Local Labor Markets and Human Capital Investments*

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Abstract

Using university- and student-level data, I study whether composition of majors at local universities responds to local, sector-specific shocks, including the dot-com crash, the 2008 financial crisis, and an important shock originating from jurisdictional competition. Universities in areas more exposed to sectoral shocks experience greater changes in sector-relevant majors, especially true among private universities. The affected universities also experience changes in total enrollment, suggesting some of the within-university effect on college majors may be explained by students changing university as well as major. The results suggest local markets matter for human capital decisions, and allocation of talent across sectors and universities.

1 Introduction

Sector-specific local labor demand shocks are prevalent. Many recent examples originate from jurisdictional competition, in which local governments compete for large firms, in industries ranging from automotive manufacturing to finance. Given that

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many industries are geographically concentrated, global shocks to particular sectors may also have differential effects on local markets (as in Autor, Dorn, and Hanson 2013).[1] Natural resource shocks, such as the impact of hydraulic fracturing (fracking) technology on areas with previously inaccessible shale reserves, represent another example of local, sector-specific shocks.

These shocks affect labor market participation, unemployment, as well as migration. However, as sector-specific shocks, they may also affect sector-specific human capital investments. Several recent papers have studied the impact of local shocks on high school completion and college enrollment (Cascio and Narayan 2015, Charles, Hurst, and Notowidigdo 2015). However, there is a particular lack of evidence on the impact of local, sector-specific shocks on local, sector-specific human capital production. This question provides important insight into labor market mobility, the allocation of talent across sectors, as well as across universities. This paper analyzes whether the effect of sector-specific shocks on sector-relevant majors is stronger at universities in regions more exposed to these shocks. I further test whether this is explained by students changing major or changing university.

Analyzing the relationship between college majors and local labor demand is challenging, as it requires an exogenous change in local labor demand. I analyze the response to three important sector-specific shocks with differential effects on local markets, using university-level data from IPEDS and individual-level data from The Freshman Survey.

First, I study the impact on college majors of the post-2000 dot-com crash and the 2008 financial crisis. I analyze whether these events had especially strong effects on computer science and business majors at universities located in regions with high share of computer or finance employment. The geographically concentrated growth of the computer or finance sectors before these crises may have been driven by the number of majors, and the presence of universities with relevant specializations. However, the dot-com and financial crises were exogenous to the number of majors. This allows me to identify the impact of an employment shock on college major.

Jurisdictional competition for firm headquarters and production facilities is another prevalent source of local labor demand shocks. Aside from their policy importance, one significant benefit of studying the impact of jurisdictional competition is

[1] Autor, Dorn, and Hanson (2013) find rising import competition from China has more negative effects in local markets with industries that compete with China.

that one jurisdiction receives the shock, and nearby jurisdictions do not. It is thus possible to study changes in the effects on college major by university distance to the shock. I can then quantify the extent to which the effects are local. This is less straightforward when studying the local effects of the dot-com or financial crisis, since many areas experience local effects, albeit to different extents. I study the impact of an important instance of such competition, which resulted in the relocation of finance firms to Delaware in the early 1980s.

The effect of sectoral shocks on sector-relevant majors may be stronger at universities in more-exposed regions for several reasons. First, students may make human capital investment decisions (either their major or where they attend university) based on local labor demand. This could be because students have better information about local labor demand. For example, after the dot-com crash students in San Antonio, Texas may hear about bankruptcies of technology companies in San Jose, California less frequently, or with less sensationalism, than students in San Jose. 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. In this case, a prospective computer science major may believe she will have better labor market prospects if she attends a university in a region not so dramatically affected by the dot-com crash. This involves students changing universities, but not necessarily majors in response to sector-specific shocks.

Second, students may have strong local preferences. While they may understand the shock is concentrated in their local market, changes in local demand are pertinent if students want to live locally after graduation. Finally, universities in areas with high sectoral employment share may actively seek to change their specialization in response to a sector-specific shock. For example, after a negative shock, these universities may choose to admit fewer students interested in the sector-relevant major, to divest resources from these departments, or these departments may lose outside funding from local corporations or governments. In this case, university resources are the direct reason for the differential drop in majors or total degrees at more-exposed universities. However, this still implies that students at universities in areas with low sectoral employment share are responding less to a national labor demand shock, potentially because of information or preferences.

I find that after the dot-com crash, there is a stronger decrease in both computer science degrees and total degrees awarded at private universities in regions more exposed to the computer industry. However, there is no differential change in total degrees awarded at public universities in these more exposed regions. This suggests that the crash disincentivizes prospective computer science students from enrolling in any of the universities in the shocked region. Universities in less-shocked regions experience increases in computer science degrees awarded, suggesting that at least some of the students are simply changing university not major. This is unlikely to be the dominating mechanism given the national decline in the proportion of computer science degrees awarded.

After the financial crisis, there is a stronger decrease in both business degrees and total degrees awarded at private universities in regions more exposed to the finance industry. However, public universities located in more-shocked regions experience differential increases in both business degrees and total degrees awarded. This also suggests that at least some of the students are simply changing university, and not major. Again, this is unlikely to be the dominating mechanism given the national decline in the proportion of business degrees awarded. Unlike the effect of the dot-com crash, students do not substitute away from universities in shocked regions, but instead appear to substitute between private and public universities. This may be explained by smaller post-college earnings differentials between private and public universities after the shock, and/or larger cost differentials due to income shocks and the resulting larger loans necessary to finance education.

After the finance shock resulting from jurisdictional competition in Delaware, there was a larger increase in the share of business degrees awarded at universities in the shocked region. I find the shock resulted in a greater proportion of nonlocal students at local universities, who were differentially more likely to major in business after the policy.

The allocation of talent across fields and universities can have important impacts on aggregate productivity (Murphy, Shleifer, and Vishny 1991). I study substitution patterns between majors after the jurisdictional competition in Delaware. This shock is particularly useful for this exercise because I compare universities in close geographic proximity, and arguably subject to more similar labor demand shocks. This is especially important when looking at changes in majors other than the major relevant to the shocked industry. 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. This finding relates to the literature on the changing finance workforce (Philippon and Reshef 2012).

Taken together, the results suggest universities in areas that are more exposed to sectoral shocks experience greater changes in sector-relevant majors, and this is especially true among private universities. There is also strong evidence that the affected universities experience changes in enrollment. The results suggest that some of the within-university effect on college majors may be explained by students changing their university, but not their major, in response to local labor demand. However, it is clear that this is not always the dominant mechanism.

Whether differential local effects are socially and individually optimal depends on the dominant mechanism, and on whether these shocks were permanent or temporary. I will not focus on whether the effect on majors represents an optimal response, since it is difficult to identify the mechanism. However, each mechanism suggests possible effects on aggregate productivity, if employers cannot hire the most productive individuals for their vacancies. Furthermore, investing based only on local conditions may reduce the gains from future migration, and thus inhibit economic adjustment to shocks. It is also possible that students in local areas suboptimally overreact to shocks, treating temporary shocks as permanent. Finally, if students leave local universities in response to a negative local labor market shock, this may have aggregate effects if these universities provide the best education. Similarly, if students enroll in local universities in response to a positive local labor market shock, this may have aggregate effects if these universities do not provide the best education.

This paper is related to a growing literature on the responsiveness of college major choice to the business cycle (see Altonji, Blom, and Meghir 2012 for a review). Recent work by Blom, Cadena, and Keys (2015) finds significant reallocation in college majors in response to unemployment rates during schooling years. However, few papers address whether college major is more responsive to local demand conditions. An exception is Long, Goldhaber, and Huntington-Klein (2014) which finds college major choice is more responsive to local compared to national wages. I contribute to this literature by identifying several exogenous local shocks, and distinguishing whether students change major or change university in response to local demand.

The paper also contributes to the discussion surrounding whether policy has a role or responsibility in guiding students to majors with higher labor market return.[2] The

[2]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

findings suggest students change their major and university in response to very local labor demand conditions. If these decisions are local because of a lack of information, they may not be individually or socially optimal. This may suggest a role for policy in improving student outcomes.

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 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.[3] 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.[4] Computer employment fell by 15% from 2001 to 2003, from approximately 4.2 million to 3.5 million.

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. FIRE employment declined by approximately 8% from 2007 to 2010, from 8.3 million to 7.7 million.

Weinstein 2013), and also that the effect of graduating in a recession varies by college major (Altonji, Kahn, and Speer 2014).

[3]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.

[4]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.

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. By 2002, employment in this industry had fallen from its 2001 peak by 12,500 jobs. This one-year employment loss represented 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 from 3300 jobs in 2001 to over 3400 jobs in 2002. The dot-com crash had no negative effects on local employment in this computer industry.

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 Jurisdictional Competition: Exogenous Shift in Labor Demand in Delaware's Finance Industry

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.[5] 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.

[5]The exogenous shock to labor demand in Delaware is described in greater detail in Weinstein (2015a).

Delaware, which had historically provided a favorable business climate, was looking to diversify its economy from the automotive and chemical industry.[6] After the *Marquette* ruling, the state recognized the opportunity to attract the finance industry.[7] In 1981, Delaware eliminated its usury laws, with the passage of the Financial Center Development Act (FCDA). This legislation formally allowed out-of-state bank holding companies to acquire a bank in Delaware, and provided an incentive to do so. In addition to eliminating ceilings on interest rates for most kinds of loans, the FCDA reduced other industry regulation and introduced a regressive tax structure for banks.[8]

As a result, many companies moved their finance or credit operations to Delaware, starting with J.P. Morgan in 1981. Weinstein (2015a) 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 (2015a), 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),[9] 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).

[6] 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).

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

[8] 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.

[9] 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.

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 on Bachelor's degrees awarded by academic discipline from IPEDS. I use two-digit CIP codes to classify majors from 1990-2013. I classify business majors as business, management, marketing, and related support services.I classify computer science majors as computer and information sciences and support services.[10] I include all universities that award at least Bachelor's degrees. 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 industries as computer-related using a BLS definition of high-technology industries by 1997 NAICS code (Hecker (2005)). Specifically, I classify as computer-related industries the high-technology industries that are relevant for the computer industry.[11] I include the FIRE industries, excluding insurance and real estate, as finance-related industries.[12]

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. Using the person weights, I obtain the weighted sum of individuals by industry and metropolitan area. I calculate total employment in a metropolitan area as the sum of the employment across all industries.

To study the effect of local labor markets on college major, the university must be merged with its MSA. 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

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

[11] Hecker (2005) 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.

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

awarded by academic discipline from 1966 through 2013 from the IPEDS Completions Survey.[13] These data are accessed from the Integrated Science and Engineering Resources Data System of the National Science Foundation (NSF). 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. The IPEDS Completions Survey also has information on the university's Carnegie classifications, the city, state, and ZIP code.

Because this was a Delaware-specific shock, rather than a national shock with local effects, I limit the sample of universities to those located in Delaware, New Jersey, Pennsylvania, Maryland, Washington, DC, Virginia, and West Virginia. I obtain the 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 Gazetteer's place files.[14] I then 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.[15] While these distances are not as optimal as driving distances, they provide a good approximation.

While the dot-com crash and 2008 financial crisis had differential local effects, there were many MSAs with presumably large negative shocks to local labor demand. In contrast, Delaware's legislation implied the shock to finance was concentrated in 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.

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

[14] 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.

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

I separate each of the broad academic disciplines into a major group and observe effects on each group.[16] I obtain data on FIRE employment by state and year using the Current Employment Statistics (CES) of the Bureau of Labor Statistics (BLS).

I use individual-level data on college freshmen from the CIRP Freshman Survey, an annual survey of college freshmen. The survey is administered by colleges and universities to the entire freshman class. These data contain information on university attended, university distance from the student's home, and high school GPA. I use these data to distinguish whether changes in major composition are due to changes in university choice or changes in major choice. These data also allow me to look at the nature of selection into major.

3.3 Summary Statistics

The Dot-Com Crash and the 2008 Financial Crisis

The national share of Bachelor's degrees in computer science increased dramatically in the mid-1990s, followed by a dramatic decline in the mid-2000s (Figure 3a). While this cycle follows the general trend of the dot-com boom and bust, it does not perfectly align with the initial fall in the NASDAQ in March 2000.

After the beginning of the dot-com crash in 2000, the share of computer science degrees falls for the first time in 2004. 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. This would have made switching majors less likely.

The light grey plot in Figure 3b shows a large proportion of computer science degrees in the US are awarded by universities in areas with low computer employment share. Specifically, I group MSAs by the 2000 share employed in computers, where groups are defined starting at zero, in intervals of .01. I then plot the total computer science degrees awarded by universities in each MSA group, as a share of all computer

[16] 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.

science degrees awarded in the US. I use this across-MSA variation to identify the local impact of sector-level shocks. If all computer science degrees were awarded by universities in high computer employment share areas, then a larger differential response in these areas would be mechanical.

The darker plot in Figure 3b shows the effect of the dot-com crash on computer science degrees was larger in high computer employment MSAs. Specifically, I calculate the share of computer science degrees in each MSA group in 2003, the year when the national share peaked, and subtract this from the share five years later 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. This effect was closer to 2.5 percentage points at universities in MSAs where 10% 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.

Figure 3c shows the national share of Bachelor's degrees in business started decreasing in 2004, though this decrease had slowed considerably leading up to the Great Recession (and there was even a slight increase in 2009). However, after 2009 the share of business degrees fell significantly. Unlike the trend in computer science degrees, the trend in business degrees is much more closely aligned with the business cycle. College graduates in 2010 were the first to show substitution away from business degrees. These students were college juniors at the time of the Great Recession in 2008-2009. This suggests that after several years of college, it may be less costly to switch from a business major than from a computer science major.

The light grey histogram plot in Figure 3d 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. Similar to the construction of the plot in 4b, for each MSA group, I subtract the share of business degrees in the year when the national share peaked (2009) from the share in 2013, the last year of the sample. 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.

The descriptive evidence in these plots will be formalized in the following sections with regression analysis.

Jurisdictional Competition and Firm Relocation

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. However, the regressions also include universities with data in only one of these periods, or only with data pre-1980 or post-1990. There are six universities within 15 miles of Wilmington, 34 within 15 to 50 miles, 56 within 50 to 100 miles, 34 within 100 to 150 miles, and 82 greater than 150 miles.

Figure 4 shows the change in majors over time for each major group, by university distance to Wilmington, Delaware. The smallest major groups are shown in the appendix. Because the share in each major differs across distance group, for presentation I show share majoring in each field minus the share in 1983, for each distance group. I subtract the share in 1983 as this is the last year that graduates were not exposed to the policy when they were sophomores (graduates in 1983 were sophomores in 1980-1981, the year before the policy). In the years following 1983, students were exposed to the policy during the crucial years for major choice.

The first plot shows that while there is no immediate effect, there is a large increase in the share of students choosing business majors in 1987 through 1990 at universities within 15 miles of Wilmington. There is very little change during these years at farther universities. The timing of the effects is consistent with the sophomore year being a crucial year for choice of major. Graduates from 1987 through 1990 were sophomores during the years of largest FIRE growth in Delaware. Graduates from 1984 through 1986 were sophomores when FIRE growth had not yet increased dramatically. The effects were smaller for graduates in 1991 through 1994. These graduates were sophomores during years of diminished FIRE growth in Delaware. We see large effects starting again in 1995, which is consistent with the return of larger FIRE growth in Delaware.

In the regressions to follow, for simplicity I include indicator variables for pre-1980, treatment years (1987 through 1990), 1990s, and 2000s.

The large increase in business majors from 1987-1990 seems to come from science; math/computer science; and other (vocational and home economics). Interestingly, while there is a clear increase in business majors in the long-run, there is also a dramatic increase in education majors. This is presumably due to the large population growth, and thus school enrollment growth, that occurred in Delaware following the policy (Weinstein 2015a). The other plots suggest these long-run increases in business and education majors are coming from science and social sciences.

4 Empirical Strategy

4.1 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:

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

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. 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.

The year group $Post$ includes the first five graduating classes which entered university after the beginning of the crash in March 2000, years 2004 through 2008. For example the graduating class of 2004 were freshmen in the Fall of 2000, after the initial drop in the NASDAQ. 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 in metropolitan area m in year t. 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. 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. 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 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 would expect preexisting trends in business and computer science majors before the financial crisis and the dot-com crash. These events were preceded by 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 estimate (1) including research, doctoral, master's and baccalaureate institutions, as well as separately for research and doctoral universities, and for master's and baccalaureate universities. I cluster standard errors at the university level.

4.2 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. The objective of the empirical strategy is to determine whether universities closer to Wilmington experience differential changes in enrollment and college major choice during the treatment years. Given that I have university-level data from 1966-2013, 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:

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

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.[17] University fixed effects are given by γ_c. I weight the observations by the number of Bachelor's degrees conferred by the university in that year.

I omit universities classified as special-focus universities (such as business and management, theological seminaries, health professions), according to the Carnegie 1994, 2005, or 2010 classifications. Given that these universities are focused on particular fields, the composition of majors should not change in response to the shock, though the number of majors may change.[18]

5 Results

5.1 Differential Effect of the Dot-Com Crash

Table 2 shows the results from the regressions studying the impact of the dot-com crash on college majors. Among students entering university after the inital crash, the decrease in computer science degrees awarded is greater at universities in higher computer-share areas. However, the effect is not statistically significant (column 1). There is suggestive evidence that the differential effect of the crash in higher computer-share areas is more negative at private universities (column 2). However, the coefficients are also not statistically significant. There is also no evidence that when including all universities, there were effects among students enrolled in university during the initial crash (rows 7 and 8). Universities in higher computer areas also experienced greater increases in computer science degrees during the dot-com boom (the effect in the pre-peak period is significantly lower than in the omitted group of the peak years).

Among students entering research and doctoral universities after the initial crash, the effect of the crash is much stronger at universities in higher computer-share areas (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 num-

[17] 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 $year \geq 2004$.

[18] While this implies the specification with university fixed-effects will not capture the total effect of the shock, there is only one special-interest university within 15 miles of Wilmington. In the online appendix, I discuss an alternative strategy to capture any reallocation across universities.

ber of computer science degrees awarded is on average approximately 1.8 percentage points lower. For example, at universities in MSAs with computer employment share at the 1st percentile (.008), the coefficients approximately suggest a predicted 13% increase in computer science degrees.[19] At universities in MSAs with computer share at the 99th percentile (.125), computer science degrees are predicted to decrease by approximately 8%, while the predicted change at Stanford is a decrease of approximately 32% (Stanford is the only research/doctoral university in San Jose, California where 26% of the workforce is employed in computers).

There is again suggestive evidence that the differential effect of the crash in high computer-share areas is significantly larger for private universities (column 4). However, this differential for private universities is not statistically significant. Among students enrolled during the initial stages of the crash, there is no statistically significant differential effect of the crash in higher computer-share areas. This suggests it may have been costly to change majors after important early investments. Research and doctoral universities in high computer-share areas also experienced greater increases in computer science degrees during the dot-com boom (rows 11 and 12).

Finally, among master's and baccalaureate universities, the crash did not differentially affect universities in higher computer-share areas. In fact, it appears that these universities experienced greater increases in computer science degrees awarded. This could represent that after the crash, students in high computer-share areas were likely to substitute from research/doctoral universities to master's/baccalaureate universities. This could be explained by differences in tuition costs. It could also suggest that lower-skilled workers who previously would not have enrolled in university are more likely to do so, because of lower employment rates. Because of high computer employment share, they may be likely to enroll in computer science programs. This mechanism may be unimportant for research and doctoral universities if students attending these universities would pursue a Bachelor's degree regardless of labor demand conditions.

5.2 Differential Effect of the 2008 Financial Crisis

Table 3 shows the results from the regression studying the impact of the financial crisis on college majors. Among students entering university after the initial crash,

[19] The appendix shows that by 2009-2013 there is a negative effect on computer science majors even among those in low computer-share areas.

the effect of the crash on business degrees is not statistically significantly different in higher and lower finance-share areas (column 1). However, among private universities, the crash did have a more negative effect on business majors at universities in higher finance-share areas. Among private 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 (column 2). For example, compare private universities in MSAs with finance employment share at the 1st percentile (.013), to private universities in MSAs with finance employment share at the 99th percentile (.059). At private universities in MSAs with finance employment share at the 1st percentile, business degrees are predicted to fall by 4%. At private universities in MSAs with finance employment share at the 99th percentile this decrease is approximately 13%.

These differential effects among private universities are similar at research/doctoral and master's/baccalaureate universities, though only statistically significant among the latter. After the crash, public universities in high finance share areas experienced greater increases in business degrees awarded. This suggests some of the decrease in computer science majors at private universities in shocked areas may represent students changing universities but not their major.

There is no statisically significant evidence that there were effects among students enrolled in university during the initial crash (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).

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, implying roughly a 15% increase. The effect declines dramatically with distance from Wilmington, and is not statistically significant from zero for any other distance group. For universities within 15 to 50 miles of Wilmington, the effect is one third the size (though not statistically significantly different). 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 that 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 there was a large percentage increase in FIRE jobs in Delaware, the level increase is still small relative to the Philadelphia labor market.[20] What is more surprising is that this causes a local effect within 15 miles of Wilmington, and that these students do not see themselves as part of a larger labor market.

In the 1990s, the magnitudes suggest smaller declines in the percent of business degrees for universities closer to Wilmington. However, the differences across distance group are not statistically significant.

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.

For robustness, rather than using distance groups, I interact year group indicators with a quadratic in distance.[21] The interactions between treatment years and distance

[20] 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.

[21] 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

are jointly significant for the share majoring in business. The coefficients suggest the share of business majors increased by 3 percentage points in Wilmington, while not increasing at all for universities 50 miles from Wilmington. While the interactions between treatment years and distance are not jointly significant for other majors, the point estimates also suggest substitution away from science and math/computer science, similar to the main specification.

6 Mechanisms

Two mechanisms may explain the effect of the local sector-specific shock on sector-relevant majors at local universities. First, this may be evidence that students change their major in response to local labor demand. Second, this may be evidence that students change their university. 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 the sections above, though with the dependent variable being $Ln(TotalDegrees)$.[22]

After the dot-com crash, total degrees awarded increased less among private universities in higher computer-share areas (Table 5, Panel A). The effect is stronger and more statistically significant among research and doctoral universities. 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%.

After the financial crisis, total degrees awarded also increased less among private universities in higher finance-share areas (Table 5, Panel B). Among public universities, degrees awarded increased more in higher finance-share areas. This suggests that in high finance-share areas, students substituted more between private and public universities. If the share of the MSA employed in finance was higher by 1 percentage

results are shown in Appendix Table A2.

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

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 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, Panel C 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. I then test whether the nonlocal students attending these universities had different high school academic achievement levels before and after the policy, relative to farther universities. Finally, I test whether the nonlocal students attending these universities were more likely to substitute into business majors after the policy, relative to local students and students at farther universities. I implement these tests using individual-level data from The Freshman Survey.

I code a student as nonlocal if the student's home is more than 50 miles from the university.[23] 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 (2) using the Freshman Survey data. Because Delaware universities are present in the data only from 1971 to 1987, I include two treatment groups: 1983-1985, and 1986-1987. Appendix Figure A4 provides summary statistics of The Freshman Survey sample.

[23] The Freshman Survey asks students how far the university is from their home.

6.1 Substitution Across Universities and Allocation of Talent

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.[24] However, we cannot rule out that 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.[25]

The appendix shows suggestive evidence that because of the policy, nonlocal students with lower GPAs were more likely to apply and enroll at Wilmington-area universities.[26] I estimate regressions similar to those in this section, with the dependent variable an indicator for whether the individual is majoring in field Y. I also include interactions between distance radius, year group, and an indicator for nonlocal.[27]

[24] 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%.

[25] An alternative is that nonlocal students choose majors once in Delaware, and they are more responsive to the Delaware labor market than students originally from Delaware. While possible, this would be rather surprising.

[26] 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.

[27] Details are in the appendix.

Change in Majors, Local versus Nonlocal Students

Table 6 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).[28] 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.[29]

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.[30] Importantly, there was no preexisting trend of nonlocal students at Wilmington-area universities being differentially more likely to choose business majors than local students.

Immediately after the policy, the average net increase in the proportion of local and nonlocal business majors at Wilmington-area universities, relative to students at universities 15-50 miles away, is approximately 2.2 percentage points.[31] Thus, without the stronger response of the nonlocal students, the change in composition would be considerably smaller.

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. While there were preexisting trends relative to nonlocal students, they were in the opposite direc-

[28] The magnitudes suggest the treatment effect is larger, though not statistically significantly, for local students at Wilmington-area universities compared to all students at universities more than 50 miles away.

[29] 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.

[30] 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 differences between nonlocal students at Wilmington-area universities and all students at universities 50 to 100 miles, and greater than 150 miles away are statistically significant. 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 the differences in 1982-1985, for both local and nonlocal students. The statistical significance of the results is larger, however.

[31] This is obtained from a similar regression, but without interactions with an indicator for the student being nonlocal.

tion as these treatment effects.

Allocation of Talent Across Majors

Finally, I study the change in composition of majors by high school GPA after the policy.[32]

The magnitudes in Table 7 suggest there may have been relative outflows of high GPA, local students from business majors at Wilmington-area universities, relative to farther universities.[33] 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.[34]

The magnitudes suggest there may have been 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).[35] 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.[36]

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.[37]

[32] I estimate regressions similar to the others in the section, with the dependent variable an indicator for whether the individual is intending on major Y. I include interactions between distance radius, year group, and indicators for nonlocal and high school GPA at least a B+. See appendix for regression specification and details.

[33] These are in the opposite direction of the pre-policy trend.

[34] 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.

[35] These effects are not part of a pre-policy trend.

[36] 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.

[37] 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.

In sum, the results suggest that immediately after the policy, low GPA students left science for business and the humanities.

6.2 University funding

Local universities may respond to local demand shocks by investing or divesting money from particular academic programs. Alternatively, local shocks may affect funding received from local or state governments or corporations. If students change their major or university only in response to these changes in university funding, this suggests that policy could have a key role in changing composition of human capital production. Given that students in less-exposed areas are not as responsive to national labor demand shocks, this still suggests students may make decisions based on local information or preferences.

I obtain data on number of faculty, tenured faculty, and total faculty salary outlays from the IPEDS Salaries, Tenure, and Fringe Benefits Survey. The data are available in 1971-1973, 1975-1983, 1985, 1986, 1990-2000, and 2002-2014. If changes in faculty or faculty salaries were concentrated in particular programs, this may not be captured when looking across all departments. However, the data provide useful information on changes in university funding after a labor demand shock.

I again focus on the shock originating from jurisdictional competition in Delaware. Given the 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 (2), 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).[38] There are no statistically significant differences in the treatment effect across region for any of these variables. This provides suggestive

[38] 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.

evidence that students are not responding to an increase in university funding alone.

7 Conclusion

This paper tests for changing composition of majors at local universities after a sector-specific local labor demand shock. I test for this local dependence 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 relocation of many finance firms to Delaware in the 1980s. Using university-level data on degree completions by academic discipline from 1966 through 2013, I test for differential changes in major composition and total degrees awarded at universities in areas more exposed to sector-specific labor demand shocks.

I find that universities in areas that are more exposed to sectoral shocks experience greater changes in sector-relevant majors, and this is especially true among private universities. There is also strong evidence that the affected universities experience changes in enrollment. The results suggest that some of the within-university effect on college majors may be explained by students changing their university, but not their major, in response to local labor demand. However, it is clear that this is not always the dominant mechanism.

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.

The change in major in response to local shocks implies that either high-skilled labor is not as mobile as previously believed, or that information frictions are prevalent among college students. Regardless of the mechanism, investing in human capital based on local labor demand may have important aggregate consequences, if individuals are not matched to the job in which they are most productive. The change in university suggests that students may understand that employers experience search frictions that increase with distance. This also may have aggregate consequences if students substitute to universities in regions experiencing positive shocks, but these universities do not provide the highest quality education.

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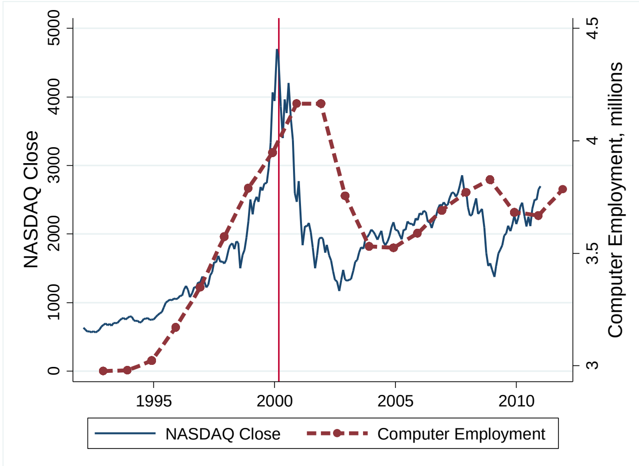
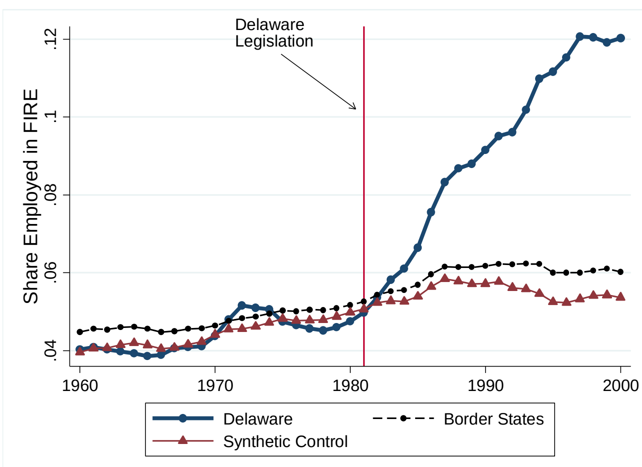
Figure 1: Sector-level Shocks

(a) Dot-Com Crash and Computer Employment



(b) 2008 Financial Crisis and FIRE Employment

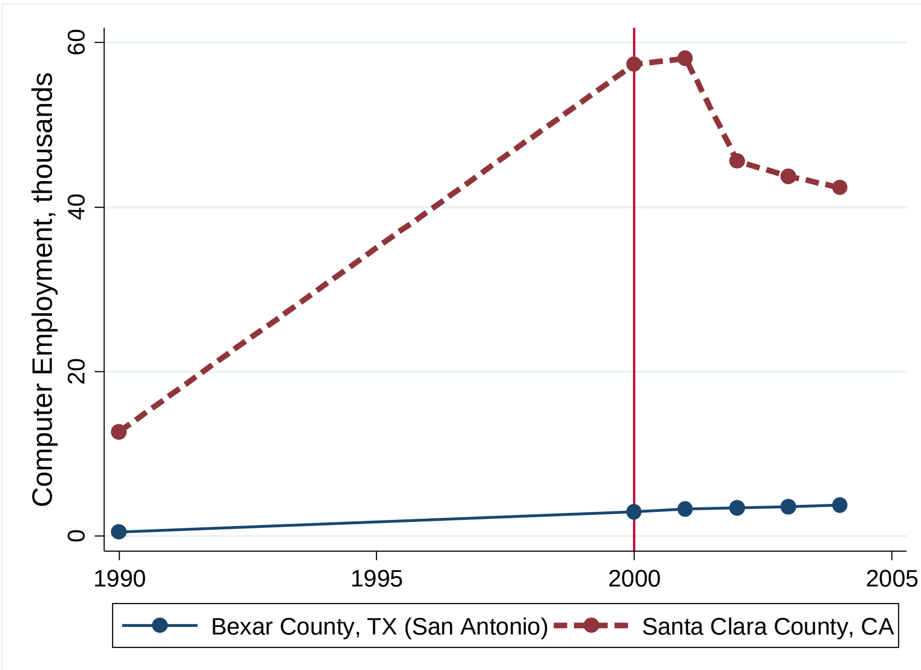
(c) Jurisdictional Competition: Finance Shock in Delaware



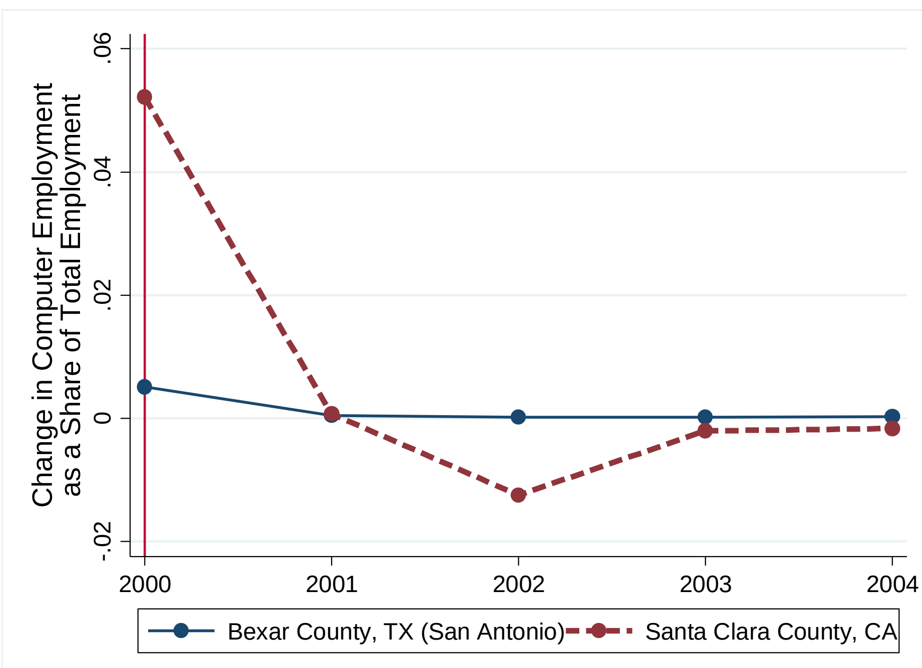
Note: Source for the data on the NASDAQ closing prices: http://www.nasdaq.com/symbol/ixic/interactive-chart, Date accessed: 3/11/2016. Source for DJIA closing prices: https://www.nyse.com/quote/index/!DJI, Date accessed 3/15/2016. Source for employment data: CES. Computer employment includes employment 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 (2015a).

Figure 2: Differential Local Effects of the Dot-Com Crash

(a) Effect on Computer Employment Levels



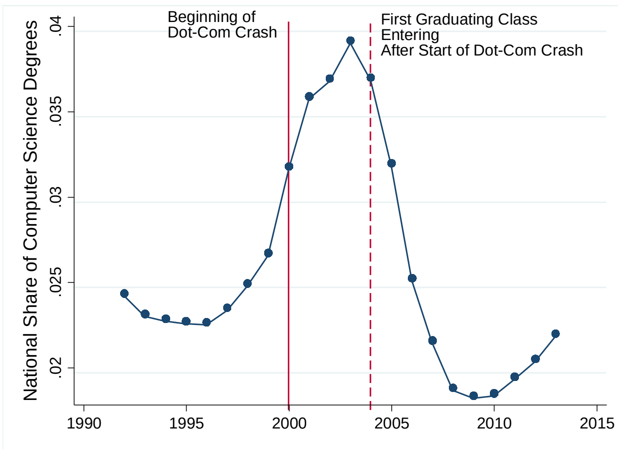
(b) Change in Computer Employment as a Share of Total Employment



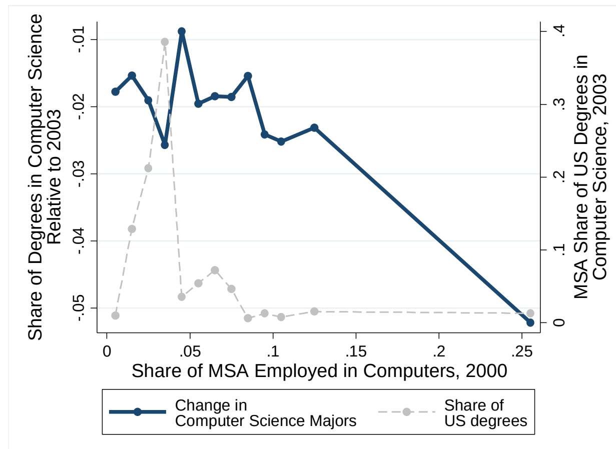
Note: County-level employment data are from the Quarterly Census of Employment and Wages. Computer Employment is defined in these plots as “Computer Systems Design and Related Services”.

Figure 3: Effects of Sectoral Shocks on Sector-Relevant Majors

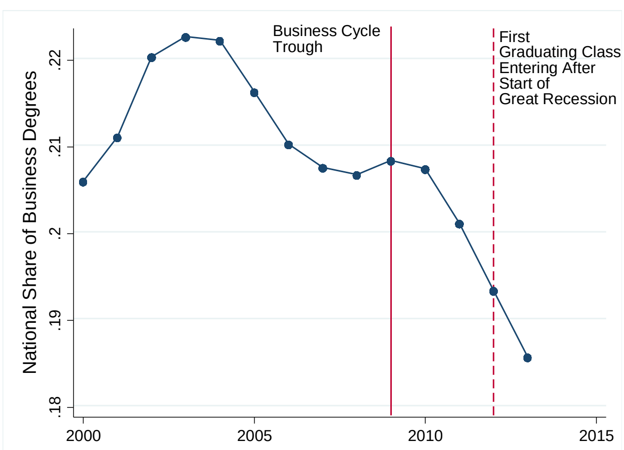
(a) Computer Science Majors: National



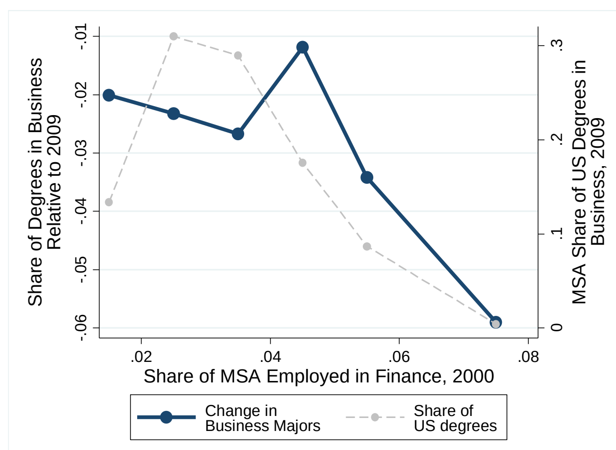
(b) Computer Science Majors by MSA



(c) Business Majors: National

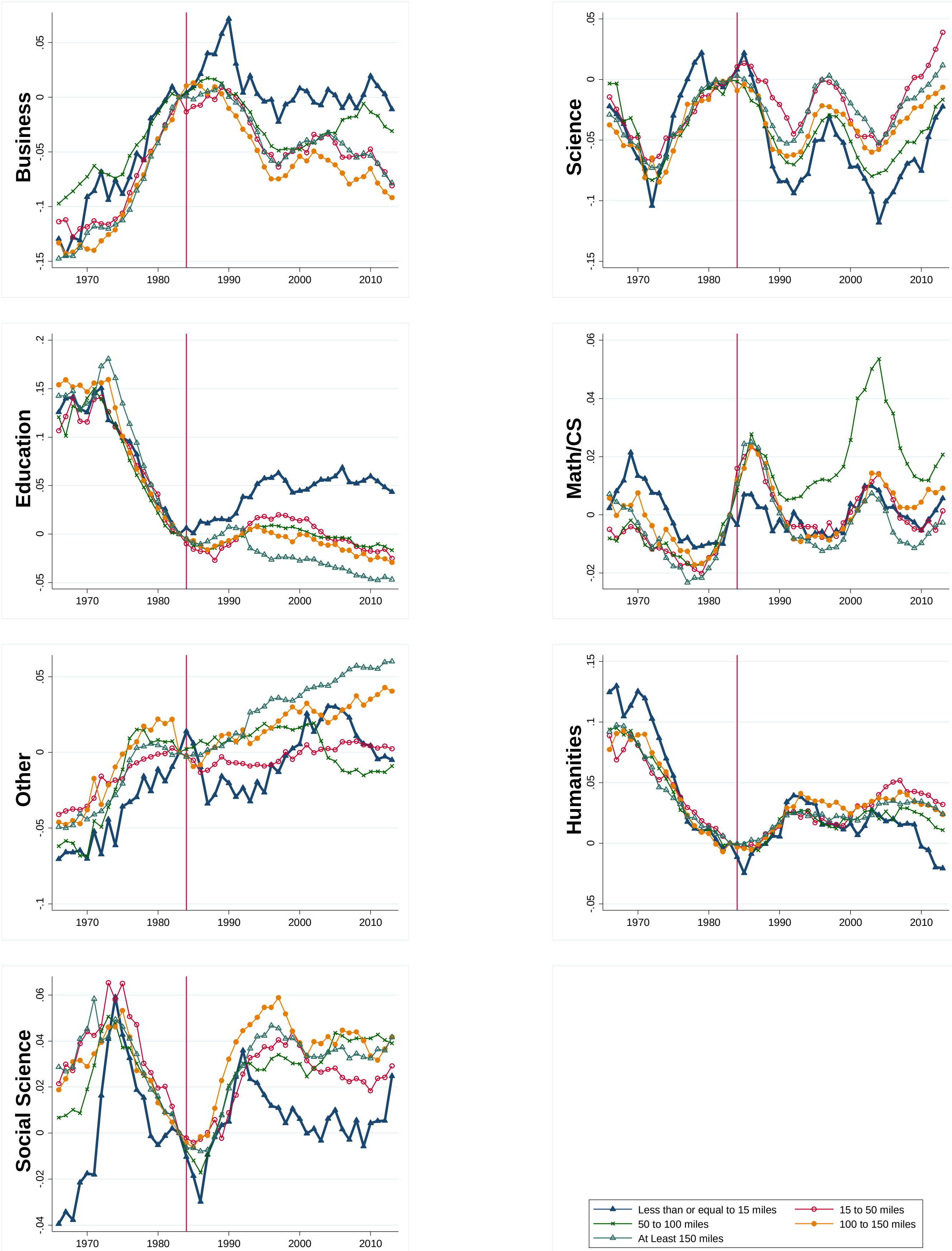


(d) Business Majors by MSA



Note: See text for details. The darker plot in Figure 4b 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 4d 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 4b and 4d are the total computer (4b) and business (4d) 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.

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



Note: See text for details.

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

	Outcome: Ln(Computer Science Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Post	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	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	-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
	Universities	All		Research/ Doctoral		Master's/ Baccalaureate	
	Observations	16,614	16,614	4,212	4,212	12,402	12,402
	Number of Universities	799	799	185	185	614	614
	R-squared	0.872	0.872	0.819	0.821	0.871	0.872
	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 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). Not shown are the interactions with Long Run, an indicator for 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. Observations weighted by the number of computer science degrees awarded at the university. See text for details.

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

	Outcome: Ln(Business Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Post	-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	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	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 (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. 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: 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	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	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 the Appendix. Observations weighted by the number of degrees awarded by the university. See text and Tables 2, 3, and 4 for definitions of Post and Treat Years.

Table 6: 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.

Table 7: 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 for all variables included in the regressions.

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

Russell Weinstein*

June 29, 2016

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).

[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.

2 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[2], 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:

$$\begin{aligned} Y_{srt} &= \alpha_0 + \beta_r Radius\_r_{sr} * TreatYears_t + \delta_r Radius\_r_{sr} * Pre1980_t \\ &\quad + \lambda_r Radius\_r_{sr} * 1990s_t + \tau_r Radius\_r_{sr} * 2000s_t + \gamma_s + \pi_r + u_{srt} \end{aligned} \quad (1)$$

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).

[2] 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.[3]

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.

3 Jurisdictional Competition in Delaware and Selection into Universities and Majors

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:

$$\begin{aligned} HSBplus_{icrt} &= \alpha_0 + \gamma_c \\ &+\beta_r Distance\_r_c * TreatYears1_t + \lambda Distance\_1_c * TreatYears1_t * Nonlocal_i \\ &+\delta_r Distance\_r_c * TreatYears2_t + \kappa Distance\_1_c * TreatYears2_t * Nonlocal_i \end{aligned}$$

[3] 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.

$$+\tau_r Distance\_r_c * pre1977_t + \pi Distance\_1_c * pre1977_t * Nonlocal_i$$
$$+\rho Distance\_1_c * Nonlocal_i + \eta year_t + u_{icrt} \qquad (2)$$

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 plus 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 Policy Effect on Major Composition: Differential Substitution Among Local and 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:

$$\begin{aligned} Y_{icrtg} &= \alpha_0 + \gamma_c + \beta_{r,g} Dist\_r_c * YearGroup\_g_t \\ &+ \lambda_g Dist\_1_c * YearGroup\_g_t * Nonlocal_i \\ &+ \rho Dist\_1_c * Nonlocal_i + \eta year_t + u_{icrtg} \qquad (3) \end{aligned}$$

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. 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.

3.3 Selection into Major by Academic Achievement

Given the evidence that local 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:

$$\begin{aligned} Y_{icrt} = \; & \alpha_0 + \gamma_c + X_i\varphi \\ & + \beta_{r,g} Dist\_r_c * YearGroup\_g_t + \lambda_{r,g} Dist\_r_c * YearGroup\_g_t * BPlus_i \\ & + \Gamma_{1,g} Dist\_1_c * YearGroup\_g_t * Nonlocal_i \\ & + \theta_{1,g} Dist\_1_c * YearGroup\_g_t * Nonlocal_i * BPlus_i \\ & + \rho_1 Dist\_1_c * Nonlocal_i + \rho_2 Nonlocal_i * BPlus_i \\ & + \Phi_r Dist\_r_c * BPlus_i + \eta year_t + u_{icrt} \end{aligned} \tag{4}$$

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.[4] The variable $YearGroup\_g_t$ is as defined above (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

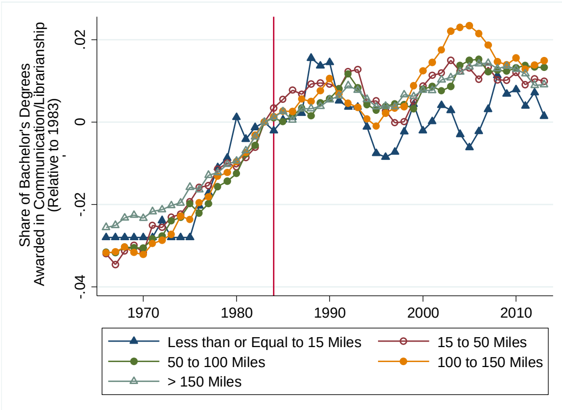
[4] I also include an indicator for whether the value of this variable is missing for the given individual, allowing me to continue to include these individuals.

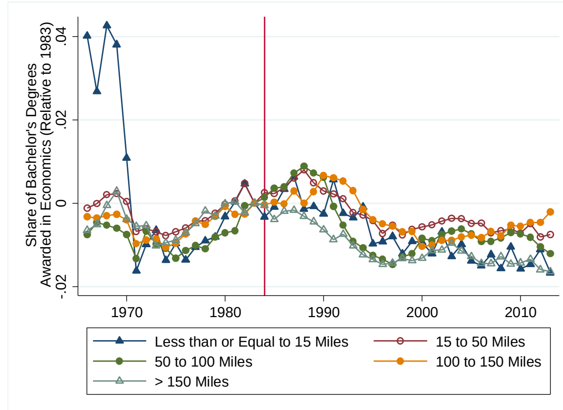
students of majoring in Y in year group g, relative to the years immediately preceding the policy. The coefficients $\lambda_{r,g}$ represent how this differential varies for local, higher GPA students.

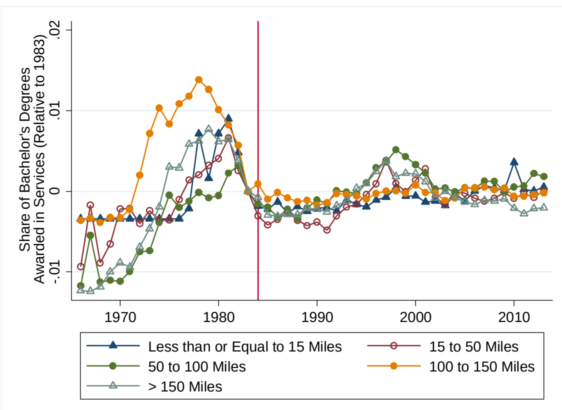
References

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

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



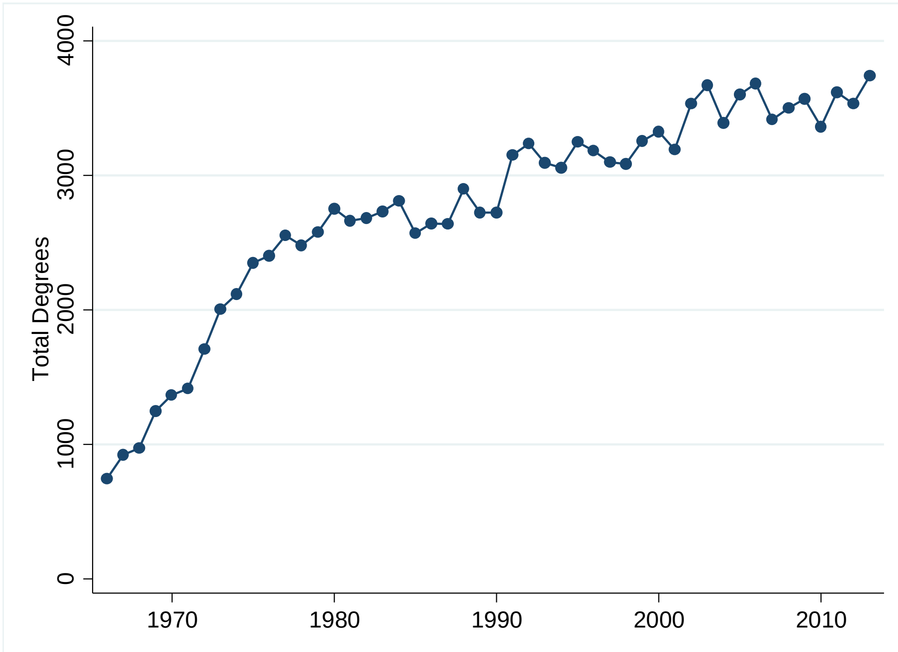




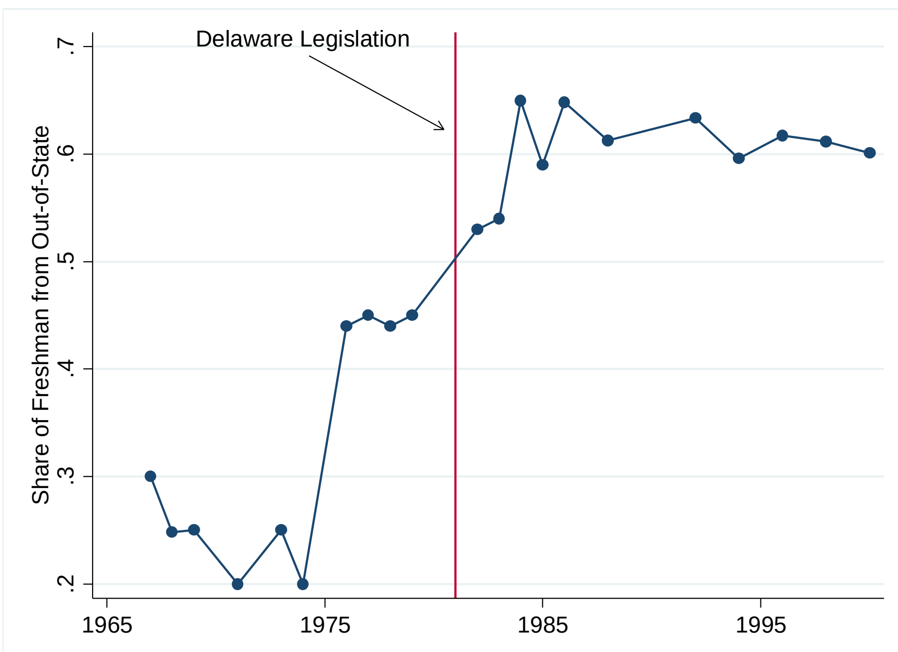
Note: See text for details.

Appendix Figure A2

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



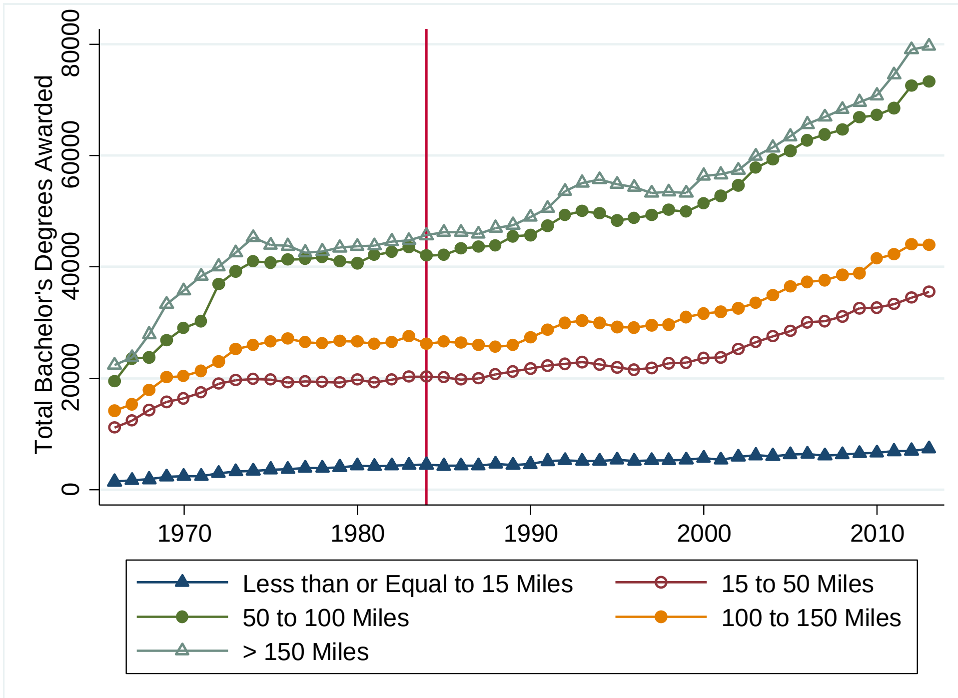
(b) Out-of-State Freshman at the University of Delaware



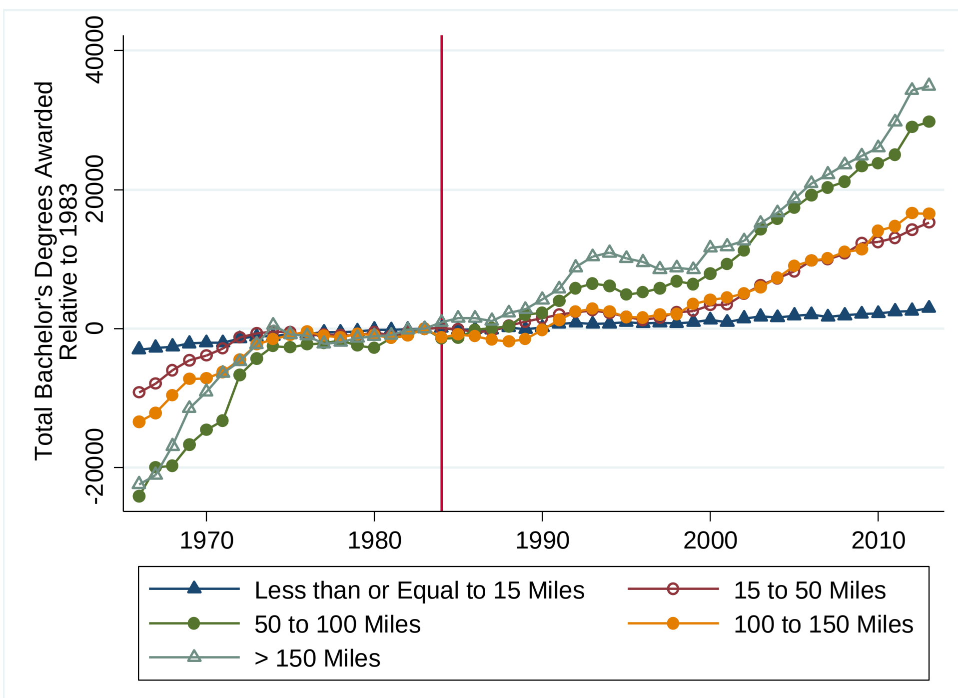
Note: See text of paper and Online Appendix for details.

Appendix Figure A3

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



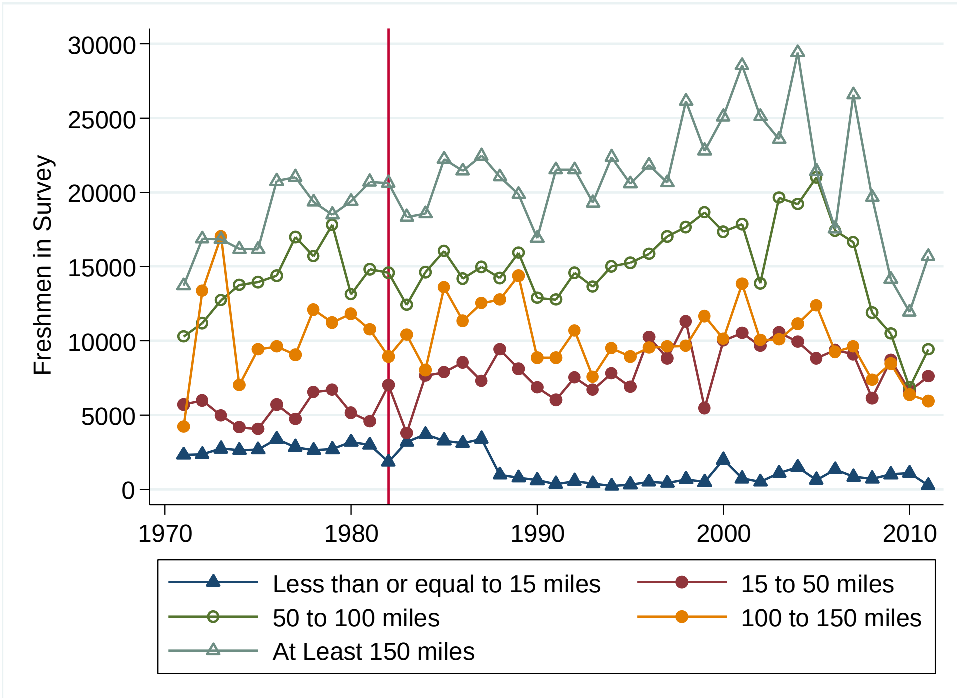
(b) Change in Total Degrees Awarded (Relative to 1983), by Distance to Wilmington, Delaware



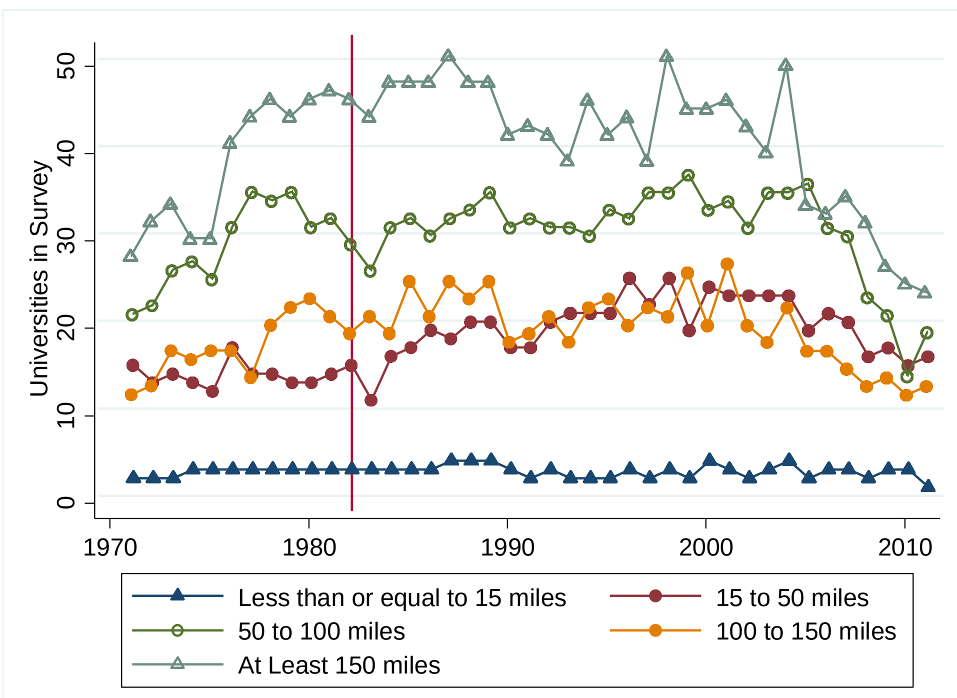
Note: See text for details.

Appendix Figure A4: Freshman Survey Sample

(a) Number of Students per Year



(b) Number of Universities per Year



Note: 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). 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). 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 Undergraduate Computer Science Degrees: Differential Effects by Share Employed in Computers

	Outcome: Ln(Computer Science Degrees)	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Post	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	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	-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	-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 (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). Not shown are the interactions with Long Run, an indicator for 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 computer science degrees awarded by the university. See text for details.

Appendix Table A9: 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
	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. Robust standard errors 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). Not shown are the interactions with Long Run, an indicator for 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 A10: 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. Robust standard errors 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.