. I obtain latitude and longitude of each university by merging the ZIP code in the IPEDS data to the ZIP code tabulation area (ZCTA) in the Census Gazetteer. For universities whose ZIP code does not match a ZCTA, I obtain the latitude and longitude of the university's city using the Census

[14] I use two-digit CIP codes to classify majors from 1990-2013. The CIP codes pertaining to these majors are listed in the appendix.

[15] The BLS definition of high-technology industries I use is from Hecker (2005). This definition 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 define the relevant sample of workers as those not living in group quarters, those who are age 18 through 65, those who worked last year, and those who were not in the military.

[18] I use the academic discipline broad (standardized) classifications, and the NCES population of institutions.

[19] 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.

Gazetteer's place files.[20] 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.[21] While not as optimal as driving distances, these distances provide a good approximation.

Unlike the dot-com crash and 2008 financial crisis, Delaware's legislation implied the shock to finance was concentrated in one area, Delaware. In particular, it was concentrated in Delaware's largest city, Wilmington. This allows me to compare universities in areas directly receiving the shock to universities in nearby areas that did not receive the shock. Since I am comparing universities in close proximity, the likelihood they experience differential shocks to other industries is lower than when studying the national shocks. As a result, studying differences in the share pursuing each major is more informative when analyzing the Delaware shock.

Assuming that college freshmen choose majors based on the labor market when they were high school seniors, the first "treatment" year is 1986. The first FCDA firm entered Delaware in late 1981, implying that the first students entering college knowledgeable about the shock would be those who entered in Fall 1982. I have data on degree completions, so the first year we might see an effect on Bachelor's degree completions would be 1986. There may be effects in 1985 if students choose majors based on the information they have in their Freshman year. Throughout the paper, I will use the term "treatment" to refer to years in which the policy could have an impact on the academic disciplines of Bachelor's degrees awarded. This contrasts with the year the policy was enacted due to the timing of college major decisions.

I separate each of the broad academic disciplines into a major group and observe effects on each group.[22] I obtain data on FIRE employment by state and year using the Current Employment Statistics (CES) of the Bureau of Labor Statistics (BLS).

[20]There were two universities, Keystone College (La Plume, PA) and St. Fidelis College (Herman, PA) whose ZIP codes did not match to a ZCTA and whose cities did not match a Census place. I determined the latitude and longitude for these cities from the website itouchmap.com.

[21]This was implemented using the *vincenty* command in Stata.

[22]These groups include business and management; economics; communication and librarianship; education; science; humanities; services; math and computer sciences; social sciences; and other. The majors in each of these groups are listed in the appendix.

4 Effects on Major, by University Exposure to Shock

The Dot-Com Crash and the 2008 Financial Crisis: Descriptive Evidence

The national share of Bachelor's degrees in computer science increased dramatically in the mid-1990s, followed by a dramatic decline starting in 2004 (Figure 1). These 2004 college graduates entered as college freshmen in the Fall of 2000, and thus were the first students to enter college after the beginning of the dot-com crash. College graduates in 2001 through 2003 did not substitute away from computer science majors, despite being enrolled during the crash. These students may have made costly investments in computer science classes at the beginning of their college careers, before the crash.

The light grey plot in 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.

The darker plot in Figure 2c shows the effect of the dot-com crash on computer science degrees was larger in high computer employment MSAs. I calculate the share of computer science degrees in each MSA group in 2003, when the national share peaked, and subtract this from the share in 2008. The share of computer science degrees fell on average by over 5 percentage points at universities in the San Jose, California MSA, where over 25% of the workforce was employed in computers. The effect was less than 2 percentage points for many of the MSAs less exposed to the computer industry.

While the national share of Bachelor's degrees in business started decreasing in 2004, this had slowed considerably leading up to the Great Recession (including a slight increase in 2009) (Figure 1). After 2009 the share of business degrees fell significantly. College graduates in 2010, juniors at the time of the Great Recession in 2008-2009, were the first to show substitution away from business degrees. This suggests it may be less costly to switch from business than from computer science.

The light grey histogram plot in Figure 2d shows across-MSA variation in the total number of business degrees awarded. The darker plot shows the Great Recession appears to have had the largest effect on business degrees at universities in MSAs with greater exposure to finance. From 2009 to 2013, the share of business degrees fell by nearly 3.5 and 6 percentage points at universities in the two MSA groups with highest exposure to finance. In MSAs with less finance exposure, the decrease was between two and three percentage points.

Jurisdictional Competition and Firm Relocation: Descriptive Evidence

Table 1 shows the number of universities with data in both the years immediately preceding the policy (1980-1986), and the years immediately following the policy (1987-1990), as these universities will provide the identifying variation. There are six universities within 15 miles of Wilmington, 34 within 15 to 50 miles, and 172 more than 50 miles away (but within the nearby states).

Figure 4 shows the change in majors over time (relative to 1983) for each major group, by university distance to Wilmington, Delaware.[23] I subtract the 1983 share as this is the last year graduates were not exposed to the policy as sophomores (a crucial year for major choice). The share of students choosing business majors increases dramatically from 1987-1990 at universities within 15 miles of Wilmington; there is little change during these years at farther universities. Given these are years of the largest FIRE growth in Delaware, the timing of the effects is consistent with the sophomore year being crucial for major choice.

The large increase in business majors from 1987-1990 seems to come from science; math/computer science; and other (vocational and home economics). Interestingly, there is also a dramatic long-run increase in education majors. This is presumably due to the large population growth, and thus school enrollment growth, occurring in Delaware following the policy (Weinstein 2017).

4.1 Empirical Strategy

The Dot-Com Crash and the 2008 Financial Crisis

I estimate the following regression separately for studying the impact of the dot-com crash on computer science majors and the financial crisis on business majors:

$$\begin{aligned} Ln(Majors_{cmtg}) &= \alpha_0 + \gamma_c + \beta_1 Ln(TotDegrees_{cmtg}) \\ &\quad + \kappa_g + \delta_g YearGroup\_g_t * Ind2000_m + u_{cmtg} \end{aligned} \tag{1}$$

[23] The smallest major groups are shown in the appendix.

When studying the dot-com crash, $Majors_{cmtg}$ denotes the number of computer science majors at university c in metropolitan area m in year t (which is classified in year group g). The variable $TotDegrees_{cmtg}$ denotes the total number of Bachelor's degrees awarded by university c in year t.

The variable $YearGroup\_g_t$ is an indicator equal to one if year t is in group g. When studying the dot-com crash, there are four year groups g. The years preceding the peak of the dot-com bubble are included in the group $PrePeak$, years 1990 through 1997. The year group $Crash$ includes the years 2001 through 2003, in which the graduating class was enrolled in university during the beginning of the crash in March 2000.[24]

The year group $Post$ includes years 2004 through 2008, the first five graduating classes which entered university after the beginning of the crash in March 2000.[25] The year group LR includes the years 2009 through 2013. The omitted year group consists of the three years preceding the dot-com crash, in which the dot-com bubble was at its peak (1998 through 2000).

The variable $Ind2000_m$ denotes the share of metropolitan area $m's$ employment in computers in 2000. I do not include $Ind2000$ uninteracted since this would be perfectly collinear with the university fixed effects (γ_c). Because of differences between private and public universities, especially in tuition, I allow for heterogeneity on this dimension. Higher tuition at private universities may be important if the shock decreases earnings differentials between private and public university graduates.

When studying the financial crisis, $Majors_{cmtg}$ denotes the number of business majors at university c. There are three year groups g. The years preceding the stock market's pre-crisis peak are included in the group $PrePeak$, years 2000 through 2005. The year group $Crash$ includes the years 2009 through 2011, in which the graduating class was enrolled in university during the initial drop in the Dow in Fall 2007.[26] The year group $Post$ includes the graduating classes entering university after the initial drop in the Dow, years 2012 and 2013. The omitted year group are the three years

[24] I do not include the year 2000 in $Crash$ since the crash began only a few months before graduation for these students, making it unlikely that college majors responded.

[25] The graduating class of 2004 were freshmen in the Fall of 2000, after the initial drop in the NASDAQ.

[26] I do not include the year 2008 in $Crash$ since the stock market began to fall only a few months before graduation for these students, making it unlikely that college majors responded.

preceding the financial crisis (2006 through 2008). I restrict the regression to the years 2000 through 2013. The variable $Ind2000_m$ denotes the share of metropolitan area $m's$ employment in finance in 2000.

We expect preexisting trends in business and computer science majors before the financial crisis and the dot-com crash, given significant growth in finance and computer employment. It would not be surprising if this growth had greater effects at universities in areas with greater employment in these industries. This growth period is not the focus of the study because of the potential for endogeneity concerns, namely that growth arose due to growing number of majors at particular universities.

I weight the observations by $Majors_{cmtg}$, which ensures that large percentage increases at larger universities are given more weight than those at smaller universities. I cluster standard errors at the university level.

Figure 3 shows the coefficients from estimating regression (1) with year-fixed effects, and year-fixed effects interacted with MSA employment share. The effects are relative to the year preceding the first year in the *Post* year group. The plots show that universities in higher computer (finance) employment areas experienced more negative effects on computer science (business) degrees after the crash. The timing of the effects is approximately consistent with the year group definitions, though the effects of the Great Recession appear to start for students entering before, but enrolled during, the crash. Public universities in higher finance employment areas experience more positive effects on business degrees after the crash. This may be evidence of substitution between private and public universities.

Jurisdictional competition

A significant benefit from studying the shock to Delaware's finance industry is that one area received the shock and nearby areas did not, due to the state legislation. This allows me to compare the effects by distance to the shock, which quantifies the extent to which the effects are local. This is less straightforward when studying the dot-com or financial crisis because many MSAs experience local effects, though to different extents. Furthermore, I am able to compare effects among universities in Delaware to effects among universities in nearby areas, arguably subject to similar regional shocks. This also helps me to study substitution into and out of other majors at Wilmington-area universities, relative to farther universities.

To exploit these advantages, I estimate a slightly different regression when studying the shock in Delaware. I include university fixed effects to get the average within-university change in the composition of majors in the treatment period. I compare this average change among universities that are close to Wilmington to those that are farther. I estimate regressions of the following type, clustering standard errors at the university level:

$$\begin{aligned} Y_{crt} &= \alpha_0 + \gamma_c + \beta_r Distance\_r_c * TreatYears_t + \delta_r Distance\_r_c * pre1980 \quad (2) \\ &+\tau_r Distance\_r_c * 1990s_t + \phi_r Distance\_r_c * 2000s_t + Z_{crt}\kappa + u_{crt} \end{aligned}$$

I estimate separate specifications in which the dependent variable Y_{crt} is equal to the share of degrees awarded in each major group at college/university c in year t. The variable $Distance\_r_c$ is an indicator for whether university c is in distance group r from Wilmington. The values of r, in miles, include: $[0, 15]; (15, 50]; (50, 100]; (100, 150]; >$ 150. The variable $TreatYears_t$ is an indicator for $1987 \leq year \leq 1990$. The variable $pre1980_t$ is an indicator for $year < 1980$, $1990s_t$ is an indicator for $1991 \leq year \leq 1999$, and $2000s_t$ is an indicator for $2000 \leq year \leq 2013$. Thus the coefficients β_r convey how the difference between the treatment years and the years immediately preceding the treatment (1980 through 1986) vary with distance to Wilmington.

The row vector Z_{crt} includes variables that vary within university across year: total degrees conferred by the university, the second lag of natural log of FIRE employment at the state level, and year and year squared to capture trends in the data.[27] I weight the observations by the number of Bachelor's degrees conferred by the university in that year.[28]

[27]Given that FIRE employment is missing post-2001, I set the second lag of the natural log of FIRE employment to zero post-2003 and include an indicator for $year \geq 2004$.

[28]I omit special-focus universities (such as business and management, theological seminaries, health professions), according to the Carnegie 1994, 2005, or 2010 classifications. The composition of majors at these universities should not change in response to the shock, though the number of majors may. This is unlikely to have a large effect given only one special-interest university within 15 miles of Wilmington. In the online appendix, I discuss a strategy to capture reallocation across universities.

5 Effects by University Exposure to Shocks: Results

5.1 Differential Effect of the Dot-Com Crash

Among students entering research and doctoral universities after the initial crash, the crash has a much stronger effect at universities in higher computer-share areas (Table 2, column 3). The differential effect is statistically significant, and suggests that if the MSA computer share is higher by 1 percentage point, the percent change in the number of computer science degrees awarded is on average approximately 1.8 percentage points lower.

At universities in MSAs with computer share at the 99th percentile (.125), the coefficients suggest computer science degrees fell after the crash by approximately 8%. Even more dramatically, the coefficients suggest computer science degrees fell at Stanford by approximately 32%.[29] The dot-com crash does not negatively affect computer science degrees at universities in MSAs with low computer employment share.[30] The magnitudes suggest the differential effect of the crash is larger among private universities (column 4).

Among students enrolled during the crash's onset, the crash does not differentially affect those in higher computer-share areas. This suggests it may have been costly to change majors after important early investments. Relative to the years preceding the crash, computer science degrees fell more among research/doctoral-university graduates from 2004 through 2008, than among these graduates from 2009 through 2012.[31] This may suggest students immediately after the crash overestimated the size or duration of the shock. Alternatively, these students may have understood poor initial placement would have long-run labor market consequences (Kahn 2010, Oreopolous et al. 2012, Oyer 2006, 2008).[32][33]

[29] Stanford is the only research/doctoral university in San Jose, California where 26% of the workforce is employed in computers.

[30] At universities in MSAs with computer employment share at the 1st percentile (.008), the coefficients suggest computer science degrees increased after the crash by approximately 13%. The coefficients on *LongRun* show that by 2009-2013 there is a negative effect on computer science degrees even among those in low computer-share areas.

[31] In column 3, the combination of the coefficients $Post$ and $Post * Ind2000$ is statistically significantly different than the combination of the coefficients $LongRun$ and $LongRun * Ind2000$ (p-value = .016).

[32] Figure 1 shows a persistent effect on computer employment ten years after the shock, though a smaller effect than immediately after the shock.

[33] This result is also consistent with a cobweb model of labor supply (Freeman 1975, 1976), though

Among master's and baccalaureate universities, those in higher computer-share areas actually experienced greater increases in computer science degrees awarded. However, the coefficients on *LongRun* suggest the differential negative effects begin with a greater delay for these universities, consistent with Figure 3.

5.2 Differential Effect of the 2008 Financial Crisis

Among students entering private universities after the financial crisis's onset, the crash more negatively affected business majors at universities in higher finance-share areas. For these universities, if the MSA finance share is higher by 1 percentage point, on average the percent change in the number of business degrees awarded is approximately 1.9 percentage points lower (Table 3, column 2). At private universities in MSAs with finance employment share at the 1st percentile (.013), business degrees are predicted to fall by 4%. At private universities in MSAs with finance employment share at the 99th percentile (.059) this decrease is approximately 13%.

After the crash, public universities in high finance share areas experienced greater increases in business degrees awarded (row 3). This suggests some of the decrease in business majors at private universities in high finance areas may represent students changing universities but not their major.

There are no statistically significant effects among students enrolled during the crash's onset (rows 7 and 8), although the magnitudes are negative, and in the case of private research/doctoral universities also large. Private universities in high finance-share areas appear to have experienced greater decreases in business degrees between the pre-peak and peak periods (rows 11 and 12).[34]

5.3 Effect of Jurisdictional Competition

The first column of Table 4 suggests that, on average, for universities within 15 miles of Wilmington, the share of business degrees was 3.8 percentage points higher in the treatment years relative to the period immediately preceding the treatment. In 1985, averaging across these universities, 26% of degrees awarded were in business, imply-

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.

[34] Appendix Tables A8 and A9 show that universities in areas more exposed to shocks also experience greater changes in total enrollment. However, it is clear this is not the dominant mechanism explaining within-university changes in majors.

ing roughly a 15% increase. For universities within 15 to 50 miles of Wilmington, the effect is one third the size and not significant from zero (though not statistically significantly different from the local effect). For all greater distances the increases are approximately 90% smaller, and the difference relative to the closest universities approaches conventional levels of statistical significance ($p = .1$ for distance ϵ $(50, 100]$, $p = .12$ for distance ϵ $(100, 150]$, and $p = .08$ for distance > 150).

Given the 15 to 50 mile distance group includes Philadelphia, it is not surprising that a large shock to Delaware's FIRE employment does not largely affect major composition there. While Delaware experienced a large percent increase in FIRE jobs, the level increase is still small relative to the Philadelphia labor market.[35] What is more surprising is this causes a local effect within 15 miles of Wilmington, and these students do not see themselves as part of a larger labor market.

During treatment years students at Wilmington-area universities, relative to farther universities, substitute into education majors, out of math/computer science and science majors, and there is no relative difference in humanities majors. On average, for universities within 15 miles of Wilmington, the share of science degrees was 8.5 percentage points lower in the treatment years relative to the period immediately preceding the treatment (column 2). In 1985, averaging across these universities, 28% of degrees awarded were in science, implying roughly a 30% decrease. For universities more than 15 miles from Wilmington, the effects are 35 to 50% smaller, and the differences relative to the closest universities are statistically significant.

Coefficients on the $Pre-1980$ interactions show no evidence that the differential increase in business majors at Wilmington-area universities was part of a preexisting trend. Substitution out of math/computer science majors may be part of a long-run trend, but the same is not true of the patterns in education and science majors.[36]

Results are similar when interacting year group indicators with a quadratic in distance, rather than distance groups (Appendix Table A2).[37]

[35] From 1981 to 1990, FIRE employment in Delaware increased by roughly 20,000 jobs according to the Bureau of Labor Statistics Current Employment Statistics (CES). Using data from the CES, in 1986, total employment in the Philadelphia PMSA was approximately 2.1 million, while FIRE employment was approximately 153,000.

[36] The appendix shows no change in total enrollment at Wilmington-area universities, but rather an increase in the share of nonlocal students at these universities.

[37] In Table 4, the differences in the treatment years relative to the years preceding the treatment are constant for the distance groups 50 to 100 miles, 100 to 150 miles, and greater than 150 miles. As a result, I only include universities with distance ≤ 150 miles in the polynomial regression. The results are shown in Appendix Table A2.

6 Mechanisms: Information or Migration Frictions

The first part of the paper shows 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.

Using rich, student-level data from the Freshman Survey, I separate the role of migration and information 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 Freshman Survey (TFS) contains detailed student-level data on major choice, academic, and family background. As alluded to above, 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. Students could respond by saying this was a very important reason, somewhat important, or not important. I include in my sample only those students who said living near home was not an important reason why they chose the university.

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.[38]

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. 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 outside 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 home location and principal cities of the top 15 computer employment MSAs.[39]

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 the information frictions, I exclude from the sample any non-San Jose or non-Austin students whose homes are within 100

[38]For robustness, I include these universities as well.

[39]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 6 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).

miles of the principal city of the top 15 MSAs by share employed in computers in 2000 (among those which are home MSAs for at least one student).[40] I also include only students at universities more than 100 miles from the principal cities of the top 15 computer employment MSAs in 2000. This ensures students only have information on labor demand in computer-area clusters from their home markets, and not from their 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 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.

I exclude individuals with missing values of any of the covariates. Assigning arbitrary values if the variable is missing would imply individuals with missing values are matched to each other. However, 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

[40] These 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.

based on the inverse standard errors of the variables.

Information frictions may be lower for San Jose/Austin students because their parents are more likely to work in the computer industry. To 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, controlling for each of the matching variables. 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 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 5 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 6). 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. This is one potentially important mechanism that may yield different information for San Jose or Austin students, and I test whether it explains the results.

Kernel-weighted local polynomial regressions show that at universities outside San Jose, 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 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. This difference would not explain why universities in low-computer share areas respond less to the bust, as found in the first part of the paper.

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 A13 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 that the muted response to the dot-com crash at universities in areas less-exposed to the crash is not explained by the fact that students at those universities had less information. Rather, the results suggests this muted response is due to stronger geographic mobility frictions at these less-exposed universities.

Robustness

I test for differential responses among less geographically mobile students. This would further support the role of migration frictions in explaining why students at less-exposed universities respond less to sector-specific shocks. I estimate two alternative specifications. First, I compare the geographically mobile students from San Jose/Austin to students at the same university who are less geographically mobile. Second, I compare less geographically mobile students from San Jose/Austin to less geographically mobile students at the same universities from areas other than these cities. In these specifications, it is not possible to separate the information and migration frictions, which is the purpose of estimating the principal specification. However, given the limited evidence of information frictions in that exercise, finding differences among less mobile students would be consistent with migration frictions.

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. Appendix Figure A5 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 these students. 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 A15 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 the bust. Appendix Table A14 shows this greater response of the San Jose/Austin students is also evident in the matching procedure, and Appendix Table A13 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. Specifically, I compare students from San Jose/Austin whose home is 100-350 miles from home to students at the same university from other areas whose home is also 100-350 miles from the university. Appendix Figure A6 shows the home and university locations for individuals in the sample. Appendix Table 15 gives sample sizes by home location and year group.

If information about demand changes with distance to San Jose/Austin even among students who 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 there should be 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 A14 shows the greater response of the San Jose students in the matching estimation, and Appendix Table A13 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 A13 and A14). 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 Allocation of Talent Across Majors

Finally, I study whether science loses its high- or low-achieving students to finance, using the shock to finance in Delaware. As discussed above, this is a unique setting for testing selection out of science and into finance given the historical importance of the chemicals sector in Delaware.

Specifically, I study the change in composition of majors by high school GPA after the policy.[41] I refer to students with a high school GPA of at least a B+ as high

[41] I estimate regressions similar to the others studying the finance shock in Delaware, with the dependent variable an indicator for whether the individual is intending on major Y. I include inter-

GPA students. The magnitudes suggest relative outflows of local, high GPA students from business majors at Wilmington-area universities, relative to farther universities (Appendix Table A12). The difference relative to universities 50 to 100 miles approaches significance with $p = .11$, and is statistically significant at the .05 level relative to farther universities. The difference in the high/low GPA differential across distance group is explained by the greater probability of local, low GPA students majoring in business at Wilmington-area universities, relative to farther universities (not shown).[42]

The magnitudes suggest relative inflows of high GPA, local students into science majors at Wilmington-area universities, relative to farther universities (the differences relative to other distance groups are statistically significant at the .01 level).[43] The very large difference in the high/low GPA differential across distance group is explained by the much greater outflows from science of local, low GPA students at Wilmington-area universities, relative to farther universities (not shown).[44]

The results also show that immediately after the policy there were relative outflows from humanities and undecided of local, high GPA students at Wilmington-area universities, compared to farther universities. On the contrary, there were relative inflows into health of high GPA students at Wilmington-area universities, compared to farther universities.[45]

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

actions between distance radius, year group, and indicators for nonlocal and high school GPA at least a B+. See appendix for regression specification and details.

[42] The coefficients on $Dist\_r * TreatYears1$ (not shown) and $Dist\_r * TreatYears1 * BPlus$ suggest the total change for local, high GPA students is fairly similar across distance group.

[43] These effects are not part of a pre-policy trend, and the results for business majors are in the opposite direction of the pre-policy trend.

[44] The coefficients on $Dist\_r * TreatYears1$ (not shown) and $Dist\_r * TreatYears1 * BPlus$ suggest the total change for local, high GPA students is still larger at Wilmington-area universities, but not by as much as the differential.

[45] The post-policy effect on majoring in health for low GPA students is very similar across regions. The high/low differential is driven by the greater substitution of high GPA students into health at Wilmington-area universities.

8 Conclusion

This paper tests 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 whether investments are based on local demand using three sector-specific shocks with local effects: the 2000 dot-com crash, the 2008 financial crisis, and a shock originating from an important instance of jurisdictional competition-the creation of an international financial services center in Delaware in the 1980s.

Using university-level data on degree completions by academic discipline from 1966 through 2013, I find universities in areas more exposed to sectoral shocks experience greater changes in sector-relevant majors, and this is especially true among private universities.

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 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 into major by student achievement. I find suggestive evidence that immediately after the policy, low GPA students at Wilmington-area universities left science for business and humanities.

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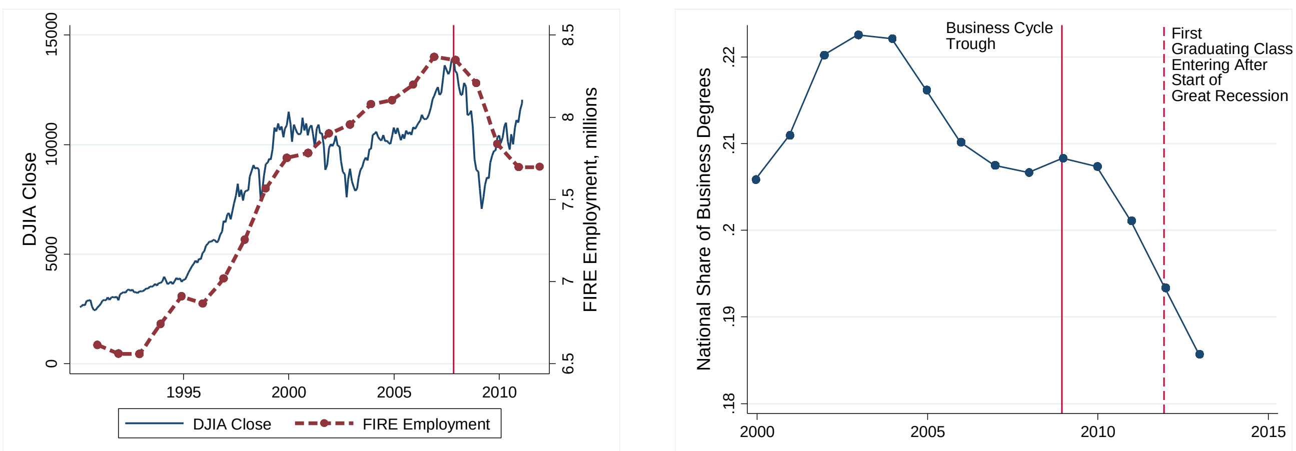
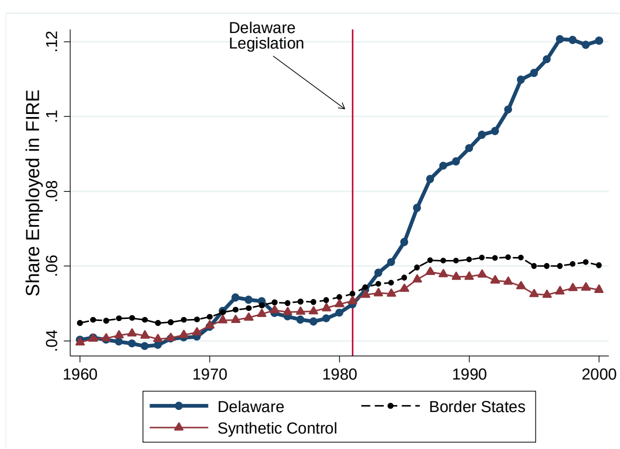
Figure 1: Sector-level Shocks and College Majors in the US

(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

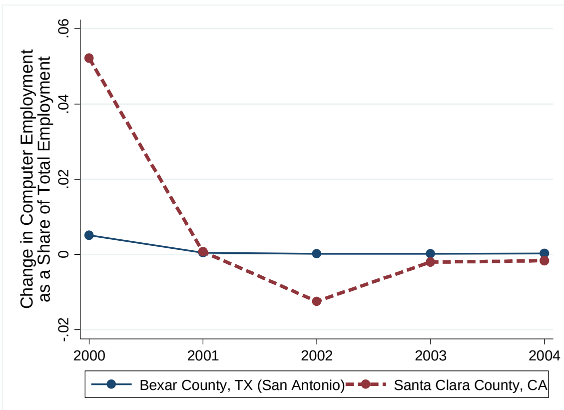


Note: Source for the data on the NASDAQ closing prices: http://www.nasdaq.com/symbol/ixic/interactive-chart, Date accessed: 3/11/2016. Source for DJIA closing prices: https://www.nyse.com/quote/index/!DJI, Date accessed 3/15/2016. Source for employment data: CES. Computer employment includes employment 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.

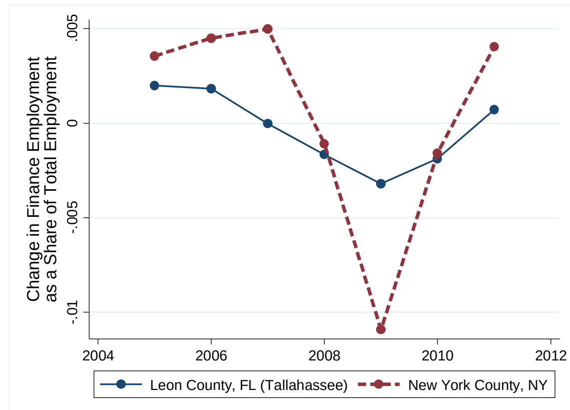
Figure 2

Differential Local Effects of National Shocks

(a) Dot-Com Crash

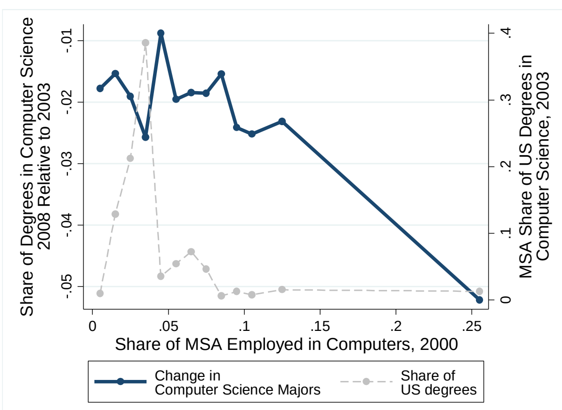


(b) Financial Crisis

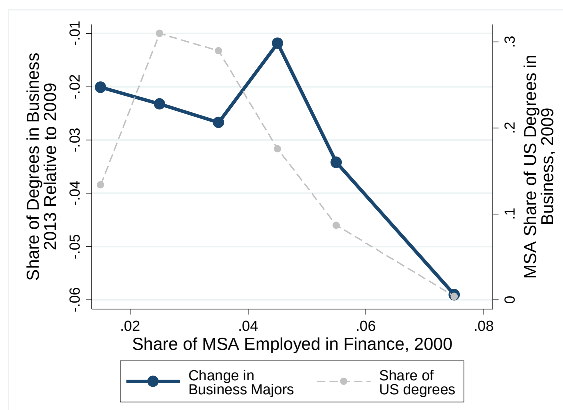


Differential Effects of Shocks on Sector-Relevant Majors, by MSA Employment Share

(c) Computer Science Majors



(d) Business Majors

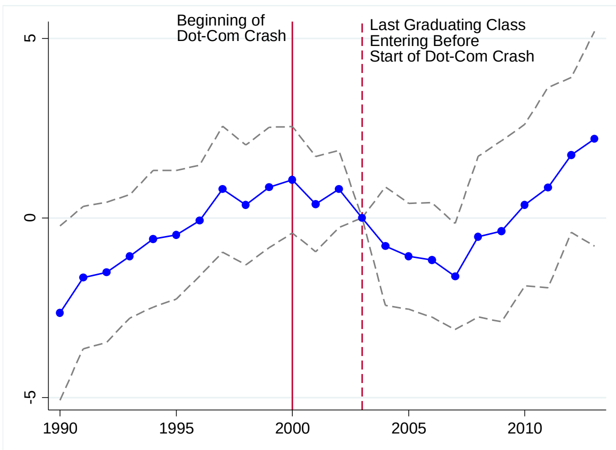


Note: County-level employment data are from the Quarterly Census of Employment and Wages. Computer Employment is defined in these plots as "Computer Systems Design and Related Services". Financial and computer employment are based on jobs in the private sector, while total employment covers jobs in all industries. The darker plot in Figure 2c is constructed by subtracting the share of computer degrees in the MSA group in 2003 from the share in 2008. The darker plot in Figure 2d is constructed by subtracting the share of business degrees in the MSA group in 2009 from the share in 2013. The lighter plots in Figures 2c and 2d are the total computer (2c) and business (2d) degrees awarded in the MSA group divided by the total of these degrees awarded in the US. MSA groups start at zero, and are in intervals of .01. The share of computer and business degrees in the MSA group is calculated by summing the total of these degrees awarded at all universities at all MSAs in the interval, and dividing this by the total degrees awarded at all universities at all MSAs in the interval. See text for details.

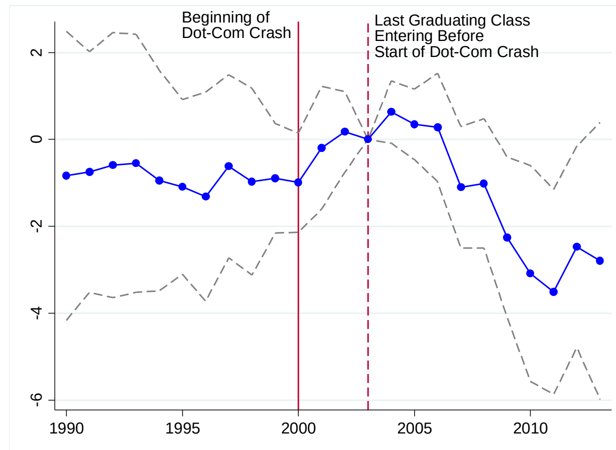
Figure 3 Sectoral Shocks and their Effect on Universities, by Sectoral Composition of University MSA

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

Research/Doctoral Universities

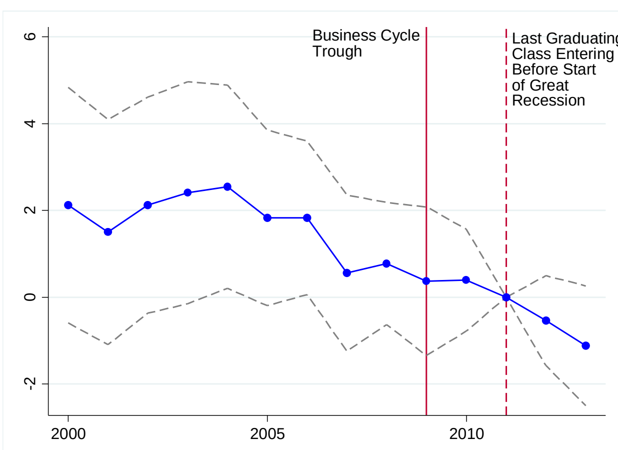


Master’s/Baccalaureate Universities

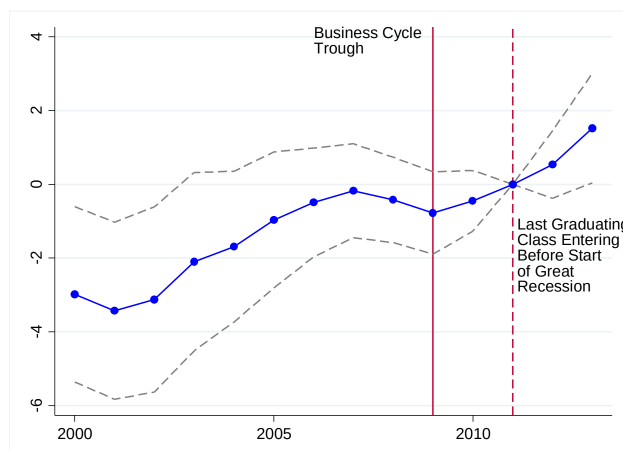


(b) Effect of MSA Finance Employment Share on Ln(Business Degrees), Relative to 2011

Private Universities

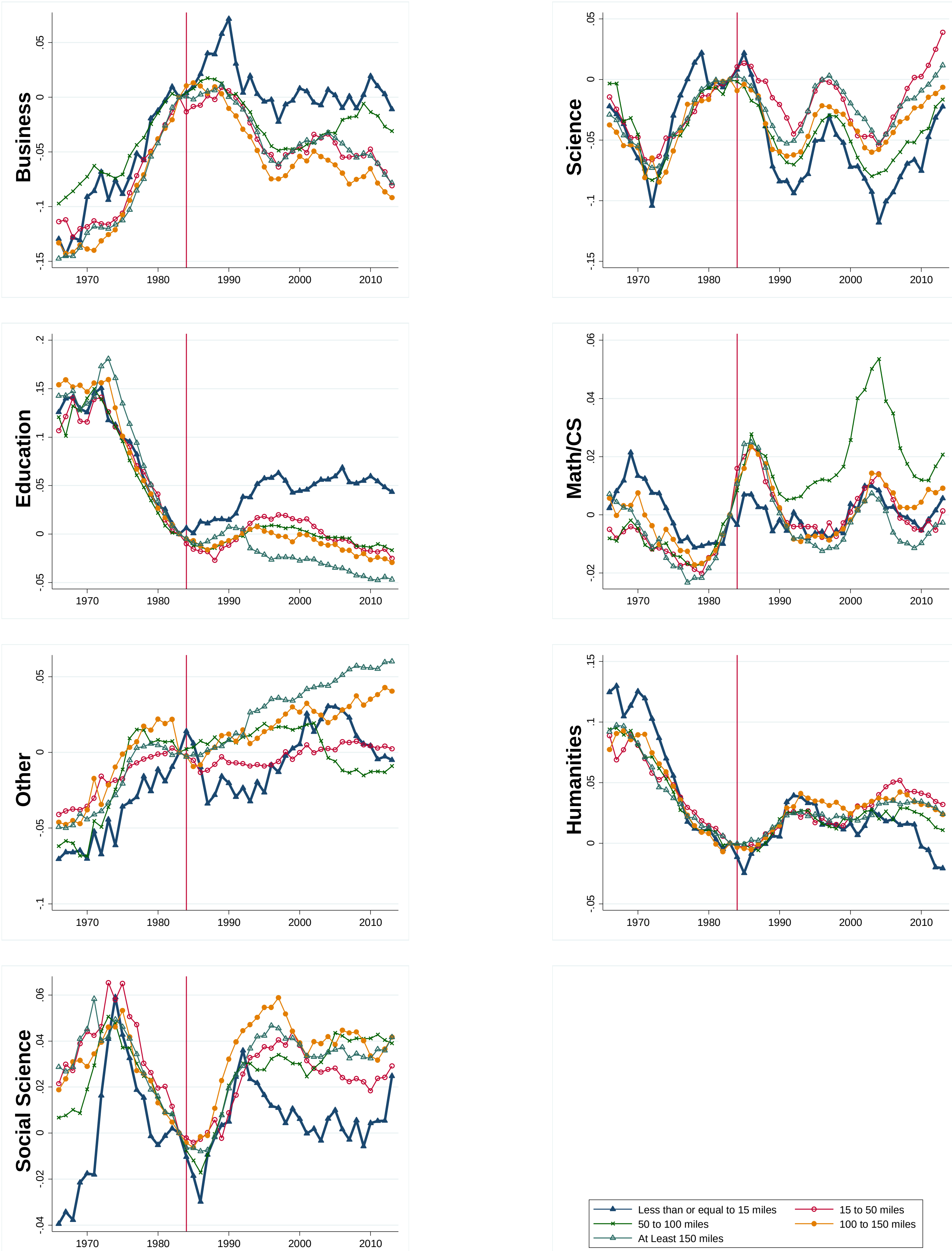


Public Universities



Note: See text for details. These plots show the coefficients on the interactions between year-fixed effects and MSA computer employment share (Panel a) and MSA finance employment share (Panel b). These coefficients are from a regression of Ln(Computer Science Degrees) (Panel a) and Ln(Business Degrees) (Panel b) on year-fixed effects, year fixed-effects interacted with MSA computer employment share (Panel a) and with MSA finance employment share (Panel b), Ln(Total Degrees) and university fixed effects. The effects are relative to the year preceding the *Post* year group (2003 in Panel (a) and 2011 in Panel (b)). The dashed lines show 95% confidence intervals for each coefficient.

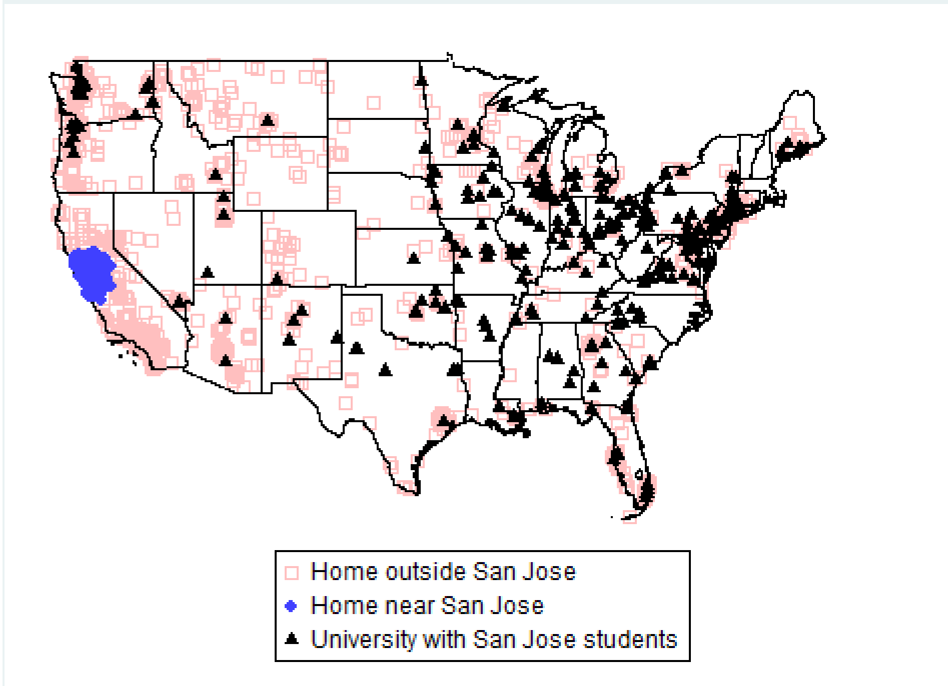
Figure 4: Changes in Major, by University Distance to Wilmington, Delaware, Relative to 1983



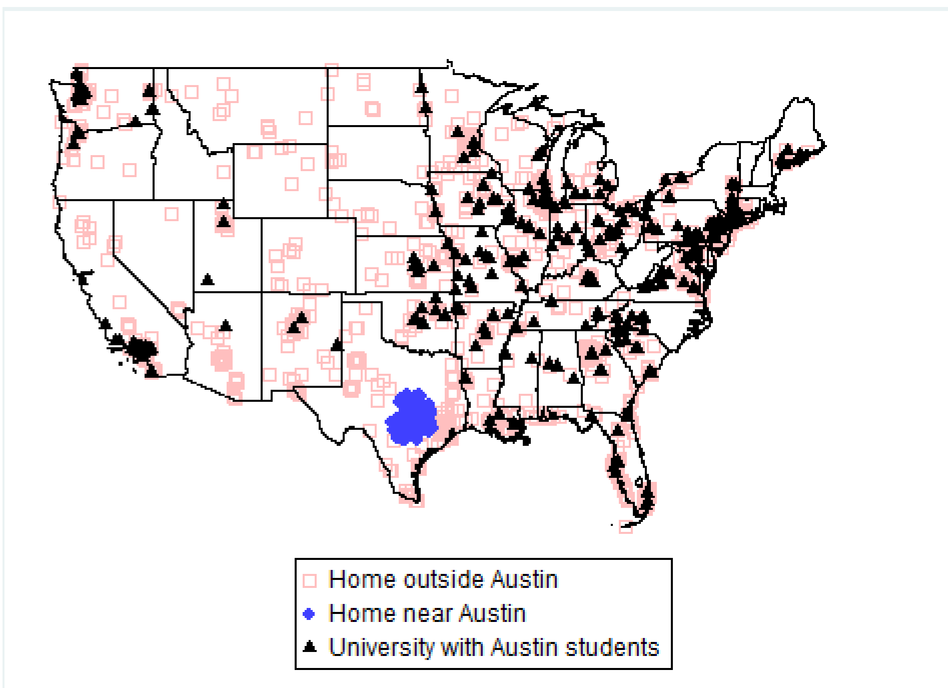
Note: These plots show the share of students in each distance group pursuing the given major, relative to the share in 1983. The darkest plot pertains to the universities less than or equal to 15 miles from Wilmington, DE. See text for details.

Figure 5

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



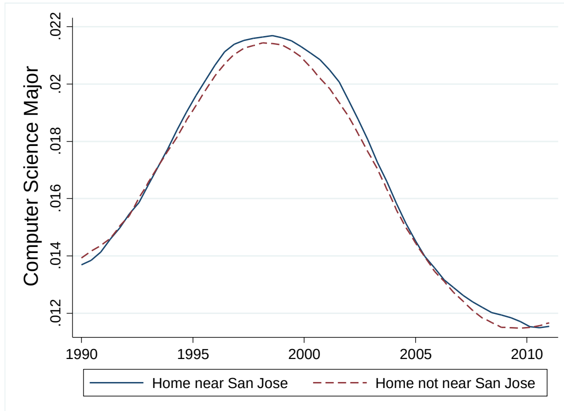
Panel B: Home and University Locations of Geographically Mobile Austin Students and Matched Counterparts



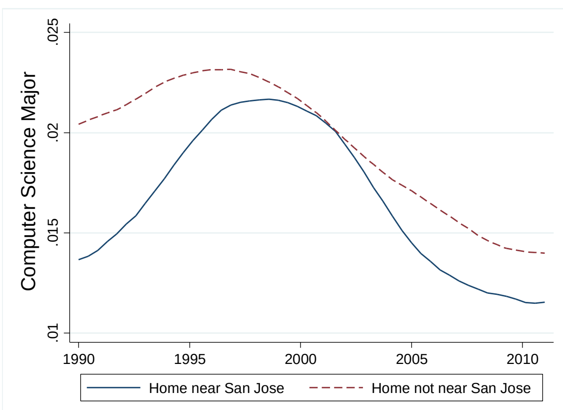
Note: This figure shows the universities (in black triangles) outside California (Panel A) or Texas (Panel B), and outside a 100 mile radius of any of the principal cities of the top 15 computer employment MSAs, with at least one San Jose (Austin) and non-San Jose (non-Austin) student in the matching 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 top15 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

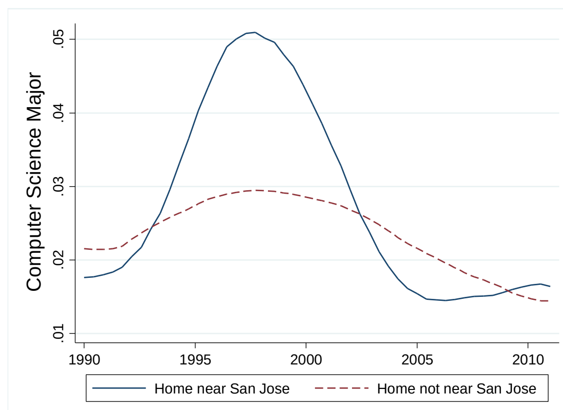
(a) Mobile San Jose Students v. Mobile Matches



(b) Mobile San Jose Students v. Less Mobile Matches



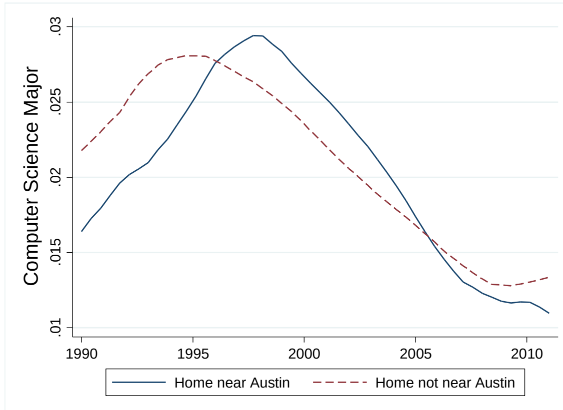
(c) Less Mobile San Jose Students v. Less Mobile Matches



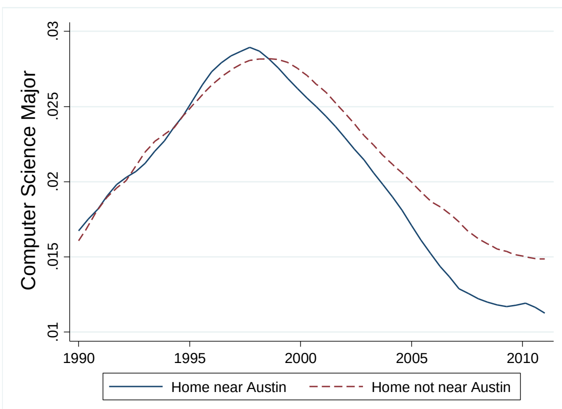
Note: The plots are the result of kernel-weighted local polynomial regressions of whether the student's intended major is computer science on year. I estimate these local polynomial regressions separately for San Jose students and their matches. Figure (a) includes individuals in the main matching sample: 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

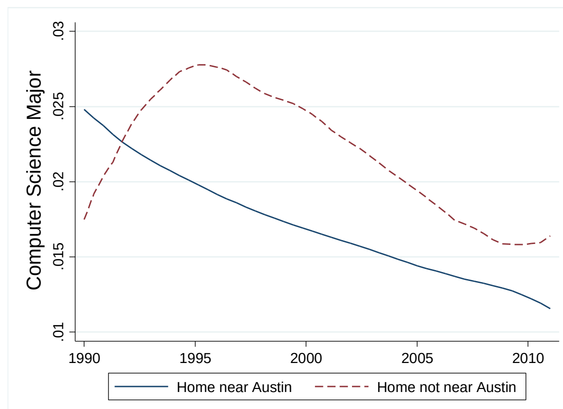
(a) Mobile Austin Students v. Mobile Matches



(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: Number of Universities by State and Distance to Wilmington, IPEDS

	Distance to Wilmington, DE in Miles				
	[0,15]	(15,50]	(50,100]	(100,150]	>150
$N_{\text{pre and post}}$	6	34	56	34	82
N_{DE}	2	2	0	0	0
N_{MD}	0	1	18	2	1
N_{NJ}	0	2	17	10	0
N_{PA}	4	29	15	14	28
N_{VA}	0	0	0	4	36
N_{DC}	0	0	6	3	0
N_{WV}	0	0	0	1	17

Note: This table does not include special-focus universities. See text for details on distance calculation and sample construction.

Table 2: The Dot-Com Crash and Undergraduate Computer Science Degrees: Differential Effects by Share Employed in Computers in University MSA

	Outcome: Ln(Computer Science Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
(1)	**Post** (2004-2008)	0.043	0.041	0.144**	0.105	-0.035	0.006
		(0.043)	(0.048)	(0.060)	(0.082)	(0.043)	(0.054)
(2)	Post*Private		0.022		0.122		-0.138
			(0.075)		(0.117)		(0.104)
(3)	Post*MSA Computer Share	-0.212	0.234	-1.782**	-0.646	1.028**	0.635
		(0.747)	(0.673)	(0.714)	(1.252)	(0.458)	(0.566)
(4)	Post*MSA Computer Share*Private		-1.448		-2.311		2.389
			(1.126)		(1.523)		(2.089)
	P-value from Joint Test of (3) and (4)		0.380		0.001		0.171
(5)	**Crash** (2001-2003)	0.307***	0.300***	0.363***	0.350***	0.263***	0.279***
		(0.023)	(0.032)	(0.039)	(0.057)	(0.021)	(0.028)
(6)	Crash*Private		0.021		0.091		-0.074
			(0.044)		(0.079)		(0.057)
(7)	Crash*MSA Computer Share	0.272	0.259	-0.473	-0.688	0.954**	0.703
		(0.375)	(0.584)	(0.533)	(0.860)	(0.380)	(0.468)
(8)	Crash*MSA Computer Share*Private		0.057		0.027		1.690
			(0.723)		(1.041)		(1.590)
	P-value from Joint Test of (7) and (8)		0.683		0.374		0.093
(9)	**Pre-Peak** (1990-1997)	-0.098***	-0.096***	-0.155***	-0.122***	-0.062	-0.041
		(0.026)	(0.029)	(0.033)	(0.044)	(0.042)	(0.045)
(10)	Pre-Peak*Private		-0.005		-0.141*		-0.132
			(0.058)		(0.077)		(0.094)
(11)	Pre-Peak*MSA Computer Share	-1.015**	-0.922*	-1.711***	-1.971**	0.220	-0.316
		(0.436)	(0.489)	(0.447)	(0.874)	(0.887)	(0.641)
(12)	Pre-Peak*MSA Computer Share*Private		-0.239		1.014		3.790**
			(0.883)		(1.031)		(1.840)
	P-value from Joint Test of (11) and (12)		0.049		0.019		0.117
(13)	**Long Run** (2009-2013)	-0.208***	-0.150**	-0.140	-0.148	-0.237***	-0.169**
		(0.058)	(0.075)	(0.094)	(0.126)	(0.067)	(0.076)
(14)	Long Run*Private		-0.149		0.006		-0.205
			(0.103)		(0.143)		(0.148)
(15)	Long Run*MSA Computer Share	-0.036	-0.337	0.408	1.659	-1.770**	-2.262***
		(0.771)	(1.151)	(0.984)	(2.184)	(0.861)	(0.853)
(16)	Long Run*MSA Computer Share*Private		0.760		-2.044		2.640
			(1.449)		(2.343)		(2.383)
	P-value from Joint Test of (15) and (16)		0.854		0.668		0.030
	Universities	All		Research/ Doctoral		Master's/ Baccalaureate	
	Observations	16,614	16,614	4,212	4,212	12,402	12,402
	R-squared	0.872	0.872	0.819	0.821	0.871	0.872

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Post denotes years in which graduates entered university after the initial stages of the dot-com crash. Crash denotes years in which college graduates were enrolled during the initial stages of the dot-com crash. Pre-Peak denotes years before the peak of the dot-com boom. The omitted year group is the group of years immediately preceding the dot-com crash (1998 through 2000). MSA Computer Share denotes the share of the MSA employed in computers in 2000. Private is an indicator equal to one if the university is private. Regressions include university fixed effects, and observations are weighted by the number of computer science degrees awarded by the university. See text for details.

Table 3: The 2008 Financial Crisis and Undergraduate Business Degrees: Differential Effects by Share Employed in Finance in University MSA

	Outcome: Ln(Business Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
(1)	**Post** (2012-2013)	-0.0795***	-0.112***	-0.0967***	-0.129***	-0.0676***	-0.097***
		(0.0200)	(0.026)	(0.0364)	(0.046)	(0.0233)	(0.030)
(2)	Post*Private		0.092**		0.142		0.076*
			(0.041)		(0.108)		(0.045)
(3)	Post*MSA Finance Share	0.0212	1.286*	0.828	1.960	-0.487	0.807
		(0.571)	(0.780)	(1.045)	(1.493)	(0.663)	(0.843)
(4)	Post*MSA Finance Share*Private		-3.166***		-3.955		-2.999**
			(1.149)		(2.553)		(1.313)
	P-value from Joint Test of (3) and (4)		0.022		0.267		0.060
(5)	**Crash** (2009-2011)	0.00548	-0.002	0.00397	-0.007	0.0106	0.012
		(0.0129)	(0.015)	(0.0230)	(0.027)	(0.0149)	(0.019)
(6)	Crash*Private		0.027		0.082		-0.002
			(0.029)		(0.084)		(0.031)
(7)	Crash*MSA Finance Share	-0.325	-0.097	-0.464	-0.191	-0.306	-0.183
		(0.367)	(0.467)	(0.642)	(0.852)	(0.438)	(0.559)
(8)	Crash*MSA Finance Share*Private		-0.688		-1.774		-0.216
			(0.798)		(1.938)		(0.907)
	P-value from Joint Test of (7) and (8)		0.472		0.523		0.812
(9)	**Pre-Peak** (2000-2005)	0.0784***	0.114***	0.113***	0.125***	0.0480**	0.081**
		(0.0218)	(0.029)	(0.0364)	(0.043)	(0.0243)	(0.032)
(10)	Pre-Peak*Private		-0.092**		-0.098		-0.067
			(0.040)		(0.086)		(0.044)
(11)	Pre-Peak*MSA Finance Share	-0.599	-1.905**	-1.405	-1.723	0.0285	-1.661
		(0.616)	(0.880)	(0.957)	(1.270)	(0.765)	(1.063)
(12)	Pre-Peak*MSA Finance Share*Private		2.935**		2.104		3.172**
			(1.145)		(2.112)		(1.343)
	P-value from Joint Test of (11) and (12)		0.036		0.391		0.055
	Universities	All		Research/ Doctoral		Baccalaureate/ Master's	
	Observations	11,333	11,333	2,413	2,413	8,920	8,920
	Number of Universities	826	826	181	181	645	645
	R-squared	0.984	0.984	0.973	0.973	0.981	0.982
	University Fixed Effects	Y	Y	Y	Y	Y	Y

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the university level in parentheses. Post denotes years in which graduates entered university after the initial stages of the financial crisis. Crash denotes years in which college graduates were enrolled during the initial stages of the financial crisis. Pre-Peak denotes years before the pre-crisis peak. The omitted year group is the group of years immediately preceding the financial crisis (2006 through 2008). MSA Finance share denotes the share of the MSA employed in finance in 2000. Private is an indicator equal to one if the university is private. Observations weighted by the number of business degrees awarded by the university. See text for details.

Table 4: Jurisdictional Competition in Delaware and College Major Composition: Differential Effects by Distance to Wilmington, DE

Proportion majoring in:	Business	Science	Education	Math/CS	Other	Humanities	Soc. Sc.
Treat Years *Distance ϵ [0,15]	0.038	-0.085	0.041	0.006	-0.039	0.030	0.009
	(0.019)	(0.009)	(0.006)	(0.002)	(0.014)	(0.006)	(0.007)
Treat Years *Distance ϵ (15,50]	0.012	-0.039***	0.007***	0.013	-0.022	0.031	-0.006*
	(0.008)	(0.010)	(0.008)	(0.004)	(0.013)	(0.009)	(0.005)
Treat Years *Distance ϵ (50,100]	0.005	-0.053***	0.018***	0.014*	-0.018	0.027	0.002
	(0.008)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Treat Years *Distance ϵ (100,150]	0.004	-0.055**	0.017***	0.016*	-0.024	0.030	0.009
	(0.012)	(0.012)	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)
Treat Years *Distance>150	0.004*	-0.050***	0.022***	0.014***	-0.013*	0.029	0.000
	(0.006)	(0.006)	(0.006)	(0.002)	(0.004)	(0.005)	(0.004)
1990s *Distance ϵ [0,15]	-0.030	-0.119	0.101	0.008	-0.049	0.082	0.026
	(0.014)	(0.020)	(0.013)	(0.007)	(0.021)	(0.016)	(0.006)
1990s *Distance ϵ (15,50]	-0.031	-0.076*	0.054***	0.006	-0.037	0.067	0.026
	(0.012)	(0.011)	(0.009)	(0.006)	(0.008)	(0.007)	(0.006)
1990s *Distance ϵ (50,100]	-0.043	-0.083*	0.059***	0.011	-0.034	0.068	0.031
	(0.012)	(0.008)	(0.009)	(0.004)	(0.012)	(0.006)	(0.008)
1990s *Distance ϵ (100,150]	-0.051	-0.082*	0.051***	0.001	-0.026	0.075	0.040
	(0.016)	(0.012)	(0.009)	(0.003)	(0.008)	(0.007)	(0.010)
1990s *Distance>150	-0.045	-0.066**	0.030***	0.002	-0.006**	0.064	0.034
	(0.010)	(0.009)	(0.011)	(0.004)	(0.008)	(0.007)	(0.006)
Pre-1980 *Distance ϵ [0,15]	-0.024	-0.013	0.027	-0.005	-0.007	0.018	0.017
	(0.018)	(0.021)	(0.025)	(0.002)	(0.012)	(0.010)	(0.012)
Pre-1980 *Distance ϵ (15,50]	-0.049	0.000	0.030	-0.028***	0.020*	0.002	0.040
	(0.013)	(0.012)	(0.027)	(0.005)	(0.011)	(0.009)	(0.009)
Pre-1980 *Distance ϵ (50,100]	-0.039*	-0.012	0.036	-0.024***	0.017*	0.001	0.037
	(0.015)	(0.008)	(0.016)	(0.003)	(0.006)	(0.007)	(0.006)
Pre-1980 *Distance ϵ (100,150]	-0.069	-0.019	0.051	-0.018***	0.017*	0.012	0.035
	(0.016)	(0.014)	(0.021)	(0.004)	(0.010)	(0.010)	(0.006)
Pre-1980 *Distance>150	-0.054	-0.016	0.049	-0.023***	0.014*	-0.003**	0.042**
	(0.011)	(0.008)	(0.015)	(0.005)	(0.006)	(0.006)	(0.005)
N	10,469	10,469	10,469	10,469	10,469	10,469	10,469

Note: Asterisks denote statistical significance relative to coefficient on Distance ϵ [0,15] (*** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1). Standard errors clustered at the university level are in parentheses. Estimation includes university fixed effects, and observations are weighted by the number of total Bachelor's degrees conferred by the university in the given year. Coefficients are relative to the proportion in each major in the years immediately preceding the treatment (1980 through 1986). Interactions between each distance group and an indicator for year ≥ 2000 not shown. Additional controls include total degrees conferred by the university, year and year squared, the second lag of ln(FIRE employment) at the state level, and an indicator for the years when this is missing (2004-2013). See text for estimation details.

Table 5: 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 6: 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 7: 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 6 for sample sizes by year group and home location.

Local Labor Markets and Human Capital Investments

Appendix: For Online Publication

Russell Weinstein*

February 27, 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 Differential Effect of Sector-Specific Shock on Total Enrollment

In section 5 of the paper I show differential effects on major, by university exposure to the shock. This may be evidence that students change their major or their university in response to local labor demand. The latter mechanism suggests students interested in business majors may more likely enroll at a university in an area receiving a positive shock to finance labor demand. As a most basic test, I estimate regressions similar to those in section 4 of the paper, though with the dependent variable being $Ln(TotalDegrees)$.[2]

After the dot-com crash, total degrees awarded increased less among private universities in higher computer-share areas (Appendix Table A8). The effect is stronger and more statistically significant among research and doctoral universities.[3] If the share of the MSA employed in computers is higher by 1 percentage point, the percentage change in total degrees awarded after the crash was lower by 1.8 percentage points. For research/doctoral universities at the 1st percentile of computer employment share (.008), total degrees awarded were predicted to increase by 31% after the dot-com crash. However, for universities at the 99th percentile of computer employment share (.125), total degrees were predicted to increase by 14%. This effect is similar for students entering university immediately after the shock, and those entering more than five years later.

After the financial crisis, total degrees awarded also increased less among private universities in higher finance-share areas (Appendix Table A9). Among public universities, degrees awarded increased more in higher finance-share areas. This suggests that in high finance-share areas, students substituted between private and public universities. If the share of the MSA employed in finance was higher by 1 percentage point, the percentage change in total degrees awarded by private universities after the crash was lower by .6 percentage points. For private universities at the 1st percentile

[2] I no longer include total degrees awarded as an explanatory variable, and weight by total degrees awarded rather than the number of majors.

[3] There are also no long-run effects on total degrees among master's/baccalaureate universities in high computer employment areas.

of finance employment share (.013), total degrees awarded were predicted to increase after the crisis by 13%. However, for private universities at the 99th percentile of finance employment share (.059), total degrees awarded were predicted to increase by 10%.

After the instance of jurisdictional competition in Delaware, Appendix Table A6 shows there is no statistically significant difference in total degrees awarded at universities closer to the shock. Using student-level data from The Freshman Survey, I further test whether universities closer to Delaware experienced differential changes in the composition of students. In particular, out-of-state students interested in business may have crowded out in-state students.

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

In this section I test for changes in the composition of students at universities in Delaware after the finance shock. I first test whether the shock led to a greater proportion of nonlocal students, whether these nonlocal students had differing academic achievement than previously, and whether they were especially likely to major in business. This would provide evidence the shock incentivized students from other states to attend university in Delaware. I then test whether the selection into business and out of science was driven by high- or low-academically achieving students.

I code a student as nonlocal if the student's home is more than 50 miles from the university. In the regressions, I only interact this nonlocal indicator with an indicator for the closest distance radius. This implies I compare nonlocal students at Wilmington-area universities, to local students at Wilmington-area universities. I then compare these effects with all students at universities in other distance radii. I do not interact other distance groups with an indicator for the student being nonlocal, because this would imply a comparison between nonlocal students at Wilmington-area universities and nonlocal students at New Jersey universities (who may be from Delaware). I estimate regressions similar to those studying changes in major after the Delaware shock, but include two treatment groups (1983-1985 and 1986-1987) because Delaware universities are present in the Freshman Survey data only from 1971 to 1987. Appendix Figure A4 provides summary statistics of The Freshman

Survey sample for the Delaware analysis.

Change in the Proportion of Nonlocal Students

Immediately after the policy, among Wilmington-area universities, the average within-university change in the proportion of nonlocal students was an increase of 1.9 percentage points (Appendix Table A7). At farther universities, the proportion decreased by 1.3 to 4.1 percentage points. The differences between Wilmington-area and farther universities are all significant at the .05 or .01 level. There are similar effects by 1986-1987.

There is a preexisting increasing trend in the proportion of nonlocal students at Wilmington-area universities relative to farther universities.[4] However, we cannot rule out the policy further contributed to this trend. If after the policy nonlocal students had different academic achievement levels and were differentially more likely to choose business majors, and there is no pre-policy trend in the same direction, this would provide suggestive support for students choosing university based on local labor demand. I also show suggestive evidence that because of the policy, nonlocal students with lower GPAs were more likely to enroll at Wilmington-area universities.

Change in Majors, Local versus Nonlocal Students

If nonlocal students at Wilmington-area universities are differentially more likely than local students to substitute into business majors, this may suggest that students choose university based on local labor markets. I estimate:

$$\begin{aligned} Y_{icrtg} &= \alpha_0 + \gamma_c + \beta_{r,g} Dist\_r_c * YearGroup\_g_t \\ &\quad + \lambda_g Dist\_1_c * YearGroup\_g_t * Nonlocal_i \\ &\quad + \rho Dist\_1_c * Nonlocal_i + \eta year_t + u_{icrtg} \end{aligned} \tag{1}$$

The variable Y_{icrtg} is an indicator equal to one if individual i, at university c, in distance radius r, in year t (classified in year group g), is pursuing a major in field Y.

[4]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%.

I estimate separate regressions for each group of majors. The coefficients $\beta_{1,Treat1}$ and $\beta_{1,Treat2}$ give the average within-university difference in the probability of pursuing the given major in the treatment relative to pre-treatment years, for students whose home is less than or equal to 50 miles from the university. The coefficients λ_{Treat1} and λ_{Treat2} give the differential effect among nonlocal students, whose home is more than 50 miles from the university.

Appendix Table A11 shows the proportion of students majoring in business immediately after the policy, relative to before the policy, increases by 1.5 percentage points (43%) more among local students at Wilmington-area universities, compared to all students at universities 15 to 50 miles away (statistically significant at the .1 level). If local students were always likely to choose Wilmington-area universities, then this change is not due to change in university choice, but instead change in major.[5]

The total treatment effect for nonlocal students at Wilmington-area universities is larger than the effect for students at universities 15 to 50 miles away by approximately 2.6 percentage points (71%), statistically significant at the 5% level.[6] Importantly, there was no preexisting trend of nonlocal students at Wilmington-area universities being differentially more likely to choose business majors than local students. These results provide evidence that the policy affected the types of students attending Wilmington-area universities.

There is significant substitution among local students, relative to students at farther universities, into social sciences, and out of science and undecided. Substitution into education and health is much stronger among the local students. Preexisting trends relative to nonlocal students were in the opposite direction as these treatment effects.

[5] Alternatively, local students who had not planned on business majors may have been less likely to enroll or be admitted as the proportion of nonlocal students increased. This should also be true before the policy, given the preexisting decrease in the proportion of local students at Wilmington-area universities. However, before the policy the proportion of local students majoring in business actually fell at Wilmington-area universities while increasing at farther universities.

[6] The net treatment effect for nonlocal students at Wilmington-area universities (2.6 percentage points) represents a 17% increase in the proportion of nonlocal students majoring in business relative to years immediately preceding the policy. The percentage difference in the treatment effect in 1986-1987 at Wilmington-area universities relative to universities 15-50 miles away is approximately the same as, though more statistically significant than, the differences in 1982-1985, for both local and nonlocal students.

3.1 Policy Effect on High School GPA of Nonlocal Students

I consider whether nonlocal students at Wilmington-area universities had different high school academic achievement than local students after the policy, and whether this is part of a preexisting trend. I estimate:

$$
\begin{aligned}
HSBplus_{icrt} \quad = \quad & \alpha_0 + \gamma_c \\
& + \beta_r Distance\_r_c * TreatYears1_t + \lambda Distance\_1_c * TreatYears1_t * Nonlocal_i \\
& + \delta_r Distance\_r_c * TreatYears2_t + \kappa Distance\_1_c * TreatYears2_t * Nonlocal_i \\
& + \tau_r Distance\_r_c * pre1977_t + \pi Distance\_1_c * pre1977_t * Nonlocal_i \\
& + \rho Distance\_1_c * Nonlocal_i + \eta year_t + u_{icrt}
\end{aligned} \tag{2}
$$

Column 2 of Appendix Table A7 shows that immediately after the policy the percent of nonlocal students at Wilmington-area universities with a high school GPA of at least a B plus fell by 13 percentage points. This magnitude was 6 percentage points greater than the effect among local students at Wilmington-area universities (statistically significantly), and between 4 and 6 percentage points more than the effect among students at universities up to 150 miles away (statistically significantly). In 1986-1987, the effect was even stronger.

Given the proportion of nonlocal students is increasing before the policy, it is plausible that this is part of a pre-policy decreasing trend in selectivity. Before the policy, there is a decreasing trend in the proportion of students with at least a B+ GPA in high school, but importantly this is not statistically different for local and nonlocal students. This presents suggestive evidence that because of the policy, nonlocal students with lower GPAs were more likely to apply and enroll at Wilmington-area universities. This could be the case if nonlocal students interested in business were more likely to apply and enroll after the policy, and these students had lower GPAs in high school. Previously, nonlocal students interested in science (possibly with higher GPAs in high school) may have chosen Wilmington-area universities because of its proximity to the chemical industry, including DuPont.

3.2 Selection into Major by Academic Achievement

Given the evidence that local Delaware students change their major in response to the shock, I study the nature of the selection. Using the Freshman Survey data, I study the change in the composition of majors by high school GPA after the policy.

I estimate regressions separately for each major, clustering standard errors at the university level:

$$\begin{aligned}
Y_{icrt} &= \alpha_0 + \gamma_c + X_i\varphi \\
&+\beta_{r,g}Dist_r_c * YearGroup_g_t + \lambda_{r,g}Dist_r_c * YearGroup_g_t * BPlus_i \\
&+\Gamma_{1,g}Dist_1_c * YearGroup_g_t * Nonlocal_i \\
&+\theta_{1,g}Dist_1_c * YearGroup_g_t * Nonlocal_i * BPlus_i \\
&+\rho_1 Dist_1_c * Nonlocal_i + \rho_2 Nonlocal_i * BPlus_i \\
&+\Phi_r Dist_r_c * BPlus_i + \eta year_t + u_{icrt}
\end{aligned} \tag{3}$$

The variable Y_{icrt} is an indicator for whether individual i at university c in distance radius r and year t is intending on the given major. Individual characteristics include an indicator for male, black, Hispanic, whether father has a Bachelor's degree and whether mother has a bachelor's degree.[7] The variable $YearGroup\_g_t$ is equal to one if year t is in year group g, where the year groups are pre-1977, 1983-1985, 1986-1987, omitting the years immediately preceding the policy. The variable $BPlus_i$ is an indicator for whether the individual had at least a B+ GPA in high school.

The coefficients $\beta_{r,g}$ represent the differential probability among local, lower GPA students of majoring in Y in year group g, relative to the years immediately preceding the policy. The coefficients $\lambda_{r,g}$ represent how this differential varies for local, higher GPA students.

3.3 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

[7] I also include an indicator for whether the value of this variable is missing for the given individual, allowing me to continue to include these individuals.

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.[8] More formally, I obtain data on number of faculty, tenured faculty, and total faculty salary outlays (not disaggregated at the academic department level) from the IPEDS Salaries, Tenure, and Fringe Benefits Survey. Focusing on the finance shock in Delaware, I find no statistically significant differences in the treatment effect across region for any of these variables, suggesting the results are not driven by university funding.

The data are available in 1971-1973, 1975-1983, 1985, 1986, 1990-2000, and 2002-2014. Given Delaware's policy was passed in February 1981, it may have affected faculty numbers and salary starting in academic year 1981. I denote the treatment years as 1981-1986 (there is no data for 1984). I also include indicator variables for the 1990s (1990 through 2000), 2000s (2002-2014), and early years (1971-1973), implying the omitted group is 1975-1980.

I estimate a specification similar to the principal specification analyzing the Delaware shock, but no longer weight by total degrees awarded. I include $Ln(FIREemployment)_t$ rather than the second lag of this variable (again because there need not be a lag in the effect on faculty). The dependent variables include the log of the number of faculty, number of tenured faculty, total faculty salary outlays (deflated), and total faculty salary outlays divided by the number of faculty (deflated).[9] There are no statistically significant differences in the treatment effect across region for any of these variables. This provides suggestive evidence that students are not responding to an increase in university funding alone.

[8] 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).

[9] While IPEDS also has data on university revenue, by source, the data are only available beginning in 1980. This makes it very difficult to identify whether changes are part of a pre-existing trend.

4 Reallocation to Special-Interest Universities: Jurisdictional Competition in Delaware

Limiting the Sample to Universities Specializing in Business

Within-university estimates will not capture the shock's full effect if students reallocate to or from special-interest universities, which are omitted from the principal specifications. Given that there is only one special-interest university within 15 miles of Wilmington, which offered bachelor's degrees starting in 1978, it is difficult to address this question convincingly. However, limiting the sample to universities specializing in business[10], the percent increase in total degrees during the treatment years is larger in magnitude at closer relative to farther universities (9% versus -4%, results not shown). With the caveat that the results are based on one local university, they provide some evidence of student reallocation towards specialized universities, implying the within-university results are underestimates. I also see similar results when collapsing the data at the state/distance group/year level (Appendix Table A4).

Region-Level Regressions

As an alternative to the within-university estimation, I estimate changes in major composition and total degrees at the region level. I collapse the data at the state/distance group/year level, and estimate regressions of the following type:

$$\begin{aligned} Y_{srt} &= \alpha_0 + \beta_r Radius\_r_{sr} * TreatYears_t + \delta_r Radius\_r_{sr} * Pre1980_t \\ &\quad + \lambda_r Radius\_r_{sr} * 1990s_t + \tau_r Radius\_r_{sr} * 2000s_t + \gamma_s + \pi_r + u_{srt} \quad (4) \end{aligned}$$

I estimate separate specifications in which the variable Y_{srt} is the share of students attending universities in the state (s) /distance group (r) combination in each major group in year t, and also the total degrees awarded. For a given state /year, there are up to five observations. For example, we observe Y_{srt} separately for the regions of Pennsylvania within the following distance groups, relative to Wilmington, DE: $[0, 15]; (15, 50]; (50, 100]; (100, 150]; > 150$. I include state fixed effects (γ_s), and distance-group fixed effects (π_r).

[10] Carnegie 94 = 5, Carnegie 2005 = 20, or Carnegie 2010=19.

These regressions compare the share majoring in each field, and total degrees awarded, for regions close to Wilmington and farther from Wilmington, within a given state. The coefficients β_r convey the average of those differences. I report the unclustered, heteroskedasticity-robust standard errors, as these are larger than the standard errors clustered at the year or distance group level.[11]

The results on major composition, presented in Appendix Table A4, are very similar to the within-university estimates in Table 4. The principal difference is that the effects on the share of students majoring in business is larger for the local universities relative to the farther universities. Unlike in Table 4, these effects are statistically significant in the 1990s as well. This may be because of increased power from excluding university fixed effects, or because there is an increase in the number of students pursuing these majors at specialized institutions, which were removed from the main specification. As noted in the paper, there is some suggestive evidence of this latter effect, but only based on one local special-interest university with a business focus.

The results on total degrees awarded, presented in Appendix Table A5, are very similar to the within-university estimates in Table 5.

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.

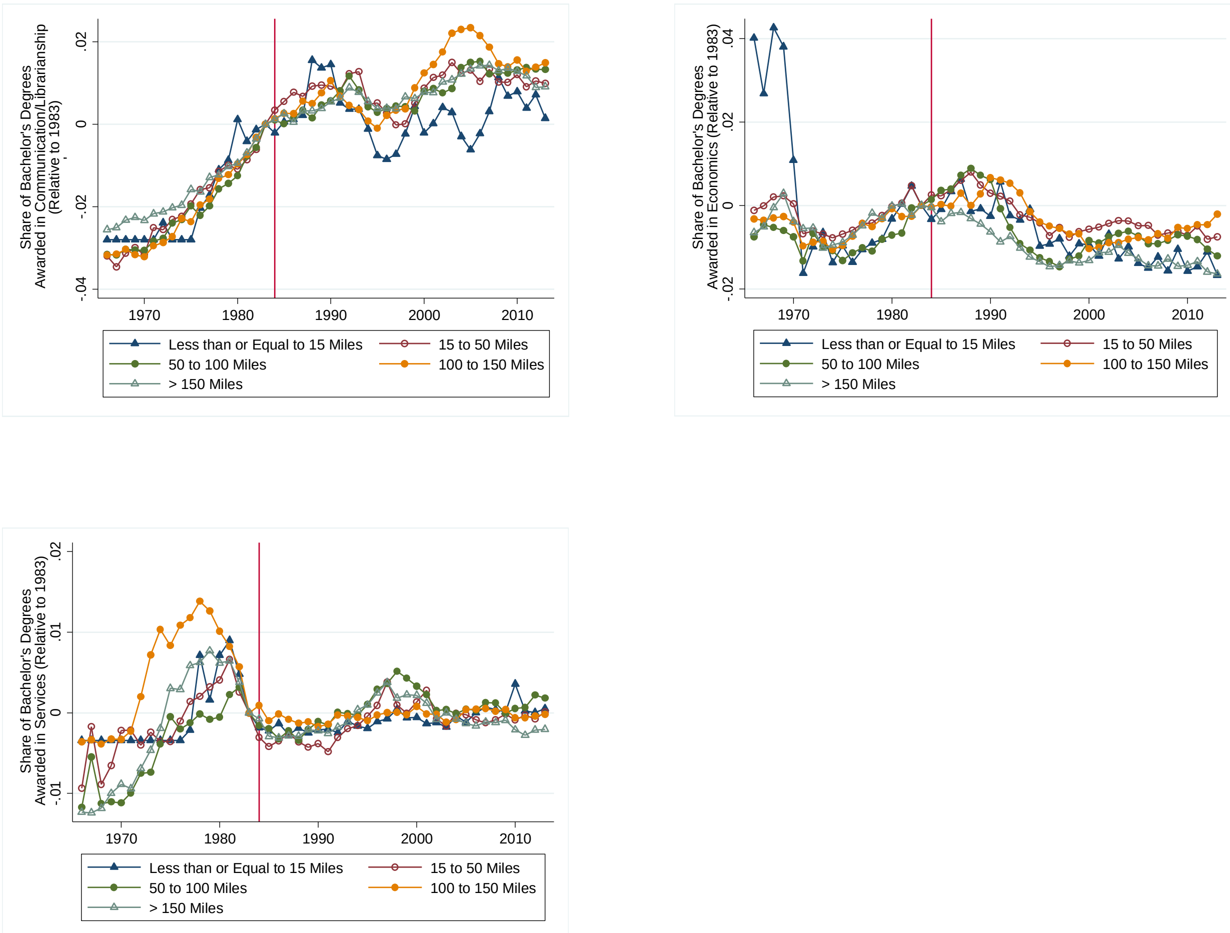
[4] Hecker, Daniel E. (2005): "High-technology employment: a NAICS based update," *Monthly Labor Review*, July.

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

[11] Given that each state has multiple distance groups, there is not perfect correlation in the main variable of interest, $Radius\_r_{sr} * TreatYears_t$, within a state during the treatment and pre-treatment years. As a result, I do not cluster the standard errors at the state level.

[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.

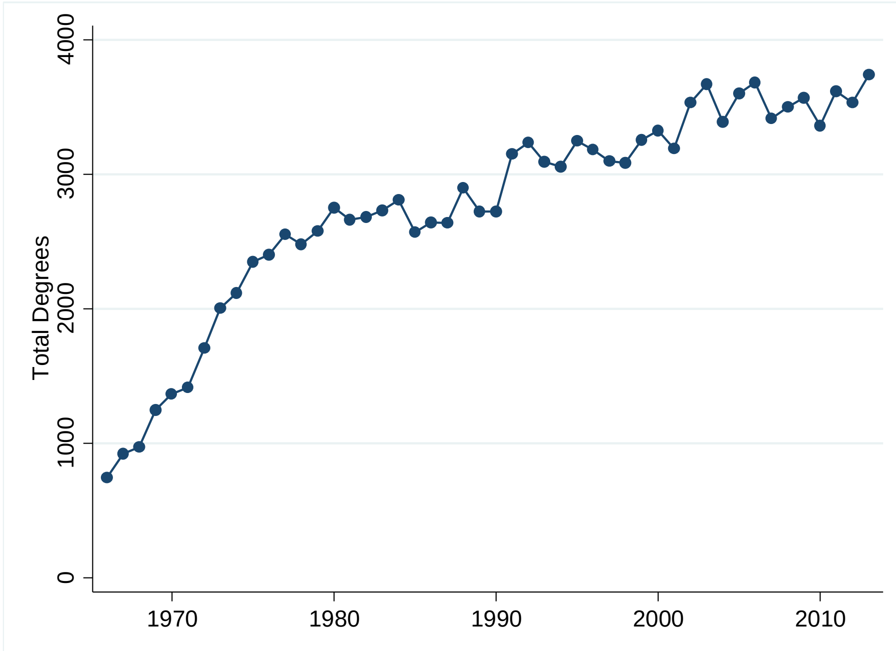
Appendix Figure A1: Change in Majors, By University Distance to Wilmington Delaware



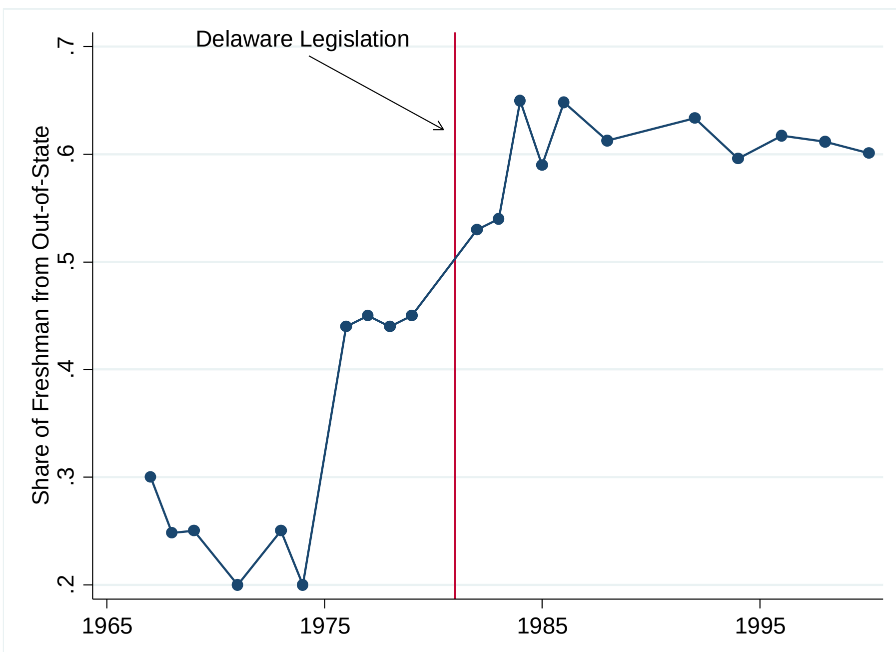
Note: These plots show the share of students in each distance group pursuing the given major, relative to the share in 1983. The darkest plot pertains to the universities less than or equal to 15 miles from Wilmington, DE. See text for details.

Appendix Figure A2

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



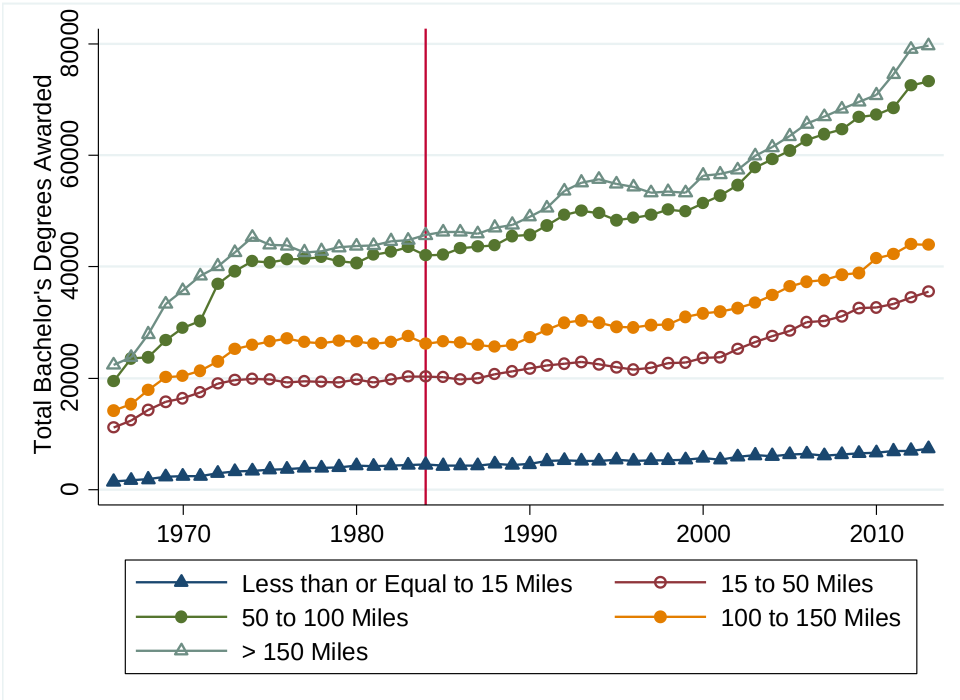
(b) Out-of-State Freshman at the University of Delaware



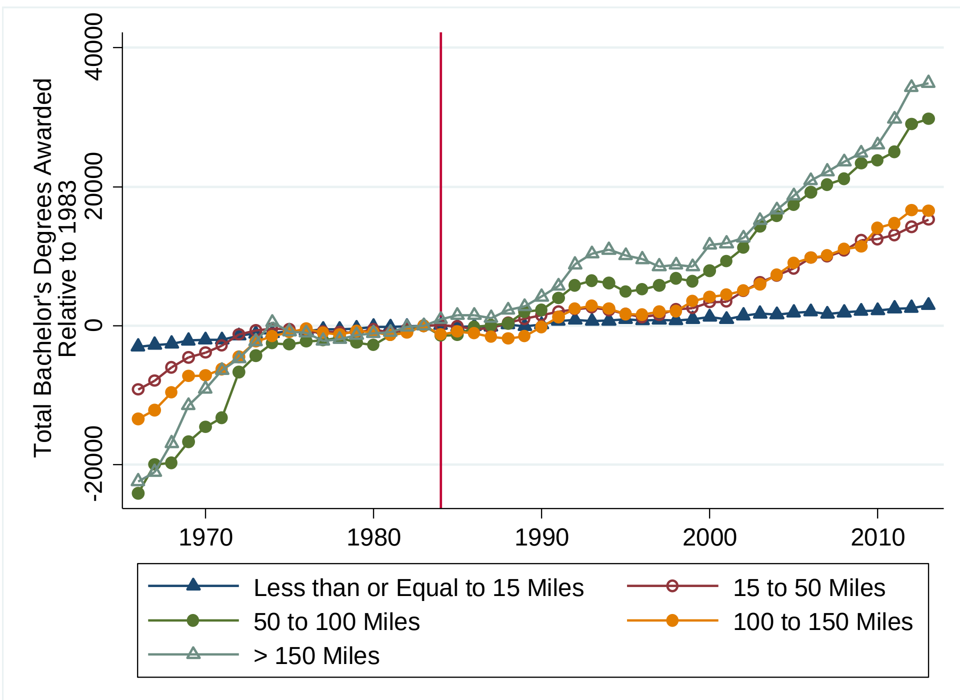
Note: Source for (a) is IPEDS (accessed through the Integrated Science and Engineering Resources Data System of the NSF). Sources for (b) include college guides (Peterson's and the College Board), as well as IPEDS. See text of paper and Online Appendix for details.

Appendix Figure A3

(a) Change in Total Degrees Awarded, by Distance to Wilmington, Delaware



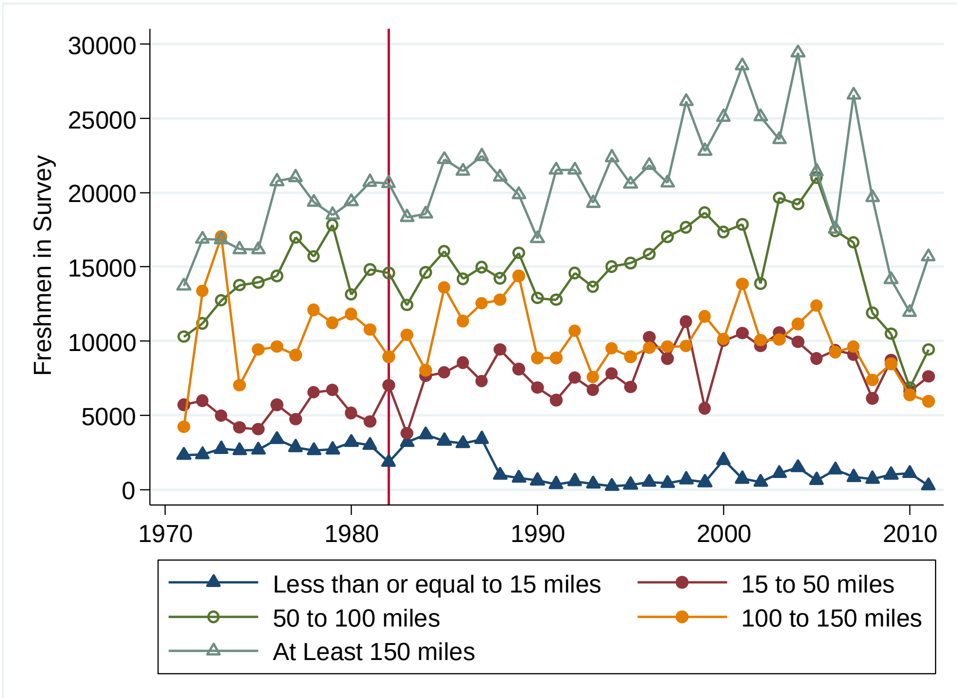
(b) Change in Total Degrees Awarded (Relative to 1983), by Distance to Wilmington, Delaware



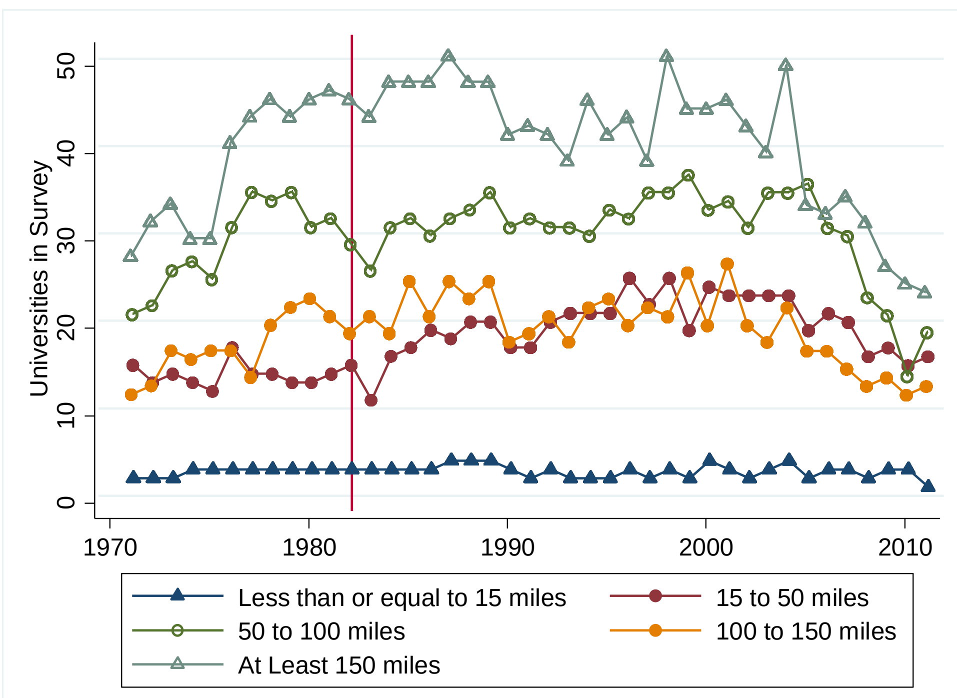
Note: Source is IPEDS accessed through the Integrated Science and Engineering Resources Data System of the NSF. See text for details.

Appendix Figure A4: Freshman Survey Sample for Delaware Analysis

(a) Number of Students per Year



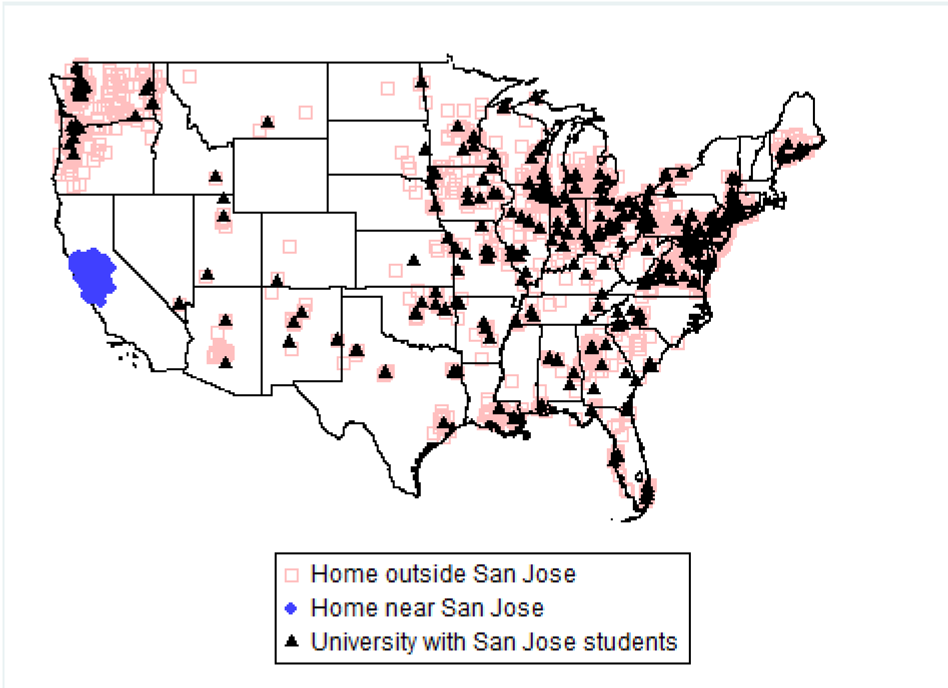
(b) Number of Universities per Year



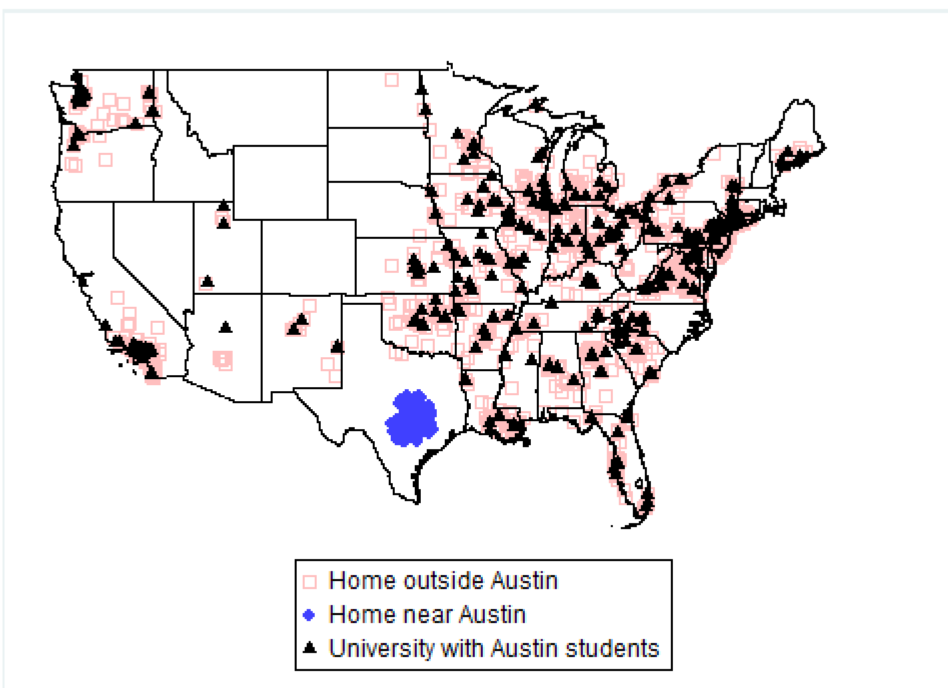
Note: These plots give the number of students and universities per year by distance to Wilmington, DE in The Freshman Survey. See text for details.

Appendix Figure A5

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



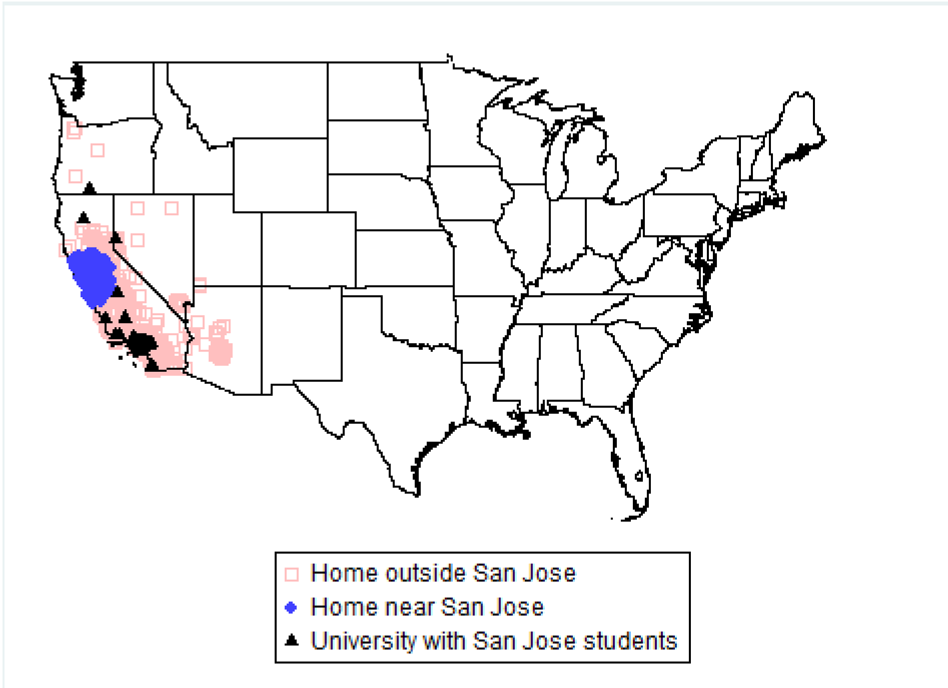
Panel B: Non-Texas Universities with Austin Students whose Home is > 350 Miles Away
and Home Locations of those Students
and Matches whose Home is ≤ 150 Miles from the University



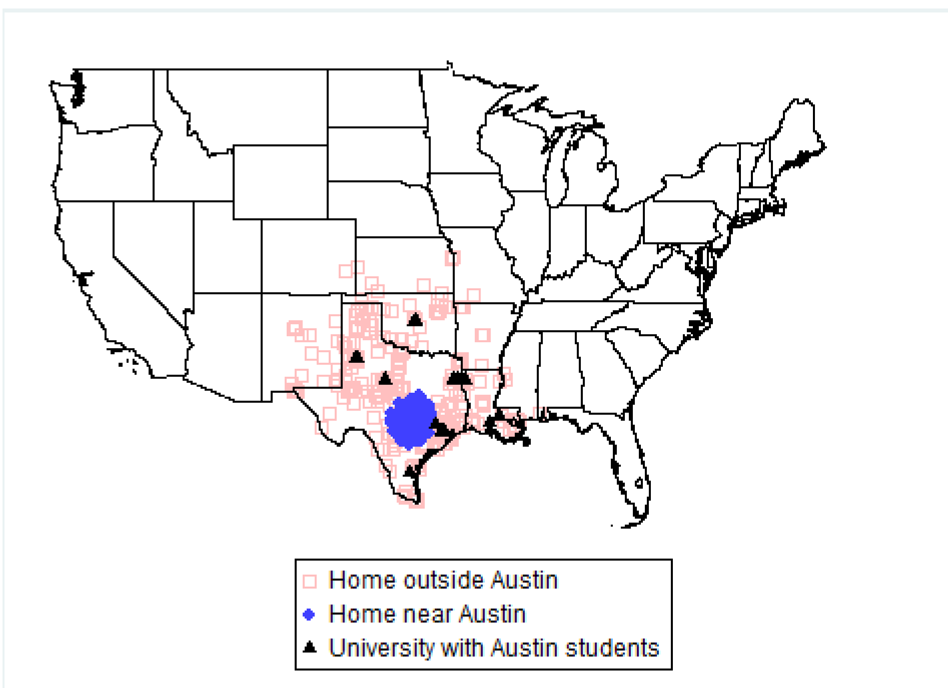
Note: This figure shows the universities (in black triangles) attended by students in the robustness matching sample with mobile San Jose/Austin students and less mobile matches (during the years of the dot-com bust). The criteria for the San Jose/Austin students is the same as in the principal sample, 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 top15 computer employment MSAs. See text for details.

Appendix Figure A6

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 (the matches). See text for details.

Appendix Table A1: Jurisdictional Competition in Delaware and Major Composition, Differential Effects by Distance to Wilmington, DE

Proportion Major in:	Comm.	Economics	Services
Treat Years *Distance ϵ [0,15]	0.009	0.001	-0.009
	(0.004)	(0.001)	(0.004)
Treat Years *Distance ϵ (15,50]	0.006	0.006*	-0.008
	(0.002)	(0.003)	(0.002)
Treat Years *Distance ϵ (50,100]	0.002	0.009*	-0.006
	(0.002)	(0.004)	(0.001)
Treat Years *Distance ϵ (100,150]	0.006	0.005	-0.009
	(0.003)	(0.005)	(0.002)
Treat Years *Distance>150	0.002	-0.000	-0.008
	(0.002)	(0.002)	(0.002)
1990s *Distance ϵ [0,15]	-0.006	-0.001	-0.011
	(0.008)	(0.002)	(0.004)
1990s *Distance ϵ (15,50]	0.000	-0.000	-0.010
	(0.005)	(0.004)	(0.002)
1990s *Distance ϵ (50,100]	0.002	-0.004	-0.007
	(0.006)	(0.004)	(0.002)
1990s *Distance ϵ (100,150]	0.001	0.002	-0.011
	(0.004)	(0.004)	(0.003)
1990s *Distance>150	0.000	-0.005	-0.009
	(0.003)	(0.004)	(0.002)
Pre-1980 *Distance ϵ [0,15]	-0.010	-0.005	0.004
	(0.007)	(0.011)	(0.004)
Pre-1980 *Distance ϵ (15,50]	-0.012	-0.011	0.007
	(0.009)	(0.005)	(0.002)
Pre-1980 *Distance ϵ (50,100]	-0.010	-0.011	0.005
	(0.005)	(0.005)	(0.002)
Pre-1980 *Distance ϵ (100,150]	-0.011	-0.009	0.012
	(0.005)	(0.004)	(0.004)
Pre-1980 *Distance>150	-0.005	-0.008	0.004
	(0.003)	(0.003)	(0.002)
N	10,469	10,469	10,469

Note: See notes to Table 4.

Appendix Table A2: Jurisdictional Competition in Delaware and Major Composition, Polynomial Regression

		Business	Science	Education	Math/CS	Other	Humanities	Soc. Sc.	Comm.	Economics	Services
	Treat Years	0.030**	-0.059***	0.019	0.008	-0.021	0.029***	-0.009	0.010**	0.004	-0.011***
		(0.014)	(0.018)	(0.015)	(0.006)	(0.021)	(0.011)	(0.008)	(0.004)	(0.005)	(0.003)
	Treat Years*Distance (tens)	-0.0092**	0.0041	-0.0009	0.0013	0.0005	0.0010	0.0021	-0.0013	0.0008	0.0016*
		(0.0039)	(0.0047)	(0.0038)	(0.0022)	(0.0048)	(0.0024)	(0.0025)	(0.0011)	(0.0022)	(0.0009)
	Treat Years*Distance^2 (hundreds)	0.0006***	-0.0003	0.0001	-0.0001	-0.0000	-0.0001	-0.0001	0.0001	-0.0000	-0.0001*
		(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
	1990s	-0.023	-0.097***	0.073***	0.003	-0.026	0.071***	0.008	-0.002	0.007	-0.014***
		(0.018)	(0.021)	(0.016)	(0.008)	(0.018)	(0.014)	(0.010)	(0.009)	(0.006)	(0.003)
	1990s*Distance (tens)	-0.0090*	0.0058	-0.0028	0.0023	-0.0041	0.0006	0.0065*	0.0008	-0.0028	0.0027***
		(0.0053)	(0.0057)	(0.0042)	(0.0020)	(0.0056)	(0.0035)	(0.0034)	(0.0025)	(0.0019)	(0.0007)
	1990s*Distance^2 (hundreds)	0.0006*	-0.0004	0.0001	-0.0002	0.0004	-0.0000	-0.0004*	-0.0000	0.0002	-0.0002***
		(0.0003)	(0.0004)	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
	Linear Combination of Treat Years, with Distance:										
(1)	10 miles	0.022	-0.055	0.018	0.01	-0.021	0.03	-0.007	0.009	0.005	-0.01
		[.011]	[.014]	[.012]	[.005]	[.016]	[.009]	[.006]	[.003]	[.004]	[.003]
(2)	25 miles	0.011	-0.05	0.017	0.011	-0.02	0.031	-0.005	0.007	0.006	-0.008
		[.008]	[.01]	[.008]	[.003]	[.011]	[.007]	[.005]	[.002]	[.002]	[.002]
(3)	50 miles	-0.001	-0.046	0.016	0.013	-0.02	0.032	-0.001	0.005	0.007	-0.006
		[.007]	[.006]	[.006]	[.004]	[.006]	[.005]	[.005]	[.002]	[.003]	[.001]
(4)	75 miles	-0.005	-0.046	0.016	0.015	-0.019	0.031	0.002	0.004	0.008	-0.005
		[.008]	[.006]	[.006]	[.005]	[.005]	[.004]	[.005]	[.002]	[.004]	[.002]
	P-values on Joint tests of										
(5)	Treat*Distance Coefficients	0.016	0.483	0.875	0.725	0.989	0.298	0.249	0.461	0.773	0.155
(6)	1990s*Distance Coefficients	0.161	0.596	0.470	0.108	0.020	0.941	0.149	0.947	0.222	0.000
(7)	2000s*Distance Coefficients	0.757	0.270	0.770	0.003	0.878	0.817	0.630	0.709	0.437	0.045
(8)	Pre-1980*Distance Coefficients	0.745	0.567	0.504	0.637	0.472	0.385	0.024	0.264	0.943	0.006
	N	6,369	6,369	6,369	6,369	6,369	6,369	6,369	6,369	6,369	6,369
	R-squared	0.7536	0.8579	0.7420	0.5043	0.7114	0.7785	0.8238	0.7468	0.7591	0.6105
	Mean(Dependent Variable) in 1985, for Universities ≤ 50 Miles from	0.230	0.242	0.073	0.053	0.061	0.159	0.129	0.019	0.027	0.007

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the university level are in parentheses. Estimation includes university fixed effects, and observations are weighted by the number of total Bachelor's degrees conferred by the university in the given year. Indicators for pre-1980 and year ≥ 2000, and their interaction with distance and distance^2 not shown. Additional controls include total degrees conferred by the university, year and year^2, the second lag of ln(FIRE employment) at the state level, and an indicator for the years when this is missing (2004-2013). Regression sample includes only universities with distance to Wilmington less than or equal to 150 miles. See text for estimation details.

Appendix Table A3: Jurisdictional Competition in Delaware and University Enrollment, Polynomial Regression

		Total Degrees	Ln(Total Degrees)
	Treat Years	-88.96**	-0.098**
		(39.52)	(0.040)
	Treat Years*Distance (in tens)	10.19	0.012
		(12.26)	(0.011)
	Treat Years*Distance^2 (in hundreds)	-0.78	-0.001
		(0.89)	(0.001)
	1990s	-82.69	-0.118*
		(54.27)	(0.065)
	1990s*Distance (in tens)	-7.62	0.005
		(19.60)	(0.020)
	1990s*Distance^2 (in hundreds)	0.77	-0.000
		(1.42)	(0.001)
	Linear Combination of Treat Years, with Distance:		
(1)	10 miles	-79.55	-0.09
		[29.94]	[.03]
(2)	25 miles	-68.39	-0.07
		[20.56]	[.02]
(3)	50 miles	-57.62	-0.06
		[17.49]	[.02]
(4)	75 miles	-56.65	-0.06
		[18.34]	[.02]
	P-values on Joint tests of		
(5)	Treat*Distance Coefficients	0.68	0.25
(6)	1990s*Distance Coefficients	0.75	0.93
(7)	2000s*Distance Coefficients	0.60	0.78
(8)	Pre-1980*Distance Coefficients	0.46	0.21
	N	6,369	6,369
	R-squared	0.94	0.962
	Mean(Dependent Variable) in 1985, for Universities ≤ 50 Miles from Wilmington	562.29	5.58

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the university level are in parentheses. Estimation includes university fixed effects, and in Column 2 observations are weighted by the number of total Bachelor's degrees conferred by the university in the given year. Indicators for pre-1980 and year ≥ 2000, and their interaction with distance and distance^2 not shown. Additional controls include year and year^2, the second lag of ln(FIRE employment) at the state level, and an indicator for the years when this is missing (2004-2013). Regression sample includes only universities with distance to Wilmington less than or equal to 150 miles. See text for estimation details.

Appendix Table A4: Jurisdictional Competition in Delaware and Regional Changes in Major Composition

Proportion Majoring in:	Business	Science	Education	Math/CS	Other	Humanities	Soc. Sc.	Comm.	Economics	Services
Treat Years *Distance ϵ [0,15]	0.036	-0.072	0.031	0.006	-0.039	0.033	0.004	0.009	0.001	-0.008
	(0.014)	(0.015)	(0.007)	(0.004)	(0.008)	(0.005)	(0.008)	(0.007)	(0.003)	(0.002)
Treat Years *Distance ϵ (15,50]	0.008*	-0.030**	0.007**	0.01	-0.023*	0.028	-0.004	0.006	0.005	-0.008
	(0.005)	(0.010)	(0.010)	(0.006)	(0.005)	(0.007)	(0.005)	(0.004)	(0.002)	(0.002)
Treat Years *Distance ϵ (50,100]	-0.0002**	-0.053	0.015*	0.015*	-0.017	0.029	0.004	0.003	0.010	-0.006
	(0.005)	(0.010)	(0.007)	(0.004)	(0.012)	(0.006)	(0.008)	(0.003)	(0.004)	(0.001)
Treat Years *Distance ϵ (100,150]	-0.001*	-0.055	0.014**	0.014	-0.018**	0.033	0.012	0.005	0.006	-0.008
	(0.013)	(0.014)	(0.006)	(0.006)	(0.008)	(0.007)	(0.012)	(0.003)	(0.003)	(0.002)
Treat Years *Distance>150	0.006**	-0.048	0.022	0.011	-0.013***	0.029	0.000	0.002	-0.001	-0.007
	(0.004)	(0.007)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.002)	(0.001)	(0.001)
1990s *Distance ϵ [0,15]	-0.018	-0.109	0.087	0.005	-0.046	0.081	0.019	-0.007	-0.002	-0.011
	(0.011)	(0.009)	(0.010)	(0.004)	(0.009)	(0.006)	(0.008)	(0.004)	(0.003)	(0.002)
1990s *Distance ϵ (15,50]	-0.035	-0.067***	0.060**	-0.000	-0.037	0.063***	0.025	-0.000	-0.001	-0.008
	(0.008)	(0.009)	(0.010)	(0.006)	(0.007)	(0.005)	(0.006)	(0.004)	(0.002)	(0.002)
1990s *Distance ϵ (50,100]	-0.042**	-0.087**	0.056**	0.014*	-0.026*	0.065***	0.028	0.002**	-0.005	-0.005**
	(0.006)	(0.008)	(0.008)	(0.005)	(0.010)	(0.004)	(0.007)	(0.002)	(0.003)	(0.001)
1990s *Distance ϵ (100,150]	-0.056**	-0.082**	0.050***	-0.001	-0.025**	0.079	0.045**	-0.001	0.003	-0.011
	(0.012)	(0.011)	(0.007)	(0.005)	(0.009)	(0.006)	(0.011)	(0.003)	(0.003)	(0.002)
1990s *Distance>150	-0.039*	-0.064***	0.031***	-0.005*	-0.005***	0.063***	0.032	0.001**	-0.007	-0.007
	(0.007)	(0.006)	(0.008)	(0.005)	(0.007)	(0.004)	(0.006)	(0.002)	(0.002)	(0.001)
Pre-1980 *Distance ϵ [0,15]	-0.046	-0.019	0.039	-0.003	-0.002	0.018	0.024	-0.010	-0.005	0.005
	(0.010)	(0.013)	(0.010)	(0.004)	(0.009)	(0.006)	(0.008)	(0.004)	(0.004)	(0.003)
Pre-1980 *Distance ϵ (15,50]	-0.045	-0.024	0.044	-0.023***	0.025***	-0.006***	0.041*	-0.009	-0.010	0.007
	(0.007)	(0.010)	(0.015)	(0.006)	(0.006)	(0.005)	(0.007)	(0.003)	(0.002)	(0.002)
Pre-1980 *Distance ϵ (50,100]	-0.026*	-0.017	0.043	-0.023***	0.011	-0.003***	0.033	-0.008	-0.013	0.004
	(0.005)	(0.008)	(0.008)	(0.004)	(0.012)	(0.004)	(0.007)	(0.002)	(0.003)	(0.001)
Pre-1980 *Distance ϵ (100,150]	-0.066	-0.023	0.052	-0.016**	0.022**	0.004*	0.035	-0.011	-0.009	0.011*
	(0.011)	(0.010)	(0.010)	(0.004)	(0.010)	(0.006)	(0.008)	(0.003)	(0.003)	(0.003)
Pre-1980 *Distance>150	-0.062	-0.027	0.058*	-0.021***	0.017**	-0.002***	0.044**	-0.005	-0.007	0.005
	(0.007)	(0.008)	(0.010)	(0.005)	(0.007)	(0.004)	(0.008)	(0.002)	(0.002)	(0.002)
N	960	960	960	960	960	960	960	960	960	960

Note: Asterisks denote statistical significance relative to coefficient on Distance ϵ [0,15] (*** p<0.01, ** p<0.05, * p<0.1). Robust standard errors are in parentheses, as these are larger than the errors clustered at the year or distance group level. The dependent variable is the share of students attending universities in the state/distance group pair who are awarded degrees in the given major. See text of Online Appendix for details on estimation.

Appendix Table A5: Jurisdictional Competition in Delaware and University Enrollment, Region-Level Regressions

	Total Degrees in Region	Ln(Total Degrees in Region)
Treat Years *Distance ϵ [0,15]	-793.16	-0.129
	(1,661.09)	(0.244)
Treat Years *Distance ϵ (15,50]	-669.23	-0.094
	(1,628.01)	(0.181)
Treat Years *Distance ϵ (50,100]	-507.35	-0.113
	(2,254.73)	(0.126)
Treat Years *Distance ϵ (100,150]	-1,154.51	-0.229
	(979.88)	(0.160)
Treat Years *Distance>150	-497.07	-0.113
	(1,484.03)	(0.062)
1990s *Distance ϵ [0,15]	-1,528.60	-0.083
	(1,644.26)	(0.212)
1990s *Distance ϵ (15,50]	-1,525.76	-0.235
	(1,572.11)	(0.164)
1990s *Distance ϵ (50,100]	-739.80	-0.188
	(2,031.97)	(0.117)
1990s *Distance ϵ (100,150]	-1,908.48	-0.321
	(1,170.23)	(0.142)
1990s *Distance>150	-177.36	-0.158
	(1,574.27)	(0.081)
Pre-1980 *Distance ϵ [0,15]	1,686.26	-0.078
	(1,252.59)	(0.194)
Pre-1980 *Distance ϵ (15,50]	1,737.43	0.222
	(1,231.97)	(0.145)
Pre-1980 *Distance ϵ (50,100]	371.44	0.133
	(1,691.31)	(0.110)
Pre-1980 *Distance ϵ (100,150]	1,746.60	0.270
	(946.75)	(0.115)
Pre-1980 *Distance>150	490.47	0.175
	(1,097.16)	(0.063)
N	960	960

Note: Asterisks denote statistical significance relative to coefficient on Distance ϵ [0,15] (*** p<0.01, ** p<0.05, * p<0.1). Robust standard errors are in parentheses, as these are larger than the errors clustered at the year or distance group level. The dependent variable is total degrees awarded (or ln(total degrees awarded)) at universities in the state/distance group pair. See text of Online Appendix for details on estimation.

Appendix Table A6: Jurisdictional Competition in Delaware and University Enrollment

	(1) Total Degrees	(2) Ln(Total Degrees)
Treat Years *Distance ϵ [0,15]	-72.996	-0.100
	(33.386)	(0.043)
Treat Years *Distance ϵ (15,50]	-58.987	-0.076
	(18.071)	(0.025)
Treat Years *Distance ϵ (50,100]	-42.067	-0.068
	(20.242)	(0.022)
Treat Years *Distance ϵ (100,150]	-80.128	-0.119
	(28.655)	(0.034)
Treat Years *Distance>150	-57.014	-0.082
	(13.790)	(0.020)
1990s *Distance ϵ [0,15]	-57.836	-0.120
	(74.352)	(0.048)
1990s *Distance ϵ (15,50]	-113.613	-0.140
	(30.577)	(0.038)
1990s *Distance ϵ (50,100]	-60.041	-0.112
	(34.614)	(0.042)
1990s *Distance ϵ (100,150]	-67.310	-0.126
	(46.532)	(0.055)
1990s *Distance>150	-80.870	-0.103
	(22.482)	(0.034)
Pre-1980 *Distance ϵ [0,15]	-55.942	-0.067
	(143.413)	(0.079)
Pre-1980 *Distance ϵ (15,50]	100.341	0.144
	(27.793)	(0.038)
Pre-1980 *Distance ϵ (50,100]	97.076	0.153
	(27.316)	(0.034)
Pre-1980 *Distance ϵ (100,150]	79.743	0.169
	(41.257)	(0.046)
Pre-1980 *Distance>150	87.392	0.143
	(25.814)	(0.039)
N	10,469	10,469

Note: Asterisks denote statistical significance relative to coefficient on Distance ϵ [0,15] (*** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1). Standard errors clustered at the university level are in parentheses. Estimation includes university fixed effects, and in Column 2 observations are weighted by the number of total Bachelor's degrees conferred by the university in the given year. Coefficients are relative to the years immediately preceding the treatment (1980 through 1986). Interactions between each distance group and an indicator for year ≥ 2000 not shown. Additional controls include year and year^2, the second lag of ln(FIRE employment) at the state level, and an indicator for the years when this is missing (2004-2013). See text for estimation details.

Appendix Table A7: Jurisdictional Competition in Delaware and Student Composition

	Nonlocal	HS GPA ≥ B+
TreatYears1 *Distance ϵ [0,15]	0.019	-0.070
	(0.024)	(0.020)
TreatYears1 *Distance ϵ [0,15]**Nonlocal*	*N/A*	-0.060
		(0.009)
TreatYears1 *Distance ϵ (15,50]	-0.013***	-0.088‡‡
	(0.026)	(0.027)
TreatYears1 *Distance ϵ (50,100]	-0.016**	-0.085‡‡
	(0.027)	(0.026)
TreatYears1 *Distance ϵ (100,150]	-0.041***	-0.067‡‡‡
	(0.029)	(0.030)
TreatYears2 *Distance ϵ [0,15]	0.022	-0.085
	(0.036)	(0.031)
TreatYears2 *Distance ϵ [0,15]**Nonlocal*	*N/A*	-0.074
		(0.014)
TreatYears2 *Distance ϵ (15,50]	0.008	-0.100‡
	(0.036)	(0.042)
TreatYears2 *Distance ϵ (50,100]	-0.017*	-0.096‡‡
	(0.040)	(0.036)
TreatYears2 *Distance ϵ (100,150]	-0.037***	-0.071‡‡‡
	(0.037)	(0.039)
Pre-1977 *Distance ϵ [0,15]	-0.086	0.047
	(0.032)	(0.024)
Pre-1977 *Distance ϵ [0,15]**Nonlocal*	*N/A*	0.018
		(0.016)
*Pre-1977** Distance ϵ (15,50]	0.022***	0.009**‡‡‡
	(0.029)	(0.028)
Pre-1977 *Distance ϵ (50,100]	0.049***	0.020***‡‡‡
	(0.026)	(0.022)
*Pre-1977** Distance ϵ (100,150]	-0.147	-0.082
	(0.080)	(0.074)
N	696,379	691,069

Note: Asterisks denote statistical significance relative to coefficient on Distance ϵ [0,15] (*** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1). The symbol ‡ denotes whether the coefficient is statistically significant relative to the effect among nonlocal students at universities within 15 miles of Wilmington (linear combination of year group*Distance ϵ [0,15], and year group*Distance ϵ [0,15]*Nonlocal) (‡‡‡ p-value ≤ .01, ‡‡ p-value ≤ .05, ‡ p-value ≤ .1). Standard errors clustered at the university level are in parentheses. Estimation includes university fixed effects. Coefficients are relative to the proportion in each major in the years immediately preceding the treatment (1977 through 1981). Coefficients on interactions between year group and distance > 150, as well as Distance ϵ [0,15]*nonlocal, not included in the table. I additionally control for a linear trend in year. See text for estimation details.

Appendix Table A8: The Dot-Com Crash and Total Degrees Awarded: Differential Effects by Share Employed in Computers

	Outcome: Ln(Total Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Post	0.229***	0.222***	0.250***	0.222***	0.210***	0.212***
		(0.012)	(0.016)	(0.018)	(0.025)	(0.015)	(0.019)
(2)	Post*Private		0.029		0.104**		-0.006
			(0.025)		(0.044)		(0.036)
(3)	Post*MSA Computer Share	-0.160	0.045	-0.263	0.348	-0.166	-0.169
		(0.258)	(0.376)	(0.383)	(0.642)	(0.324)	(0.356)
(4)	Post*MSA Computer Share*Private		-0.799		-1.848**		0.021
			(0.514)		(0.872)		(0.817)
	P-value from Joint Test of (3) and (4)		0.100		0.037		0.876
(5)	Crash	0.107***	0.089***	0.123***	0.101***	0.093***	0.072***
		(0.008)	(0.010)	(0.013)	(0.017)	(0.011)	(0.013)
(6)	Crash*Private		0.059***		0.107***		0.049*
			(0.019)		(0.033)		(0.027)
(7)	Crash*MSA Computer Share	-0.081	0.037	-0.190	0.004	-0.048	0.061
		(0.181)	(0.244)	(0.278)	(0.437)	(0.227)	(0.266)
(8)	Crash*MSA Computer Share*Private		-0.475		-0.942		-0.346
			(0.369)		(0.650)		(0.623)
	P-value from Joint Test of (7) and (8)		0.284		0.152		0.857
(9)	Pre-Peak	-0.038***	-0.036***	-0.023*	-0.022	-0.051***	-0.048***
		(0.008)	(0.010)	(0.013)	(0.016)	(0.010)	(0.014)
(10)	Pre-Peak*Private		-0.007		0.002		-0.005
			(0.016)		(0.027)		(0.023)
(11)	Pre-Peak*MSA Computer Share	0.053	0.039	-0.134	-0.207	0.180	0.199
		(0.123)	(0.146)	(0.205)	(0.261)	(0.148)	(0.172)
(12)	Pre-Peak*MSA Computer Share*Private		0.026		0.141		-0.114
			(0.272)		(0.352)		(0.474)
	P-value from Joint Test of (11) and (12)		0.927		0.704		0.504
(13)	Long Run	0.345***	0.351***	0.367***	0.337***	0.327***	0.359***
		(0.018)	(0.024)	(0.029)	(0.042)	(0.024)	(0.027)
(14)	Long Run*Private		-0.012		0.082		-0.092**
			(0.035)		(0.056)		(0.045)
(15)	Long Run*MSA Computer Share	0.102	0.376	-0.213	0.788	0.321	0.107
		(0.409)	(0.577)	(0.667)	(1.107)	(0.519)	(0.533)
(16)	Long Run*MSA Computer Share*Private		-1.042		-2.716**		0.933
			(0.783)		(1.243)		(1.074)
	P-value from Joint Test of (15) and (16)		0.367		0.003		0.525
	Universities	All		Research/ Doctoral		Master's/ Baccalaureate	
	Observations	16,614	16,614	4,212	4,212	12,402	12,402
	R-squared	0.979	0.979	0.970	0.971	0.965	0.965

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the university level in parentheses. Post denotes years in which graduates entered university after the initial stages of the dot-com crash (2004 through 2008). Crash denotes years in which college graduates were enrolled during the initial stages of the dot-com crash (2001 through 2003). Pre-Peak denotes years before the peak of the dot-com boom (1990 through 1997). Long Run denotes years 2009 through 2013. The omitted year group is the group of years immediately preceding the dot-com crash (1998 through 2000). MSA Computer Share denotes the share of the MSA employed in computers in 2000. Private is an indicator equal to one if the university is private. Regressions include university fixed effects, and observations are weighted by the number of degrees awarded by the university. See text for details.

Appendix Table A9: The 2008 Financial Crisis and Total Degrees Awarded: Differential Effects by Share Employed in Finance

	Outcome: Ln(Total Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Post	0.105***	0.072***	0.111***	0.073**	0.102**	0.073***
		(0.0265)	(0.020)	(0.0309)	(0.034)	(0.0424)	(0.022)
(2)	Post*Private		0.068		0.036		0.066
			(0.083)		(0.064)		(0.108)
(3)	Post*MSA Finance Share	1.315*	2.897***	0.966	2.766***	1.568	2.987***
		(0.755)	(0.589)	(0.909)	(1.025)	(1.164)	(0.592)
(4)	Post*MSA Finance Share*Private		-3.541*		-3.493**		-3.104
			(2.091)		(1.652)		(2.817)
	P-value from Joint Test of (3) and (4)		0.000		0.024		0.000
(5)	Crash	0.0474***	0.031**	0.0459**	0.025	0.0499**	0.040**
		(0.0143)	(0.015)	(0.0209)	(0.026)	(0.0203)	(0.018)
(6)	Crash*Private		0.028		0.020		0.018
			(0.038)		(0.054)		(0.048)
(7)	Crash*MSA Finance Share	0.792*	1.631***	0.751	1.724*	0.807	1.489***
		(0.442)	(0.523)	(0.701)	(0.964)	(0.578)	(0.480)
(8)	Crash*MSA Finance Share*Private		-1.730*		-1.843		-1.362
			(1.034)		(1.452)		(1.304)
	P-value from Joint Test of (7) and (8)		0.008		0.204		0.008
(9)	Pre-Peak	-0.103***	-0.099***	-0.0917***	-0.082***	-0.113***	-0.124***
		(0.0146)	(0.019)	(0.0243)	(0.031)	(0.0175)	(0.022)
(10)	Pre-Peak*Private		0.021		0.012		0.041
			(0.030)		(0.065)		(0.034)
(11)	Pre-Peak*MSA Finance Share	-0.620	-1.110*	-0.963	-1.497	-0.322	-0.613
		(0.429)	(0.620)	(0.755)	(1.089)	(0.488)	(0.635)
(12)	Pre-Peak*MSA Finance Share*Private		0.460		0.548		0.142
			(0.870)		(1.705)		(0.961)
	P-value from Joint Test of (11) and (12)		0.115		0.302		0.508
	Universities	All		Research/ Doctoral		Baccalaureate/ Master's	
	Observations	11,333	11,333	2,413	2,413	8,920	8,920
	R-squared	0.985	0.985	0.977	0.978	0.975	0.976

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the university level in parentheses. Post denotes years in which graduates entered university after the initial stages of the financial crisis (2012 and 2013). Crash denotes years in which college graduates were enrolled during the initial stages of the financial crisis (2009 through 2011). Pre-Peak denotes years before the pre-crisis peak (2000 through 2005). The omitted year group is the group of years immediately preceding the financial crisis (2006 through 2008). MSA Finance share denotes the share of the MSA employed in finance in 2000. Private is an indicator equal to one if the university is private. Regressions include university fixed effects, and observations are weighted by the number of degrees awarded by the university. See text for details.

Appendix Table A10: Effect of Local Shocks on Total Bachelor's Degrees Awarded by Local Universities

	Outcome: Ln(Total Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Differential Effects of the Dot-Com Crash by MSA Computer Share							
(1)	Post (2004-2008)	0.229***	0.222***	0.250***	0.222***	0.210***	0.212***
		(0.012)	(0.016)	(0.018)	(0.025)	(0.015)	(0.019)
(2)	Post*Private		0.029		0.104**		-0.006
			(0.025)		(0.044)		(0.036)
(3)	Post*MSA Computer Share	-0.160	0.045	-0.263	0.348	-0.166	-0.169
		(0.258)	(0.376)	(0.383)	(0.642)	(0.324)	(0.356)
(4)	Post*MSA Computer Share*Private		-0.799		-1.848**		0.021
			(0.514)		(0.872)		(0.817)
	P-value from Joint Test of (3) and (4)		0.100		0.037		0.876
	Observations	16,614	16,614	4,212	4,212	12,402	12,402
	R-squared	0.979	0.979	0.970	0.971	0.965	0.965
Panel B: Differential Effects of the Financial Crisis by MSA Finance Share							
(5)	Post (2012-2013)	0.105***	0.072***	0.111***	0.073**	0.102**	0.073***
		(0.0265)	(0.020)	(0.0309)	(0.034)	(0.0424)	(0.022)
(6)	Post*Private		0.068		0.036		0.066
			(0.083)		(0.064)		(0.108)
(7)	Post*MSA Finance Share	1.315*	2.897***	0.966	2.766***	1.568	2.987***
		(0.755)	(0.589)	(0.909)	(1.025)	(1.164)	(0.592)
(8)	Post*MSA Finance Share*Private		-3.541*		-3.493**		-3.104
			(2.091)		(1.652)		(2.817)
	P-value from Joint Test of (7) and (8)		0.000		0.024		0.000
	Observations	11,333	11,333	2,413	2,413	8,920	8,920
	R-squared	0.985	0.985	0.977	0.978	0.975	0.976
Panel C: Differential Effects of Jurisdictional Competition by Distance to Wilmington, Delaware							
(9)	*Treat Years* *Distance ϵ [0,15]	-0.100					
		(0.043)					
(10)	*Treat Years* *Distance ϵ (15,50]	-0.076					
		(0.025)					
(11)	*Treat Years* *Distance ϵ (50,100]	-0.068					
		(0.022)					
	Observations	10,469					
	Universities	All		Research/ Doctoral		Master's/ Baccalaureate	
	University Fixed Effects	Y	Y	Y	Y	Y	Y

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the university level in parentheses. Panel A shows the results from estimating the effect of the dot-com crash on total degrees awarded. Panel B shows the results from estimating the effect of the financial crisis on total degrees awarded. Panel C shows the results from estimating the effect of the jurisdictional competition on total degrees awarded. The table shows only the coefficients for the treatment years (and only for the closest distance groups in Panel C); the full results are in other appendix tables. Observations weighted by the number of degrees awarded by the university. See text and Table 4 for definition of Treat Years.

Appendix Table A11: Within University Changes in Major Choice After Jurisdictional Competition in Delaware, Local Relative to Nonlocal Students

	Proportion majoring in:							
	Nonlocal	Business	Science	Education	Humanities	Social Sciences	Undecided	Health
TreatYears1 *Distance ϵ [0,15]	0.019	-0.020	-0.040	0.008	0.015	0.012	-0.011	0.054
	(0.024)	(0.006)	(0.006)	(0.003)	(0.004)	(0.003)	(0.002)	(0.005)
TreatYears1 *Distance ϵ [0,15]**Nonlocal*	*N/A*	0.011	-0.036	-0.001	0.015	0.001	0.031	-0.037
		(0.004)	-0.007	(0.000)	(0.002)	(0.001)	(0.001)	(0.004)
TreatYears1 *Distance ϵ (15,50]	-0.013***	-0.035*‡‡	-0.018*‡‡‡	-0.001	0.014‡‡	-0.009***‡‡‡	-0.002‡‡‡	0.031**
	(0.026)	(0.010)	(0.013)	(0.010)	(0.008)	(0.007)	(0.006)	(0.011)
TreatYears1 *Distance ϵ (50,100]	-0.016**	-0.028‡	-0.030‡‡‡	0.001	0.018‡‡	0.000***‡‡‡	-0.002**‡‡‡	0.029***‡
	(0.027)	(0.012)	(0.012)	(0.007)	(0.006)	(0.004)	(0.004)	(0.008)
TreatYears1 *Distance ϵ (100,150]	-0.041***	-0.022	-0.016*‡‡‡	-0.006*	0.018‡‡	0.008	-0.004*‡‡‡	0.043**‡‡‡
	(0.029)	(0.012)	(0.012)	(0.009)	(0.005)	(0.005)	(0.005)	(0.007)
TreatYears2 *Distance ϵ [0,15]	0.022	-0.031	-0.105	0.051	0.055	0.022	-0.006	0.031
	(0.036)	(0.009)	(0.009)	(0.005)	(0.007)	(0.004)	(0.004)	(0.008)
TreatYears2 *Distance ϵ [0,15]**Nonlocal*	*N/A*	0.021	-0.050	-0.027	-0.016	0.027	0.053	-0.030
		(0.009)	(0.018)	(0.003)	(0.011)	(0.003)	(0.003)	(0.008)
TreatYears2 *Distance ϵ (15,50]	0.008	-0.055**‡‡‡	-0.050***‡‡‡	0.012***‡	0.040	0.010***‡‡‡	0.009**‡‡‡	0.033‡‡
	(0.036)	(0.014)	(0.015)	(0.007)	(0.012)	(0.006)	(0.006)	(0.014)
TreatYears2 *Distance ϵ (50,100]	-0.017*	-0.046‡	-0.084*‡‡‡	0.024***	0.051	0.023‡‡‡	0.003‡‡‡	0.021‡
	(0.040)	(0.018)	(0.014)	(0.010)	(0.009)	(0.006)	(0.006)	(0.010)
TreatYears2 *Distance ϵ (100,150]	-0.037***	-0.047‡	-0.056***‡‡‡	0.025***	0.037***	0.024‡‡‡	0.004*‡‡‡	0.038‡‡‡
	(0.037)	(0.022)	(0.017)	(0.008)	(0.009)	(0.007)	(0.006)	(0.010)
Pre-1977 *Distance ϵ [0,15]	-0.086	0.018	-0.014	0.041	-0.017	0.001	0.008	-0.042
	(0.032)	(0.007)	(0.007)	(0.004)	(0.005)	(0.004)	(0.003)	(0.006)
Pre-1977 *Distance ϵ [0,15]**Nonlocal*	*N/A*	-0.011	0.049	-0.029	-0.007	-0.012	-0.021	-0.007
		(0.014)	(0.017)	(0.005)	(0.001)	(0.006)	(0.003)	(0.004)
*Pre-1977** Distance ϵ (15,50]	0.022***	-0.015***	0.009*	-0.002***	0.004**‡‡‡	0.010‡‡	0.001‡‡	-0.048
	(0.029)	(0.011)	(0.011)	(0.006)	(0.010)	(0.006)	(0.006)	(0.009)
Pre-1977 *Distance ϵ (50,100]	0.049***	-0.018***	0.019**	0.012***	-0.004*‡‡‡	0.006‡	0.006‡‡‡	-0.034‡‡‡
	(0.026)	(0.011)	(0.011)	(0.006)	(0.006)	(0.005)	(0.003)	(0.006)
*Pre-1977** Distance ϵ (100,150]	-0.147	-0.004	0.012***	0.029	-0.016	0.007‡‡	0.007‡‡‡	-0.036‡
	(0.080)	(0.019)	(0.013)	(0.009)	(0.011)	(0.004)	(0.005)	(0.007)
N	696,379	696,379	696,379	696,379	696,379	696,379	696,379	696,379

Note: Asterisks denote statistical significance relative to coefficient on Distance ϵ [0,15] (*** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1). The symbol ‡ denotes whether the coefficient is statistically significant relative to the effect among nonlocal students at universities within 15 miles of Wilmington (linear combination of year group*Distance ϵ [0,15], and year group*Distance ϵ [0,15]*Nonlocal) (‡‡‡ p-value ≤ .01, ‡‡ p-value ≤ .05, ‡ p-value ≤ .1). Standard errors clustered at the university level are in parentheses. Estimation includes university fixed effects. Coefficients are relative to the proportion in each major in the years immediately preceding the treatment (1977 through 1981). Coefficients on interactions between year group and distance > 150, as well as Distance ϵ [0,15]*Nonlocal, not included in the table. I additionally include a linear trend in year. See text for estimation details.

Appendix Table A12: Within University Changes in Major Choice After Jurisdictional Competition in Delaware, by High School GPA and Distance From Home

	Business	Science	Humanities	Social Sciences	Undecided	Health	Education
TreatYears1 *Distance ϵ [0,15]**HSBPlus*	-0.014	0.062	-0.008	-0.017	-0.016	0.016	0.003
	(0.001)	(0.002)	(0.002)	(0.006)	(0.005)	(0.001)	(0.002)
TreatYears1 *Distance ϵ [0,15]**HSBplus*Nonlocal*	-0.014	0.011	0.008	0.009	-0.008	-0.024	0.000
	(0.004)	(0.001)	(0.006)	(0.005)	(0.001)	(0.003)	(0.001)
TreatYears1 *Distance ϵ (15,50]**HSBPlus*	-0.019	-0.006***	0.010**	-0.000*	0.007***	-0.029***	0.014
	(0.017)	(0.014)	(0.008)	(0.008)	(0.008)	(0.013)	(0.008)
TreatYears1 *Distance ϵ (50,100]**HSBPlus*	-0.009	-0.011***	0.003**	0.009***	0.000***	-0.017***	0.008
	(0.009)	(0.009)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)
TreatYears1 *Distance ϵ (100,150]**HSBPlus*	-0.003	-0.003***	0.003	0.001**	0.001***	-0.002***	0.014
	(0.009)	(0.012)	(0.005)	(0.006)	(0.004)	(0.007)	(0.008)
TreatYears2 *Distance ϵ [0,15]**HSBPlus*	0.014	-0.012	0.007	0.013	-0.012	-0.016	-0.026
	(0.005)	(0.009)	(0.003)	(0.002)	(0.001)	(0.003)	(0.001)
TreatYears2 *Distance ϵ [0,15]**HSBplus*Nonlocal*	-0.001	0.023	-0.003	0.010	-0.006	-0.003	0.030
	(0.024)	(0.023)	(0.013)	(0.007)	(0.011)	(0.013)	(0.003)
TreatYears2 *Distance ϵ (15,50]**HSBPlus*	0.007	-0.040	0.020	0.013	-0.000*	-0.035	0.009***
	(0.020)	(0.018)	(0.010)	(0.008)	(0.006)	(0.013)	(0.007)
TreatYears2 *Distance ϵ (50,100]**HSBPlus*	-0.006	-0.017	0.009	0.010	0.010***	-0.009	0.002***
	(0.012)	(0.011)	(0.008)	(0.005)	(0.005)	(0.008)	(0.006)
TreatYears2 *Distance ϵ (100,150]**HSBPlus*	0.015	0.002	-0.005	0.008	-0.005	-0.002	0.014***
	(0.014)	(0.014)	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)
Pre1977 *Distance ϵ [0,15]**HSBPlus*	-0.041	-0.027	0.020	0.010	0.022	-0.011	-0.010
	(0.004)	(0.006)	(0.001)	(0.001)	(0.002)	(0.004)	(0.002)
Pre1977 *Distance ϵ [0,15]**HSBplus*Nonlocal*	0.021	-0.007	-0.012	0.001	-0.003	-0.013	-0.003
	(0.017)	(0.010)	(0.009)	(0.009)	(0.005)	(0.011)	(0.004)
Pre1977 *Distance ϵ (15,50]**HSBPlus*	-0.000**	0.000*	-0.000**	0.005	-0.001***	-0.024	-0.016
	(0.017)	(0.013)	(0.009)	(0.007)	(0.008)	(0.012)	(0.009)
Pre1977 *Distance ϵ (50,100]**HSBPlus*	0.027***	-0.033	0.005***	-0.006***	-0.004***	-0.011	-0.014
	(0.011)	(0.012)	(0.005)	(0.006)	(0.003)	(0.009)	(0.008)
Pre1977 *Distance ϵ (100,150]**HSBPlus*	0.015***	-0.031	0.003***	-0.002*	0.014*	-0.006	-0.003
	(0.008)	(0.014)	(0.004)	(0.007)	(0.004)	(0.012)	(0.006)
N	691,069	691,069	691,069	691,069	691,069	691,069	691,069

Note: Asterisks denote statistical significance relative to coefficient on year group *Distance ϵ [0,15]*HSBPlus (*** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1). Standard errors clustered at the university level are in parentheses. Estimation includes university fixed effects. The omitted year group is 1977-1981, the years immediately before the policy. I include the year, and the following individual characteristics as covariates: indicators for male, black, hispanic, father has a Bachelor's degree, and mother has a Bachelor's degree. I also include indicators for whether these variables have missing values. Many interactions are not included in this table. See paper and appendix for details, and all variables included in the regressions.

Appendix Table A13: 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 7. 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 6 for sample sizes by home location and year group for the principal matching sample. See Appendix Table A15 for sample sizes by home location and year group for robustness samples.

Appendix Table A14: 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 7, though I exclude distance to university from home as a matching variable here). The bias adjustment from Abadie and Imbens (2011) is used for each matching variable. The mahalanobis matrix is used for weighting. See Appendix Table A15 for sample sizes by home location and year group.

Appendix Table A15: 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 A14.