Local Labor Markets and Human Capital Investments*

Russell Weinstein†

June 1, 2020

Abstract

I study whether human capital investments are based on local rather than national demand, using two positive and two negative shocks with differential local effects: the dot-com crash, the fracking boom, the 2008 financial crisis, and the shock making Delaware a financial headquarters. I find impacts on the share of sector-relevant degrees awarded following these shocks, on average across the U.S. However, universities in areas more exposed to sectoral shocks experience greater changes in sector-relevant majors. Differential impacts on major choice at the most exposed universities account for 15%-45% of the overall national effect on sector-relevant degrees.

JEL Classification Codes: J24, I20, R12

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

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

1 Introduction

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

This paper analyzes whether individuals choose sector-specific human capital investments, specifically college major, based on local labor demand, rather than national demand. The relevance of this question is underscored by two facts. First, there are dramatic differences in labor demand across local markets, and substantial geographic concentration of industries. In the US, examples include the computer sector in Silicon Valley, finance in New York, and oil and gas in Wyoming.[2] Second, geographic mobility is limited and declining even among highly-educated individuals. From 2001 to 2010, annual interstate migration of college-educated individuals was 2.1%, roughly half the rate in the 1980s (Molloy, Smith, and Wozniak 2011).[3] The first fact suggests investments based on local demand may differ significantly from those based on national demand. The second suggests local demand may affect investments, given that college-educated individuals are increasingly less likely to move across markets.

This is the first paper, of which I am aware, studying the impact of local, sector-specific labor demand on local, sector-specific human capital production (college major) across the entire United States. Individuals may make investments based on local rather than national demand because of migration frictions or because of information frictions that cause a lack of awareness of nationwide job prospects. Investments based on local demand may be individually optimal if they are explained by strong location preferences. However, if individuals make investments based on local demand due to information frictions, this suggests an important role for policy improvements. Regardless of the mechanism, the consequences for the aggregate economy are potentially large if individuals invest based on local demand, and this causes mismatch between the aggregate supply of sector-specific skills and demand for these skills.[4]

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

[2] Based on the QCEW, in 2007 FIRE employment comprised 16% of employment in New York County (Manhattan), but 7% in the US. Similarly, in 2001, employment in computer systems design and related services comprised 6% of employment in Santa Clara County (home of Silicon Valley), but only 1% in the US. In 2014, employment in natural resources and mining comprised 10% of employment in Wyoming, but 1.5% in the US. Ellison and Glaeser (1997) show geographic concentration of manufacturing industries.

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

[4] Several recent papers, including Hastings, Nielson, and Zimmerman 2015, Stinebrickner and Stinebrick-

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

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

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

I show that, on average, universities experience a change in the share of sector-relevant degrees after these shocks, using university-level data on completions by major from The Integrated Postsecondary Education Data System (IPEDS). At their lowest post-bust levels in 2009, the share of CS/CE degrees awarded had fallen 2.2 percentage points (51%) on average at universities across the U.S. At their highest post-fracking boom levels in 2014, the share of geology degrees awarded had increased .12 percentage points (52%) on average. At their lowest post-financial crisis levels in 2013, the share of finance degrees awarded had fallen .36 percentage points (15%) on average. The creation of a financial services center in Delaware did not affect average share of business degrees awarded at universities in Delaware and nearby states. This is consistent with this shock having an effect on financial employment in Delaware, but not in the broader region.

Second, I show college majors respond differentially in areas more exposed to these labor demand shocks. I compare universities more geographically exposed to these shocks, to less-exposed universities whose students experience the same national shock. I estimate the

ner 2013, and Wiswall and Zafar 2014 present evidence suggesting factors other than information are more important in explaining why students pursue lower-earning majors. Hastings, Nielson, and Zimmerman (2015) look specifically at the role of location preferences, showing Chilean students' institution/major choices would respond more to earnings information if not for strong preferences over geography and institution.

effect of exposure by year, as well as use a more parametric dynamic specification, enabling identification of preexisting trends.

These differential local effects are important in explaining the shocks' effects on majors nationally. Of the aggregate decline in CS/CE after the dot-com crash, over 20% can be explained by differential impacts on majors in top-quartile exposed areas, as opposed to the shock's national impact on majors affecting all universities equally. Of the overall increase in geology majors after the fracking boom, 14% can be explained by differential effects in top-quartile-exposed counties. Of the national decline in finance degrees after the crisis, over 45% can be explained by differential impacts in top-quartile-exposed MSAs.

The paper contributes to an established and growing literature on how individuals choose human capital investments, and particularly college majors (see Altonji, Blom, and Meghir 2012 for a review).[5] A number of these papers have studied how majors respond to national economic conditions.[6] Several studies analyze how major choice is affected by local demand.[7]

A related literature shows local shocks affect the extensive margins of high school completion and college enrollment (Betts and McFarland 1997, Cascio and Narayan 2015, Charles, Hurst, and Notowidigdo forthcoming). These reflect responses to the opportunity costs of an additional year of schooling. This paper's focus on majors reflects whether individuals tailor those large investments to labor demand, conditional on college attendance.

I contribute to these literatures by focusing on salient national sectoral shocks, which map closely to majors, and how these salient national shocks differentially affect major choice across local labor markets. Except for the financial crisis, I focus on the impact of sectoral shocks that have received little or no coverage in the literature.[8] More generally, there are few papers studying changes in major choice after shocks that are highly sector specific.[9] The analysis of the finance shock in Delaware is the first analysis of how human

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

[6]Papers include Blom, Cadena, and Keys (2015), Ersoy (2017), Liu, Sun, and Winters (2017).

[7]Using data on graduates of eight Washington state public universities from 2007-2012, Long, Goldhaber, and Huntington-Klein (2015) find major choice is more strongly correlated with major-specific wages of recent same-state graduates than with CPS wages of major-related occupations. Ersoy (2017) studies changes in major allocation after the Great Recession based on the local severity of the recession. Foote and Grosz (forthcoming) study the effect of local mass layoffs in any industry on enrollment at two-year colleges and field of study for subbaccalaureate degrees.

[8]Bound, Braga, Golden and Khanna (2015) develop a model of the labor market for computer scientists, in which the supply of recent graduates is one factor, but do not focus on response to the bust. Han and Winters (2019) study major choice during the energy boom and bust of the 1970s using the American Community Survey.

[9]Choi, Lou, and Mukherjee (2016) study changes based on skewness of stock market returns within an industry, and Bardhan, Hicks and Jaffee (2013) use occupation-specific age structure. Freeman's cobweb models (1975 and 1976) study engineering and law.

capital investments respond to place-based and local economic development policies, which are prevalent around the world.[10]

The paper also contributes to current policy discussions on CS majors. The current and previous presidential administrations enacted policies to increase access to CS education ("Computer Science for All" 2016, Presidential Memorandum 2017). Further, a recent report requested by the National Science Foundation addressed the current all-time high enrollment in CS, and how universities should respond in the short- and long-run (National Academies 2018).[11] Understanding students' decisions to major in CS, and how this is affected by geography and sectoral demand, is crucial for maintaining a strong CS-skilled workforce.

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

This paper proceeds as follows. Section 2 describes the sectoral shocks, and shows they have differential employment effects across local labor markets. Section 3 presents the data. Section 4 describes the empirical strategy identifying the shocks' impact on major composition, and differential impacts across markets. Section 5 contains the results, and Section 6 concludes.

2 Sectoral Shocks with Local Labor Market Impacts

I show these four shocks affected sector employment share differentially across markets, using the Quarterly Census of Employment and Wages. If students chose majors based on local labor demand, those in negatively-shocked areas would substitute away from sector-relevant degrees. However, if students chose majors based on national demand, these substitutions would be smaller in magnitude.

The dot-com crash began in March 2000 with a steep decline in internet stock prices.[12] Figure 1a shows this differentially affected computer employment relative to other sectors, and the effect was much stronger in Silicon Valley. Between 2001 and 2002, the percent of workers employed in "Computer Systems Design and Related Services" fell .76 percent-

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

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

[12] This occurred for reasons arguably unrelated to negative news about internet stock fundamentals (DeLong and Magin 2006, Ofek and Richardson 2001). Similarly, the NASDAQ nearly doubled in the year leading up to its peak in the first months of 2000, without positive news about stock fundamentals to justify this increase (DeLong and Magin 2006).

age points in Santa Clara County, California, the home of Silicon Valley. In the US, this percentage fell only .1 percentage points.

For the second shock, I use the dramatic increase in oil and gas production from the introduction of hydraulic fracturing (fracking) and horizontal drilling in the mid-2000s (Figure 1b). Between 2005 and 2011, the percent of workers employed in natural resources and mining increased 15.6 percentage points in McKenzie County, North Dakota. This county experienced the greatest cumulative increase in the value of new fossil fuel production from 2004 to 2014. Nationally, the percent employed in natural resources and mining increased only .14 percentage points.

The third shock, the 2008 financial crisis and the subsequent Great Recession, had a differential effect on employment in Finance, Insurance, and Real Estate (FIRE) relative to other sectors in New York County (Manhattan). Between 2007 and 2010 the percent employed in FIRE in New York County fell .85 percentage points (Figure 1c). Nationally, the percent employed in FIRE had been falling before the 2008 financial crisis. The effect of the crisis and subsequent Great Recession on national FIRE employment relative to other sectors was much weaker than the effect in New York County.

For the fourth shock, I use the creation of an international headquarters for the finance industry in the state of Delaware, resulting from jurisdictional competition and firm relocation. This is likely the least well known of these shocks, but nonetheless represented a dramatic change in the finance industry. Weinstein (2018) analyzes labor market adjustment to this shock.

Prior to 1978, state usury laws determined the interest rate that credit card companies could charge the state's residents. The US Supreme Court's ruling in *Marquette National Bank of Minneapolis v. First Omaha Service Corp.* (1978) allowed a bank to export the highest interest rate allowed by the state in which it is headquartered. In 1981, Delaware eliminated its usury laws, with the passage of the Financial Center Development Act (FCDA). The FCDA also reduced other industry regulation and introduced a regressive tax structure for banks.[13] As a result, many companies moved their finance or credit operations to Delaware, starting with J.P. Morgan in 1981. Between 1981 and 1991, the percent of Delaware workers employed in FIRE sectors increased 4.5 percentage points (Figure 1d), based on BLS Current Employment Statistics (CES). Nationally, the increase was only .3 percentage points.

Each of these sectoral shocks differentially affected sectoral employment share across local labor markets. I will study whether sector-relevant majors differentially respond in areas more exposed to the shocks, which would suggest investments based on local, not just

[13]Weinstein (2018) lists other provisions. The description of the FCDA is based on Moulton (1983).

national, demand.

3 Data

I obtain university-level data on Bachelor's degrees awarded by academic discipline. For the dot-com crash, the fracking boom, and the financial crisis, I use IPEDS data.[14] For the dot-com crash, I classify CS (computer and information sciences and support services) and CE (computer engineering) majors as sector-relevant degrees. For the financial crisis, I classify finance majors as sector-relevant degrees.[15]

For the fracking boom, I classify geology majors as the sector-relevant degrees. I focus on geology for several reasons. First, geology is crucial for understanding where to drill. Given the fracking boom involved innovations in horizontal drilling and hydraulic fracturing, these skills were arguably especially in demand (Vita 2015). Second, geology is offered at universities around the country regardless of their fracking exposure. Excluding petroleum engineering degrees will very likely lead to underestimating the local elasticity. However, these degrees are offered by very few universities, and mostly in fracking-exposed areas.[16] Oil and gas companies certainly demand other more widely-offered engineering degrees, such as chemical, mechanical, and civil engineering. However, these degrees are also demanded by other sectors that may have their own cycles during this period.

Studying Delaware's finance labor demand shock requires earlier university-level data. I obtain Bachelor's degrees awarded by university and academic discipline from 1966 through 2013 from the IPEDS Completions Survey. These data are accessed from the Integrated Science and Engineering Resources Data System of the National Science Foundation. I focus on business and management majors in this part of the analysis as degrees by four-digit CIP codes are not available in these earlier years.[17]

Using the American Community Survey (ACS), and pooling the 2009 through 2017 surveys, Table 1 confirms these are the relevant degrees for the industry. I show the share of

[14] For these shocks, I limit the sample to universities existing in the 2013 IPEDS data with a 2000 Carnegie code. I include only Doctoral/Research, Master's, Baccalaureate, and Baccalaureate/Associates Colleges as ranked in the 2000 Carnegie rankings. To calculate total degrees by major, I include both first and second majors in the given field, except prior to 2001 when this distinction is not available. Total degrees awarded at the university also sums all first and second majors. Degrees awarded by field excludes students who initiated a degree in the field, but did not successfully complete the degree in that field. This misses some aspect of how students choose major field.

[15] See appendix for CIP codes (section 1.2), and results using only CS majors (Figure A3 and Table A3). Universities differ in whether they offer CS and CE, or only one. Both CS and CE responded to the dot-com cycle (National Academies 2018).

[16] See appendix section 1.2.

[17] See appendix section 1.2 for data details.

employed 23-25 year olds working in the affected industry by field of degree.[18] To focus on degrees that are similarly awarded, I limit to majors comprising at least .2% of all degrees awarded, which is the proportion for the oil-and-gas relevant majors. There may be some very relevant majors that are not widely offered across the US, making it difficult to study differential responses by shock exposure. For example, 46% of petroleum engineering majors work in the oil-and-gas sector, but they comprise only .06% of degrees, reflecting that few universities offer these degrees.

Recent graduates with majors classified as relevant are much more likely employed in the computer, oil and gas, and finance industries than graduates in majors with the highest proportion employed in the sector, outside of those classified as relevant. The sector-relevant majors are also much more likely to work in the sector than the average major, excluding classified sector-relevant majors, the top three majors not classified as relevant, and the bottom five not classified as relevant. If few students would switch between the sector-relevant major and these least-relevant majors, changes in the latter around the sectoral shock may imply the shock affected student composition at the university. I will use the Table 1 categories to implement a placebo analysis testing for this possibility.

To determine the exposure of the university's local labor market to the dot-com crash and financial crisis, I obtain the share employed in computers and finance using the IPUMS USA 2000 Census 5% sample (Ruggles et al. 2015). I classify as computer-related industries the BLS-defined high-technology industries that are relevant for the computer industry.[19] I include the FIRE industries, excluding insurance and real estate, as finance-related industries.[20] Using the person weights, I obtain the weighted sum of individuals by industry and metropolitan area.[21] I merge the data on share employed in computers and finance to the university-level data using the 2013 MSA.

Many universities are not in MSAs, and some MSAs are not represented in the Census. For these categories, the principal results assume percent employed in computers or finance is zero. Approximately 32% of universities, and 25% of all degrees (in 2000), cannot be matched to MSA employment for one of the reasons above. For robustness, I exclude these universities from the sample.

[18] I use the Census general field of degree codes. However, I use the detailed codes for business, social sciences, physical sciences, and engineering, as the sector-relevant majors are classified under the detailed codes in these fields. I use the detailed codes for social sciences to evaluate the extent to which Economics majors enter finance, as this field is potentially much more likely to enter finance than other social sciences.

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

[20] See appendix section 1.1.

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

For fracking exposure, I obtain annual data on the value of oil and gas production from wells drilled for the first time that year (in 2014 dollars), within 200 miles of each county, from Feyrer, Mansur, and Sacerdote (2017).[22] Papers studying the impact of fracking on the local economy often use an instrument for fracking exposure, since the decision of where to frack within the shale may be correlated with local economic characteristics, and trends in the outcome. However, it is much less likely that the decision of where to frack is correlated with trends in oil-and-gas-related degrees awarded by local universities.[23] This measure of exposure captures geographic areas experiencing new production due to fracking by directly using drilling data; this may not be as cleanly identified using industry employment.[24]

To determine the university's local labor market exposure to Delaware's finance shock, I calculate distance between the university and Wilmington, Delaware (the city where the shock was concentrated) using the university's latitude and longitude.[25] Because this was a Delaware-specific shock, I limit the sample of universities to those in Delaware, New Jersey, Pennsylvania, Maryland, Washington, DC, Virginia, and West Virginia.

I confirm the sector-relevant majors are awarded widely across the U.S, in areas with lower and higher sectoral employment concentration (Appendix Figure A1). This validates the exercise of studying differential response of these majors by shock exposure. While their pre-shock share is lowest in the least exposed areas, it is still nontrivial. Comparing areas with medium exposure to the most exposure, the share sector-relevant degrees is often quite similar before the shock. It is clear that the most-exposed areas do not award all of the sector-relevant degrees. For three out of the four shocks, the top 1% of exposed areas, unweighted by total degrees awarded, award no more than 3% of sector-relevant degrees in the year before the graduates were freshman at the shock's onset. For the 2008 financial crisis, the top 1% of exposed areas produce approximately 12% of sector-relevant degrees.[26]

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

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

[24]One potential reason is that an employment-based measure may include areas with high industry concentration, but not experiencing the fracking boom. Additionally, employment data may not always correspond with where the work is peformed, as BLS asks employers to report workers at the office responsible for their supervision. This could yield some areas with high fracking exposure, but less high employment if it is reported at a farther away branch office.

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

[26]The statistic is 2.7% for CS/CE degrees, 2.8% for geology degrees, and 11.6% for finance degrees. For

4 Identifying Sectoral Shocks' Effects on Majors

I start by estimating:

$$Share(Majors_{ct}) = \alpha_0 + \gamma_c + \delta_t + \eta TotDegrees_{ct} + u_{ct} \tag{1}$$

The regression estimates the share of sector-relevant majors over time, relative to the omitted year, t^*. Because I include university fixed effects this regression gives the average within university change in sector-relevant major share after the sectoral shock.

The variable $Share(Majors_{ct})$ denotes the share of relevant majors at university c in year t. The coefficients δ_t identify the average within-university change in share relevant majors in year t relative to t^*, in which the graduates were freshmen at the shock's onset (2003 for the dot-com shock, 2009 for the fracking boom, 2011 for the finance shock, and 1985 for the Delaware shock).[27] As a rough measure of the fracking boom onset, I use the year in which fracking success had been publicized in at least 25% of shale plays (2006), using publicity data from Bartik, Currie, Greenstone, and Knittel (forthcoming).

The variable $TotDegrees_{ct}$ denotes the total Bachelor's degrees awarded by university c in year t. I weight the observations by $TotDegrees_{ct}$, ensuring changes at larger universities get more weight than those at smaller universities. I cluster standard errors at the university level.[28]

The coefficients δ_t are the coefficients of interest for understanding the nationwide impact of the shock on relevant degrees. The main identification assumption is that the shocks' timing is not caused by changes in major, or correlated with other factors differentially affecting sector-relevant majors. Estimating the effects by year provides important evidence on the strength of the identification assumption.

Estimating effects by year is important for two additional reasons. First, these were not one-time shocks. Their magnitude changed over time, and perceptions about the shock's persistence may also have changed. Second, these specifications allow me to identify how quickly degree completions respond to the initial shock. I do not separately identify dynamic effects from an original shock relative to contemporaneous effects as the shock evolves. How-

the Delaware shock, 2.9% of business degrees in the sample were awarded within 15 miles of Wilmington.

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

[28] Following Feyrer, Mansur, and Sacerdote (2017), I estimate the fracking regressions using two-way clustering at the county and year level, to address spatial correlation from including new production in a county for multiple county groups in the regression. This results in smaller standard errors on the interactions between year fixed effects and *Exposure*, and so I report those clustered at the university level.

ever, I will analyze changes in major composition in the years after the shock's onset, and relate those changes to demand.

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

$$\begin{aligned} Share(Majors_{ct}) \;=\;& \alpha_0 + \gamma_c \\ & +1(t \geq t^*)\beta_{jump} + 1(t \geq t^*)(t - t^*)\beta_{phasein} \\ & +(t - t^*)\beta_{trend} + \eta TotDegrees_{ct} + u_{ct} \end{aligned} \tag{2}$$

To best capture immediate effects, I include only post-policy years within five years of the shock. I include the ten years preceding the shock, and censor the trend variable $(t - t^*)$ at -5 (as in Lafortune, Rothstein, and Schanzenbach 2018). The ten years preceding the Great Recession includes another recession and recovery. To best capture the boom immediately preceding the shock, for this shock I include only the five years preceding t^*. The coefficients β_{trend} reflect whether universities experienced greater changes in sector-specific majors preceding these shocks.

Based on the coefficients in (2), I obtain the effect of these sectoral shocks relative to the year preceding the shocks. I present results showing the effect for the first graduates exposed as freshmen (t^*), and five years after the first graduates exposed as freshmen ($t^* + 5$). The impact of the shock in year t^* relative to $t^* - 1$ is: $(\beta_{jump} + \beta_{trend})$. The impact in year $t^* + 5$ relative to $t^* - 1$ is: $(\beta_{jump} + 5\beta_{phasein} + 6\beta_{trend})$.

Differential Impacts in Exposed Areas

Next, I identify whether universities in more exposed areas experience larger changes in major composition:

$$\begin{aligned} Share(Majors_{c_m t}) \;=\;& \alpha_0 + \gamma_{c_m} + \delta_t + \sum_{r=k_{min}}^{k_{max}} Exposure_m * (1(t = t^* + r))\,\beta_r \\ & +\eta TotDegrees_{c_m t} + u_{c_m t} \end{aligned} \tag{3}$$

The variable $Exposure_m$ denotes the extent to which university c is exposed to the shock, given its location in area m. For the dot-com crash and 2008 financial crisis, this is the share of metropolitan area $m's$ employment in 2000 in the computer sector and the share in the finance sector, respectively. For the fracking boom, I use whether the county's cumulative value of new oil and gas production from 2004 to 2014 is within the top quartile. For

Delaware's shock, $Exposure$ is one for universities within 15 miles of Wilmington, Delaware.[29]

The coefficients β_r identify the differential effect on majors in each year in areas more exposed to the industry. These effects are also estimated in years before t^* as $k_{min} < 0$. The main identification assumption is that the timing and local exposure to the shocks are not caused by local changes in major, or correlated with other factors differentially affecting majors in exposed areas.

I also estimate the counterpart to (2):

$$\begin{aligned} Share(Majors_{c_m t}) &= \alpha_0 + \gamma_{c_m} \\ &+1(t \geq t^*)\beta_{jump} + 1(t \geq t^*)(Exposure_m)\beta_{jumpdiff} \\ &+1(t \geq t^*)(t-t^*)\beta_{phasein} + 1(t \geq t^*)(t-t^*)(Exposure_m)\beta_{phaseindiff} \\ &+(t-t^*)\beta_{trend} + (t-t^*)(Exposure_m)\beta_{trenddiff} \\ &+\eta TotDegrees_{c_m t} + u_{c_m t} \end{aligned} \tag{4}$$

Specifications (3) and (4) identify differential changes in major composition at more exposed universities. These may be driven by students at these universities changing majors, or by changing composition of students at these universities. Either suggests these shocks have effects on human capital investment decisions, either where or what to study. Changes in the national proportion of sector-relevant degrees surrounding these shocks suggests significant numbers of students changed majors in response to the shocks, and differential local effects are not explained by students changing universities. The placebo analysis and robustness section present further evidence suggesting the results are not driven by changing student composition.

5 The Effect of Sectoral Shocks on Major Composition

Average Effect Across All Universities

National sectoral shocks cause large within-university changes in major composition. Figure 2 shows the nonparametric (equation 1) and parametric (equation 2) results closely match for most of the shocks. However, the speed of the response differs across shocks. This is not surprising given differences in the shocks' evolution, and potential differences across major in the cost of switching. This implies difference-in-difference estimates from the parametric specification, which assume t^* as the first treatment year, will not capture the true effect.

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

For consistency, I report these results as well as differences-in-differences based on the non-parametric specification, and identifying the first year in which sector-relevant major share appears to respond.

The share of degrees awarded in CS/CE began a sharp decline starting in 2004, the year after the first graduates exposed as freshmen. The share continued to decline through 2009. For graduates in 2009, the share CS/CE majors was on average 2.2 percentage points lower ($p \leq .01$) than the share at the same university in 2003, the year before the decline began. In 2003, on average 4.3% of a university's degrees awarded were in CS/CE (weighted by total degrees). Thus, a decline of 2.2 percentage points reflects a $2.2/4.3 = 51\%$ decline in the proportion of CS/CE degrees awarded as a result of the dot-com crash. This almost exactly reverses the increase in share CS/CE degrees during the dot-com boom, when the share CS/CE degrees increased on average 1.9 percentage points from 1995 through 2003.

The share of degrees awarded in geology increased first in 2008, two years after publicity of success in 25% of shale plays, and the year before the first graduates exposed as freshmen. The share continued to increase through 2014. For graduates in 2014, the share geology majors was on average .12 percentage points higher ($p \leq .01$) than the share at the same university in 2007, the year before the increase began. In 2007, on average .23% of a university's degrees are awarded in geology. Thus, universities experience an average $.12/.23 = 52\%$ increase in the proportion of geology degrees awarded as a result of the fracking boom.

The share of degrees awarded in finance fell for the first time in 2010, two years after the onset of the crisis, and the year before the first graduates exposed as freshmen. The share continued to fall through 2013. For graduates in 2013, the share finance majors was on average .36 percentage points lower than the share at the same university in 2009, the year before the decrease began ($p \leq .01$). In 2009, on average 2.43% of a university's degrees awarded are in finance. Thus, universities experience an average $.36/2.43 = 15\%$ decline in the proportion of finance degrees awarded.

Financial relocation to Delaware did not on average affect the share of business majors, at all universities in Delaware, Maryland, New Jersey, Pennsylvania, Virginia, and West Virginia. This is consistent with this shock being highly localized, without broad effects on regional employment.

The response to the dot-com crash appears to operate with a greater lag, relative to the other shocks.[30] Initial course investments presumably make switching majors costly, and this may be most costly in STEM fields. Lagged effects imply potentially very adverse effects for students entering during a boom, but graduating during a bust. In the case of a positive

[30] Bound and Morales (2018) and Hunt (2018) also show lagged response of national CS degrees to the dot-com crash.

shock, it may mean students miss entering an industry at an advantageous time.

For each shock that affects major choice, sector-relevant majors in the pre-shock period were not trending in the same direction as in the post-shock period. For the dot-com crash and financial crisis, the pre-shock trend was the reverse of the post-shock trend.[31] This is consistent with the periods preceding the dot-com crash and financial crisis being sectoral boom periods (Figure 1). These pre-trends mitigate concerns that the identification assumption is violated.

Effects on major composition during these pre-shock boom periods also implies a relationship between demand and human capital investments, although is subject to endogeneity concerns. Job growth may have responded to university specialization, rather than the reverse. I focus on the crashes since these shocks are more clearly exogenous.

Differential Effects at More Geographically Exposed Universities

Effects on sector-specific majors are larger at universities in more exposed areas. Figure 3 shows the coefficients from estimating regressions (3) and (4). As above, I report differences-in-differences based on the nonparametric specification, and based on the parametric specification in Table 3.

For 2009 graduates, the dot-com crash reduced the share of CS/CE majors by an additional 1.7 percentage points at universities whose MSA computer employment share was higher by ten percentage points, relative to graduates from the same university in 2003 (row 8).[32] This effect is statistically significant at the 1% level. In 2003, on average 5.4% of degrees awarded are in CS/CE, among universities whose MSA computer employment share is at least .1 (weighted by total degrees). For these universities, this additional decline of 1.7 percentage points represents a 31% decline in their share CS/CE degrees awarded.

For 2014 graduates, the fracking boom increased the share of geology majors an additional .1 percentage points at universities in top-quartile-exposed counties, relative to graduates from the same university in 2007 ($p \leq .05$). In 2007, on average .28% of degrees are awarded in geology at universities in top-quartile-exposed counties. For these universities, this additional increase of .1 percentage points represents a 36% increase in their share geology degrees awarded.

For 2013 graduates, the 2008 financial crisis reduced the share of finance majors by an additional .25 percentage points at universities whose MSA finance employment share was higher by five percentage points, relative to 2009 graduates from the same university ($p =$

[31] The flat trend at the beginning for the dot-com crash, the fracking boom, and the Delaware shock exists because I only fit the trend starting five years before the shock, censoring $t - t^*$ at minus 5.

[32] There are six MSAs with computer employment share $\geq .1$, and 20 universities in those MSAs.

.12).[33] In 2009, on average 3.5% of degrees awarded are in finance, among universities where MSA finance employment share is at least .05. For these universities, this additional decline of .25 percentage points represents a 7% decline in their share finance degrees awarded.[34]

Five years after the first-exposed graduates, Delaware's finance shock increased the share of business majors by an additional 5.9 percentage points at Wilmington-area universities, relative to graduates the year before the first-exposed graduates. In 1984, on average 21.6% of degrees awarded are in business, among universities within 15 miles of Wilmington, Delaware. For these universities, this additional increase of 5.9 percentage points represents a 27% increase in their share business degrees awarded.

Figure 3 shows pre-shock trends in the effect of exposure are not in the same direction as post-shock trends. Further, for three of the shocks, the pre-shock trend in the effect of exposure on sector-relevant majors was the reverse of the post-shock trend. This is consistent with the periods preceding the negative dot-com crash and financial crisis being boom periods for the industry, and the period preceding Delaware's positive shock being a bust period for FIRE Employment in Delaware (Figure 1). Differential effects in more exposed areas during these pre-shock boom or bust periods also implies a relationship between local demand and human capital investments, although is subject to the endogeneity concerns discussed above.

However, larger increases at exposed universities in the preceding booms may suggest new majors produced during the boom were more marginal at these universities. This may explain the greater decline in the bust rather than locally driven investments. However, except for the dot-com crash and the 2008 Financial Crisis, for the other shocks there was no national pre-trend in the opposite direction that created or eliminated marginal majors. These shocks also produce differential local responses, reducing concerns that results reflect more marginal majors at exposed universities. Further, if exposed universities produced the most marginal CS or finance majors during the boom, this may quite plausibly be explained by investments based on local demand.

Local Exposure's Role in Explaining National Changes

I next determine the extent that national changes in CS/CE, geology, and finance degrees are explained by national conditions equally affecting universities, as opposed to differential impacts in more exposed areas. I use the coefficients from regression (3) to implement a simple accounting exercise. I do not focus on Delaware's finance shock since this less clearly

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

[34] See appendix for results showing no differential effect on business majors, consistent with these demanded by nonfinance sectors also affected by the recession (Figure A4).

represented a national increase in demand for business majors.

The year fixed effects, δ_t, from regression (3) identify the impact on share relevant majors experienced by all universities, regardless of their exposure.[35] I multiply $\hat{\delta}_t * TotDegrees$ to obtain the change in relevant degrees at each university attributed to national factors, as predicted by the regression. Summing across all universities, I obtain the national change in relevant degrees attributed to national factors, equally affecting all universities.

Similarly, I multiply $\hat{\beta}_r$ by $Exposure_m * TotDegrees$ to obtain the change in relevant degrees at each university attributed to differential shock exposure. Summing across all universities, I obtain the national change in relevant degrees attributed to differential exposure. If all universities were equally affected by these shocks, regardless of exposure, this would be zero.

I evaluate the contribution of local exposure over the same period as the difference-in-difference above. Relative to 2003, the number of CS/CE degrees awarded in 2009 was lower by 25,293. Approximately 32% of this decrease is explained by differential impacts in more exposed areas, and 23% by differential impacts in MSAs at the 75th percentile or above (MSA computer-employment share greater than about 3.5%), impacts over and above those experienced by all universities regardless of exposure.[36]

Relative to 2009, the number of finance degrees awarded in 2013 was lower by 2,980. Approximately 67% of the decline is explained by differential impacts in more exposed areas, and 46% by differential impacts in MSAs at the 75th percentile or above (MSA finance-employment share greater than about 3%). Relative to 2007, the number of geology degrees awarded in 2014 was higher by 2,671. Approximately 14% of this increase is explained by differential impacts in top-quartile-exposed areas. Because the exposure variable for this shock is an indicator, this underestimates the contribution of local exposure by ignoring areas with exposure less than or equal to the 75th percentile.

Differential effects at universities in top-quartile-exposed areas explain less of the overall change after the fracking boom relative to the dot-com crash and financial crisis, although the percentage is still important. This may be explained by fewer universities in top-quartile fracking exposed areas (300) than top-quartile dot-com or financial crisis exposed areas (439 and 523 respectively). Total degrees awarded in these areas as a percent of all US degrees is similarly smaller (21% for fracking, 39% for the dot-com crash, and 41% for the financial

[35] This is because $Exposure = 0$ denotes zero exposure.

[36] This does not imply that if individuals invested only based on national conditions the aggregate response would have been smaller. One possibility is that the national decline would have been the same if the greater response of CS majors in exposed markets would all be shifted to less-exposed markets. Alternatively, investments based on national demand may yield a smaller aggregate effect if individuals in exposed markets overresponded relative to the extent of the local shock.

crisis). Fracking exposure within 200 miles may also include universities at which students do not view the shock as local, reducing the estimated effect of differential local exposure.

Response to Temporary vs. Long Run Shocks

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

After first falling in 2003, computer employment began to grow again in 2006 (Figure 1a) though had not quite fully recovered by 2015. The differentially negative effects of the dot-com crash on CS/CE majors at exposed universities began to reverse by 2010 (Figure 3).[37] The differentially negative effects of the financial crisis on finance majors at exposed universities do not appear to reverse when FIRE employment eventually increases, although the estimates are imprecise.

Unlike the dot-com crash and the 2008 financial crisis, Delaware's finance shock had a long-run impact on sectoral employment. Delaware's FIRE employment share continued to grow over the twenty years following the policy (Figure 1). If students immediately after the policy understood the long-run employment effects, the effect on business majors may be quite stable over the post-policy period, as we eventually see in Figure 3. Alternatively, the university may not have expanded capacity for business majors, keeping the effects stable despite continued FIRE growth.

Change in Student Composition vs. Change in Major Choice: Placebo Analysis

A university's geographic exposure to shocks may also affect students' application and enrollment decisions. Universities' major composition may have changed because of changes in student composition, rather than students changing their major. However, total degrees

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

awarded do not vary by university's exposure to the shock (Appendix Figure A5, Appendix Table A5).

Nonetheless, despite constant enrollment, the students selecting into exposed universities may change. To test this, I implement a placebo exercise, using majors for which we expect few students to be on the margin, and thus minimal substitution, between these and the sector-relevant majors. As a result, any change in these sector-distant majors timed with the sector-specific shock likely does not reflect substitution between majors, but may reflect changes in student composition at the university.[38]

I identify majors for which we expect minimal substitution using those with the lowest likelihood of employment in the affected sector, based on the ACS and shown in Table 1. These majors arguably require interests and skills quite different from those that are required by the sector, and the sector-relevant major. The students who would have chosen the sector-relevant degree preceding a negative shock (e.g. CS/CE) are unlikely choosing the sector-distant degree after the negative shock (e.g. Education).

For each university, I obtain the percent of degrees awarded in each year in the five most sector-distant fields.[39] I then estimate regressions (3) and (4) using this as the dependent variable. Sector-distant degrees do not appear to change in the opposite direction as the sector-relevant degrees, and with the same timing (Figure 4, Appendix Table A9).

While exposed areas experience a larger increase in share sector-distant degrees after the dot-com crash, this is part of a longer trend starting before the shock. Although the individual coefficients from the nonparametric specification are statistically significant only in the post period, the parametric results suggest the trend in the post period is not statistically distinguishable from the pre-trend. The trend also continues after 2009 when CS/CE degrees start differentially increasing in exposed areas.[40] This suggests the increase in sector-distant

[38]A potential concern is that these majors are aligned with sectors receiving spillover effects from the affected sector. For example, areas experiencing a differential decline in the computer industry may also experience a differential decline in construction. This may yield differential changes in construction services majors timed with the dot-com crash, and this may reflect change in major choice between non-CS majors and construction services, rather than change in student composition.

[39]I use all seven fields that are tied for the most sector distant for the oil and gas industry. For the Delaware finance shock, I use the same fields as those for the finance industry in Table 1. However, as discussed above, it is not possible to use the current IPEDS data due to the years of the shock. I have only 21 broad major classifications. For the Delaware shock, the sector-distant degrees are Architecture and Environmental Design (corresponding to Architecture in Table 1), Physical Sciences (corresponding to Chemistry in Table 1), and Engineering (corresponding to Aerospace Engineering in Table 1). I do not identify majors corresponding to Health or Transportation. Health would be included under Life Sciences, but the health degrees listed under sector-distant degrees (such as nursing) are quite different from biology degrees. Similarly, Transportation would be included in another grouping that also included very different majors.

[40]Further, there is a sizable increase in the coefficient on exposure in $t^* + 1$. However, the differential decrease in CS/CE majors starts the next year. Finally, if exposure to the computer sector affected student

degrees does not reflect changing student composition due to a decline in CS/CE degrees, but is instead part of a pre-existing trend in exposed areas.

This pre-existing increasing effect of exposure on sector-distant degrees is explained by education degrees, the largest component of computer-distant degrees (Appendix Figure A6).[41] Nationally, education degrees fell sharply over this period. In 1990-1991, education degrees comprised 10% of all bachelor's degrees awarded in the US. By 2013-2014, they were roughly 5% (National Center for Education Statistics, 2018).

Education degrees are also much more concentrated in low-computer employment MSAs. In 1990, the average education degree share in MSAs least exposed to the computer industry was roughly 15%, dividing universities into equally-sized bins of share computer employment, and weighting by total degrees awarded at the university. In the highest-computer exposure MSAs, this was roughly 6%. While education degree share fell everywhere, these declines were largest in levels and percentages in MSAs with higher education degree share. Because these are also MSAs with low computer employment share, we see a differential trend in education degree share by computer exposure. Importantly, this starts before, and continues after, the differential negative effect of exposure on share CS/CE degrees.

There is some evidence of a differential decline in sector-distant majors following Delaware's finance shock. As mentioned, I use a different data source for this shock, and I have only 21 broad major classifications for this analysis. Part of the reason we may see a response is because the broad groupings include some less-distant fields, and so this may reflect substitution rather than compositional changes.[42] However, Appendix Figure A7 shows an increase in share of out-of-state students around the time of Delaware's legislation, though this was also part of a pre-existing trend.

With the possible exception of the Delaware shock, these results suggest changes in share sector-relevant majors do not simply reflect changes in the types of students selecting into

composition at local universities after the shock, we might expect the opposite effect during the boom preceding the crash. However, preceding the crash, sector-distant degrees are differentially moving in the same direction as sector-relevant degrees.

[41] None of the other components show statistically significant changes in the opposite direction relative to exposure's effect on share CS/CE degrees. There is an increasing trend in the effect of computer exposure on family sciences degrees starting in 2006, though the coefficients are not significant. The coefficients from 2005-2009 fall in half when omitting University of Texas at Austin. This is a very large university in a high computer-exposure MSA, where share family sciences degrees increased substantially over this period. The university's Department of Human Ecology (housing these majors) became a School in 2008, after three years of significant fundraising ("School of Human Ecology", 2008). The increasing coefficients from 2010 to 2013 do not suggest changing student composition as a result of the dot-com bust, as this is after the period in which computer exposure had a negative effect on share CS and CE degrees. By this period, the effect of computer exposure on share CS and CE degrees is again trending upward.

[42] For example, Table 1 shows aerospace engineering as a sector-distant major, and I observe only total engineering degrees. Some engineering degrees are much more relevant for finance.

exposed universities. Instead, the evidence is consistent with students changing major choice differentially in exposed markets.

Robustness

For robustness, I estimate the principal specifications excluding universities not located in an MSA, or whose MSA was not represented in the Census (rather than setting MSA employment share to zero for those universities). The results show a similar, statistically significant effect for the dot-com crash (Appendix Table A4). The effect for the financial crisis is large in magnitude, but unsurprisingly given the drop in sample size, not statistically significant from zero.

Section two of the online appendix shows the results are robust to using alternative definitions of exposure (Appendix Figure A2, Appendix Tables A1 and A2), and to using $Ln(Majors)$ as the dependent variable (Appendix Table A7). This mitigates concerns that the larger drop in major share at more-exposed universities is explained by larger levels at these universities. Section two of the appendix also shows results from testing for differential impacts at top 20 US News and World Report universities (Appendix Table A6). The magnitudes are generally larger at non-top 20 universities, except for the fracking boom for which only two of the top 20 universities are in the top quartile of exposure. However, differences are not always precisely estimated.

6 Conclusion

This paper studies whether college majors are influenced by local rather than national labor demand. I test for changes in sector-relevant majors after sector-specific local labor demand shocks, and whether these changes are greater at more geographically-exposed universities. I analyze four sectoral shocks with local effects: the 2000 dot-com crash, the fracking boom, the 2008 financial crisis, and the shock making Delaware a global financial headquarters.

First, these sectoral shocks affect within-university sector-relevant major share, using university-level data on degree completions by academic discipline from 1966 through 2016. Second, universities in areas more exposed to these shocks experience greater changes in sector-relevant majors. Of the national change in sector-relevant degrees after these shocks, differential effects at the most-exposed universities explain 23% (dot-com), 14% (fracking), and 46% (financial crisis). These are impacts over and above those experienced by all universities regardless of exposure.

Investing in human capital based on local labor demand may yield mismatch between aggregate supply of skills and aggregate demand. This may help explain why young college-educated individuals have much higher unemployment rates than older individuals (National Center for Education Statistics 2015), a puzzle from an earlier literature (Blanchflower and Freeman 2000). This local dependence may also affect aggregate productivity if individuals are not matched to the job in which they are most productive.

Policy implications depend on whether the local elasticity is explained by information frictions or location preferences. If students invest based on local demand due to location preferences, encouraging human capital investments based on national demand may increase mismatch for students with strong preferences. Identifying the mechanism explaining the local elasticity is an important area for research, as some recent initiatives have provided information on national demand to college-going students, while others provide information on local demand.[43]

Most generally, the results show individuals make human capital investment decisions that enhance their ability to benefit from local economic shocks.

References

[1] Agulnick, Seth (1999): "Careers Come Calling," *The News Journal* [Wilmington, DE], November 1, 1999.

[2] Altonji, Joseph G., Erica Blom, and Costas Meghir (2012): "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers," *Annual Review of Economics*, Vol. 4.

[3] Altonji, Joseph G., Lisa B. Kahn, and Jamin D. Speer (2016): "Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success," *Journal of Labor Economics*, Vol. 34(S1, Part 2).

[4] Amadeo, Kimberley (2018): "Stock Market Crash of 2008," the balance, November 6, 2018, https://www.thebalance.com/stock-market-crash-of-2008-3305535, Accessed 2/25/2019.

[5] Bardhan, Ashok, Daniel L. Hicks, and Dwight Jaffee (2013): "How Responsive is Higher Education? The Linkages Between Higher Education and the Labor Market," *Applied Economics*, Vol 45(10).

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

[6] Bartik, Alexander W. (2018): "Moving Costs and Worker Adjustment to Labor Demand: Evidence from Longitudinal Census Data," Working Paper.

[7] Bartik, Alexander W. , Janet Currie, Michael Greenstone, and Christopher R. Knittel: "The Local Economic and Welfare Consequences of Hydraulic Fracturing," *American Economic Journal: Applied Economics.*

[8] Beso, Michele (2005): "Delaware Colleges Look Ahead to a Post-MBNA World," *The News Journal* [Wilmington, DE], July 1, 2005.

[9] Betts, Julian R. and Laurel L. McFarland (1995): "Safe Port in a Storm: The Impact of Labor Market Conditions on Community College Enrollment," *Journal of Human Resources*, Vol. 30(4).

[10] Blanchflower, David G. and Richard B. Freeman (2000): "Introduction," Youth Employment and Joblessness in Advanced Countries, Ed. David G. Blanchflower and Richard B. Freeman. Chicago: University of Chicago Press for NBER.

[11] Blom, Erica, Brian C. Cadena, and Benjamin J. Keys (2015): "Investment over the Business Cycle: Insights from College Major Choice," *IZA Discussion Paper Series*, Number 9167.

[12] Bound, John, Brad Hershbein, and Bridget Terry Long (2009): "Playing the Admissions Game: Student Reactions to Increasing College Competition," *Journal of Economic Perspectives*, Vol. 23(4).

[13] Bound, John, Breno Braga, Joseph M. Golden, and Gaurav Khanna (2015): "Recruitment of Foreigners in the Market for Computer Scientists in the United States," *Journal of Labor Economics*, Vol. 33(3).

[14] Bound, John and Nicolas Morales (2018): "Workforce Trends in Computer Science," In National Academies of Science, Engineering, and Medicine ed. *Assessing and Responding to the Growth in Undergraduate Computer Science Enrollments*, Washington, DC: The National Academies Press.

[15] Cascio, Elizabeth U., and Ayushi Narayan (2015): "Who Needs a Fracking Education? The Educational Response to Low-Skill Biased Technological Change," NBER Working Paper 21359.

[16] Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo (forthcoming): "Housing Booms and Busts, Labor Market Opportunities, and College Attendance," *American Economic Review.*

[17] Choi, Darwin, Dong Lou, and Abhiroop Mukherjee (2016): "The Effect of Superstar Firms on College Major Choice," Working Paper.

[18] "Computer Science for All," The White House: President Barack Obama, January 30, 2016, https://obamawhitehouse.archives.gov/blog/2016/01/30/computer-science-all, Accessed 8/14/2018.

[19] DeLong, J. Bradford and Konstantin Magin (2006): "A Short Note on the Size of the Dot-Com Bubble," NBER Working Paper 12011.

[20] Ellison, Glenn and Edward L. Glaeser (1997): "Geographic Concentration in US Manufacturing Industries: A Dartboard Approach," *Journal of Political Economy*, Vol. 105(5).

[21] Erdevig, E. (1988): "New Directions for Economic Development-The Banking Industry," *Economic Perspectives*, Vol. 12.

[22] Ersoy, Fulya Y. (2017): "Reshaping Aspirations: The Effects of the Great Recession on College Major Choice," Working Paper.

[23] Feyrer, James, Erin T. Mansur, and Bruce Sacerdote (2017): "Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution," *American Economic Review*, Vol. 107(4).

[24] Foote, Andrew and Michel Grosz: "The Effect of Local Labor Market Downturns on Postsecondary Enrollment and Program Choice," *Education Finance and Policy*, Forthcoming.

[25] Freeman, Richard (1976): "A Cobweb Model of the Supply and Starting Salary of New Engineers," *Industrial and Labor Relations Review,* Vol. 29(2).

[26] Freeman, Richard (1975): "Legal "Cobwebs": A Recursive Model of the Labor Market for New Lawyers," *The Review of Economics and Statistics*, Vol. 57 (2).

[27] Han, Luyi and John V. Winters (2019): "Industry Fluctions and College Major Choices: Evidence from an Energy Boom and Bust," IZA Discussion Paper No. 12614.

[28] Hastings, Justine, Christopher A. Neilson, and Seth D. Zimmerman (2015): "The Effects of Earnings Disclosure on College Enrollment Decisions," NBER Working Paper 21300.

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

[30] Hunt, Jennifer (2018): "Does the Recent Increase in Computer Science Degrees Reflect Increase Demand?" In National Academies of Science, Engineering, and Medicine ed. *Assessing and Responding to the Growth in Undergraduate Computer Science Enrollments*, Washington, DC: The National Academies Press.

[31] Kahn, Lisa (2010): "The Long-Term Labor Market Consequences of Graduating in a Bad Economy," *Labour Economics*, Vol. 17(2).

[32] Kaplan, Greg and Sam Schulhofer-Wohl (2017): "Understanding the Long-Run Decline in Interstate Migration," *International Economic Review*, Vol. 58(1).

[33] Kinsler, Josh and Ronni Pavan: "The Specificity of General Human Capital: Evidence from College Major Choice," *Journal of Labor Economics*, forthcoming.

[34] Lafortune, Julien, Jesse Rothstein, and Diane Schanzenbach (2018): "School Finance Reforn and the Distribution of Student Achievement," *American Economic Journal: Applied Economics*, Vol. 10(2).

[35] Lang, Kevin and Russell Weinstein (2013): "The Wage Effects of Not-for-Profit and For-Profit Certifications: Better Data, Somewhat Different Results," *Labour Economics*, Vol. 24.

[36] LinkedIn: *Training Finder,* https://www.linkedin.com/training, Accessed February 24, 2017.

[37] Liu, Shimeng, Weizeng Sun, and John V. Winters (2017): "Up in STEM, Down in Business: Changing College Major Decisions with the Great Recession," IZA Discussion Paper 10996.

[38] Long, Mark C., Dan Goldhaber, and Nick Huntington-Klein (2015): "Do Students' College Major Choices Respond to Changes in Wages?" *Economics of Education Review*, Vol. 49.

[39] Manning, Alan and Barbara Petrongolo (2017): "How Local are Labor Markets? Evidence from a Spatial Job Search Model," *American Economic Review,* Vol. 107(10).

[40] Molloy, Raven, Christopher L. Smith, and Abigail Wozniak (2011): "Internal Migration in the US: Updated Facts and Recent Trends," *Journal of Economic Perspectives*, Vol. 25(3).

[41] Moulton, J. (1983): "Delaware Moves Toward Interstate Banking: A Look at the FCDA," *Business Review*, July/August.

[42] National Academies of Science, Engineering, and Medicine (2017): *Assessing and Responding to the Growth of Computer Science Undergraduate Enrollments,* The National Academies Press, Washington DC, https ://doi.org/10.17226/24926.

[43] National Center for Education Statistics, US Department of Education (2015): *Digest of Education Statistics* (Table 501.80), http://nces.ed.gov/programs/digest/d15/tables/dt15_501.80.asp. Accessed 8/4/2016.

[44] National Center for Education Statistics, US Department of Education (2018): *Digest of Education Statistics* (Table 322.10), https://nces.ed.gov/programs/digest/d18/tables/dt18_322.10.asp. Accessed 5/26/20.

[45] Ofek, Eli and Matthew Richardson (2003): "DotCom Mania: The Rise and Fall of Internet Stock Prices," *Journal of Finance*, Vol. 58.

[46] Oreopoulos, Philip, Till von Wachter, and Andrew Heisz (2012): "The Short- and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, Vol. 4(1).

[47] Oyer, Paul (2006): "Initial Labor Market Conditions and Long-Term Outcomes for Economists," *The Journal of Economic Perspectives*, Vol. 20(3).

[48] Oyer, Paul (2008): "The Making of an Investment Banker: Stock Market Shocks, Career Choice, and Lifetime Income," *The Journal of Finance*, Vol. 63(6).

[49] Presidential Memorandum "Increasing Access to High-Quality Science, Technology, Engineering, and Mathematics (STEM) Education," 82 FR 45417 (9/28/2017), https://www.federalregister.gov/documents/2017/09/28/2017-21032/increasing-access-to-high-quality-science-technology-engineering-and-mathematics-stem-education, Accessed 8/14/2018.

[50] Rothstein, Jesse (2012): "The Labor Market Four Years Into the Crisis: Assessing Structural Explanations," *ILR Review*, Vol. 65(3).

[51] Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek (2015): *Integrated Public Use Microdata Series*: Version 6.0 [Machine-readable database]. Minneapolis: University of Minnesota.

[52] Sahin, Aysegul, Joseph Song, Giorgio Topa, and Gianluca Violante (2014): "Mismatch Unemployment," *American Economic Review*, Vol. 104(11).

[53] "School of Human Ecology Established," The University of Texas at Austin, College of Natural Sciences, October 7, 2008, https://cns.utexas.edu/news/human-ecology-established, Accessed 5/27/20.

[54] Shimer, Robert (2007): "Mismatch," *American Economic Review*, Vol. 97(4).

[55] Stinebrickner, Ralph and Todd R. Stinebrickner (2014): "A Major in Science? Initial Beliefs and Final Outcomes for College Major and Dropout," *Review of Economic Studies*, Vol. 81.

[56] Story, Louise (2012): "As Companies Seek Tax Deals, Governments Pay High Price," The New York Times, December 1, 2012. Accessed online 12/24/2014, http://www.nytimes.com/2012/12/02/us/how-local-taxpayers-bankroll-corporations.html?pagewanted=all&_r=0.

[57] Vita, Stephen (2015): "4 Degrees Most Oil Companies Are Looking For," Investopedia, December 29, 2015. Accessed online 12/26/2018, https://www.investopedia.com/articles/professionals/122915/4-degrees-most-oil-companies-are-looking.asp.

[58] Wang, Zhu (2007): "Technological Innovation and Market Turbulence: The Dot-Com Experience," *Review of Economic Dynamics*, Vol. 10.

[59] Weinstein, Russell (2018): "Dynamic Responses to Labor Demand Shocks: Evidence from the Financial Industry in Delaware," *Journal of Urban Economics*, Vol. 106.

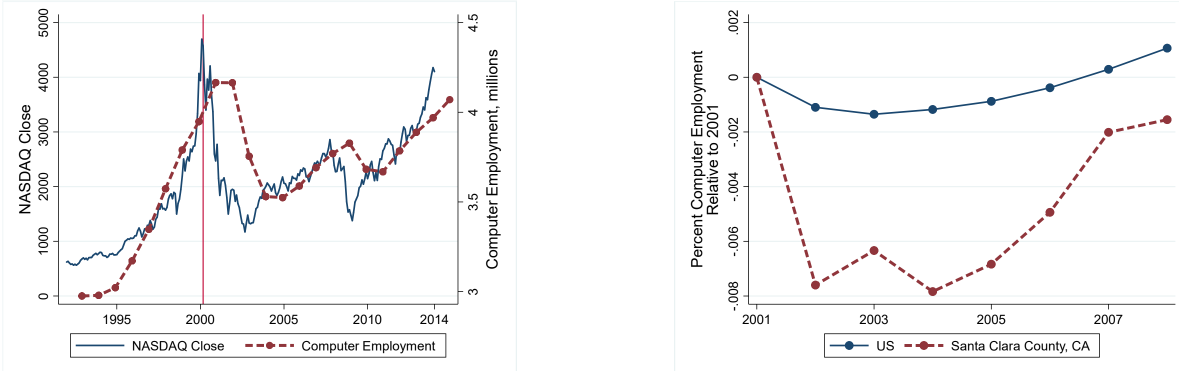
[60] White House: *Higher Education*, https://www.whitehouse.gov/issues/education/higher-education, Accessed December 13, 2016.

[61] Wiswall, Matthew and Basit Zafar (2015): "Determinants of College Major Choice: Identification using an Information Experiment," *Review of Economic Studies*, Vol. 82.

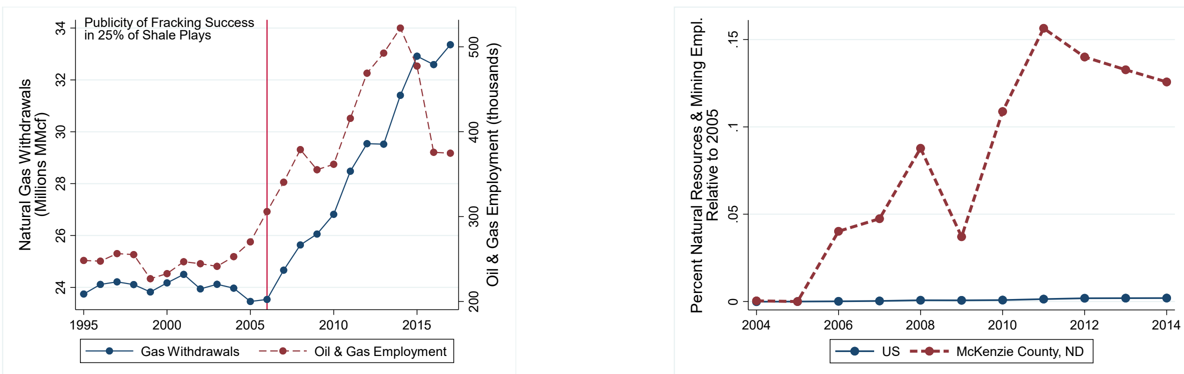
[62] Yagan, Danny (2018): "Employment Hysteresis from the Great Recession," *Journal of Political Economy*, Forthcoming.

Figure 1: Sectoral Shocks and Differential Effects on Local Labor Markets

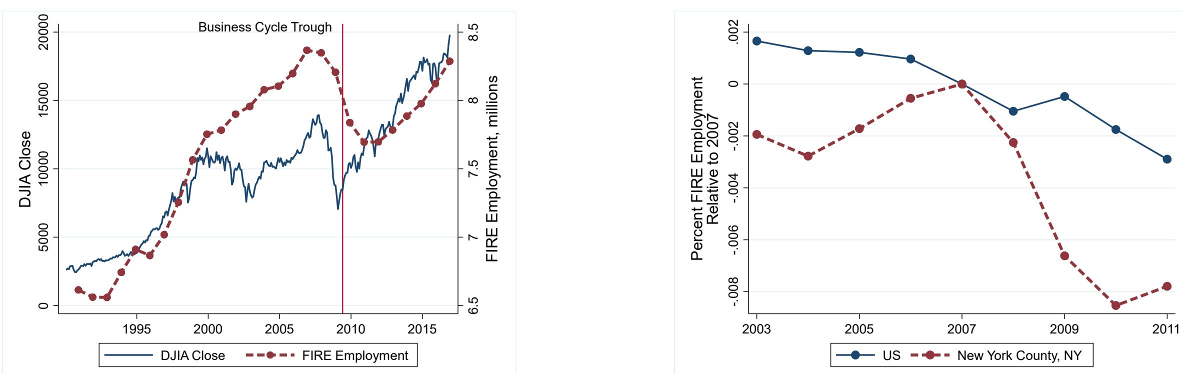
(a) The Dot-Com Crash and Differential Local Effects on Computer Employment



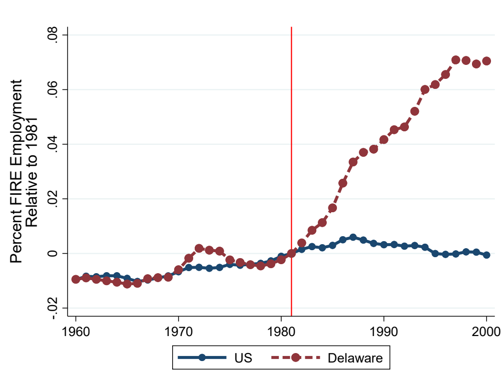
(b) Fracking and Differential Local Effects on Natural Resources Employment



(c) 2008 Financial Crisis and Differential Local Effects on FIRE Employment



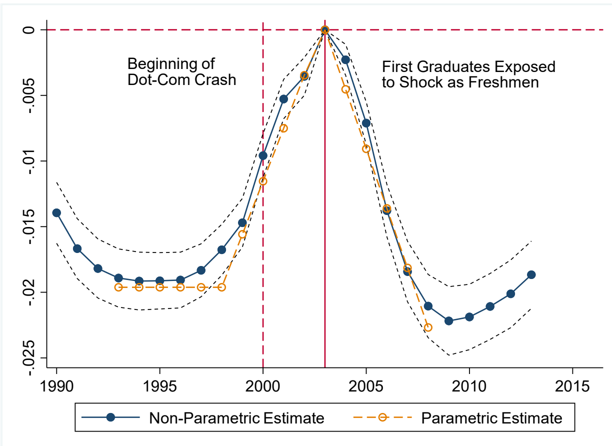
(d) Financial Relocation to Delaware and Differential Local Effects on FIRE Employment



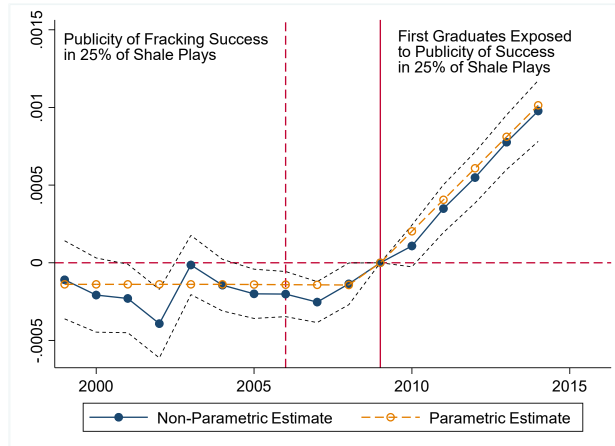
Note: Source for NASDAQ and DJIA monthly closing prices: Yahoo Finance. Gas withdrawals are Natural Gas Gross Withdrawals from the US Energy Information Administration. Source for employment data in the left-hand plot of each panel, and plot (d): CES. Computer employment includes employment in: computer and electronic products; software publishers; data processing, hosting, and related services, computer systems design and related services; and scientific research and development services (based on Hecker (2005)). Oil and gas employment includes oil and gas extraction and support activities for oil and gas operations. Source for employment in right-hand plots in each column: Quarterly Census of Employment and Wages. Computer Employment is "Computer Systems Design and Related Services." The right-hand plots in Panels (a) and (c) are based on private employment, while (b) is based on all ownerships.

Figure 2: Sectoral Shocks and Within University Changes in Major Composition, Average Across All Universities

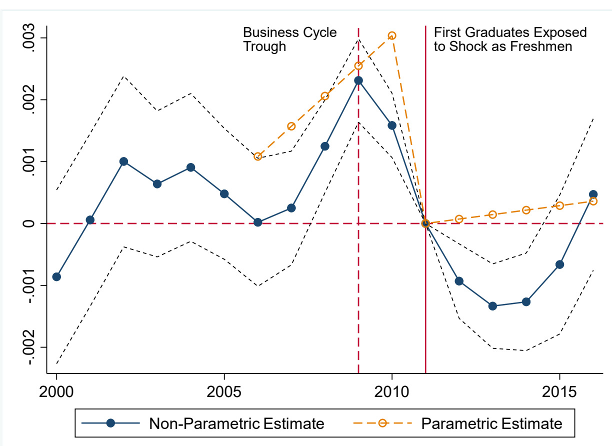
(a) The Dot-Com Crash and the Effect on Share Computer Science and Computer Engineering Degrees, Relative to 2003



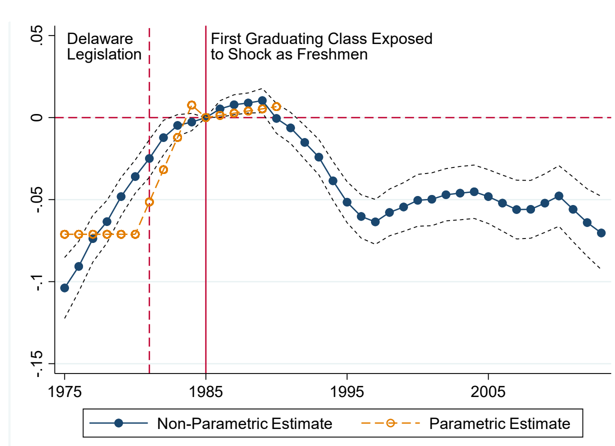
(b) The Fracking Boom and the Effect on Share Geology Degrees, Relative to 2009



(c) The 2008 Financial Crisis and the Effect on Share Finance Degrees, Relative to 2011



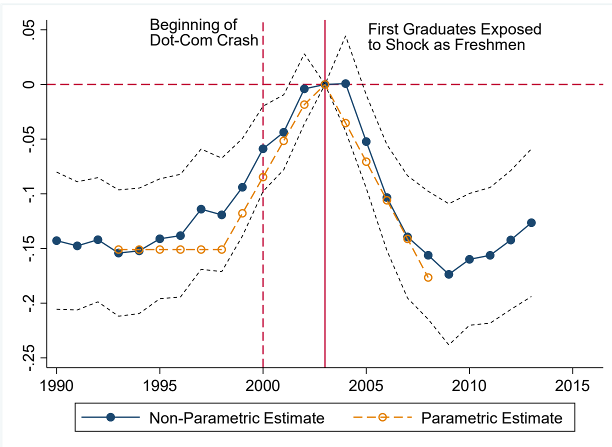
(d) Financial Relocation to Delaware and the Effect on Share Business Degrees, Relative to 1985



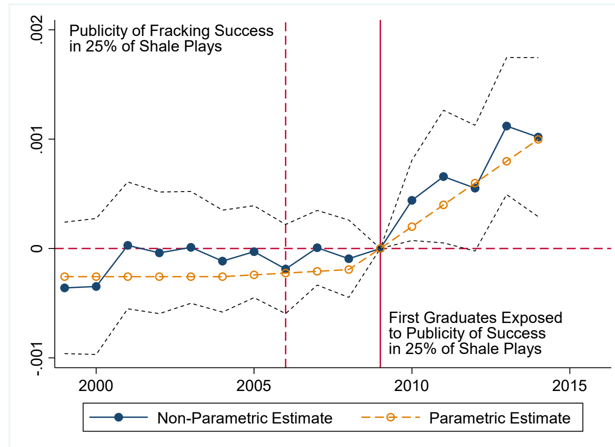
Note: Closed circles show coefficients on year fixed effects. Dotted lines are 95% confidence intervals for these coefficients. These regressions also include university fixed effects and total degrees. Open circles show fitted values for the effect of the shock, based on coefficients from the parametric regression (interactions between indicators for post shock, and years relative to first treated year, when the first graduates were exposed to the shock as freshmen). Fitted values are relative to the value in the first treatment year. The parametric regressions also include university fixed effects and total degrees. Observations are weighted by total degrees awarded. Standard errors are clustered at the university level.

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

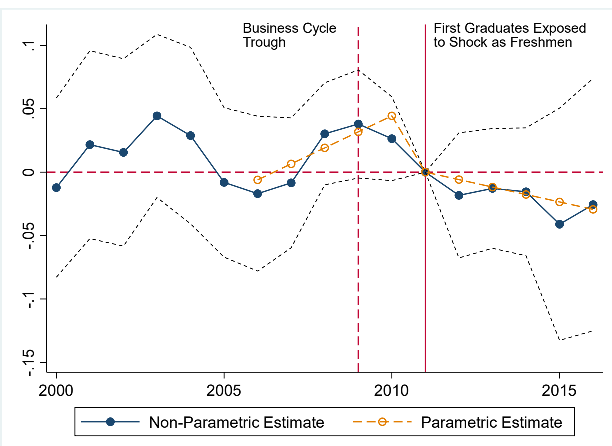
(a) MSA Computer Employment Share and the Effect on Share Computer Science and Computer Engineering Degrees, Relative to 2003



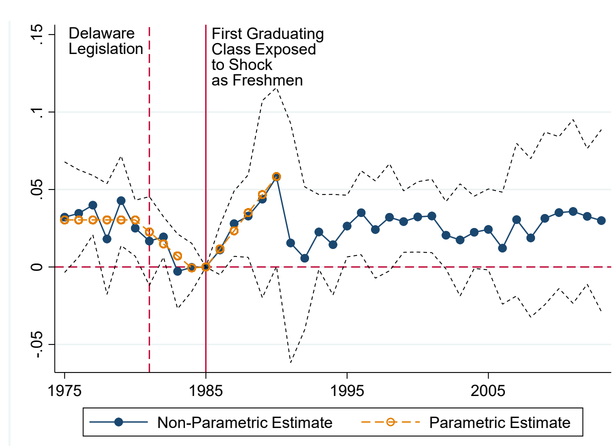
(b) Top Quartile, Cumulative Value of New Fossil Fuel Production within 200 miles, and the Effect on Share Geology Degrees, Relative to 2009



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



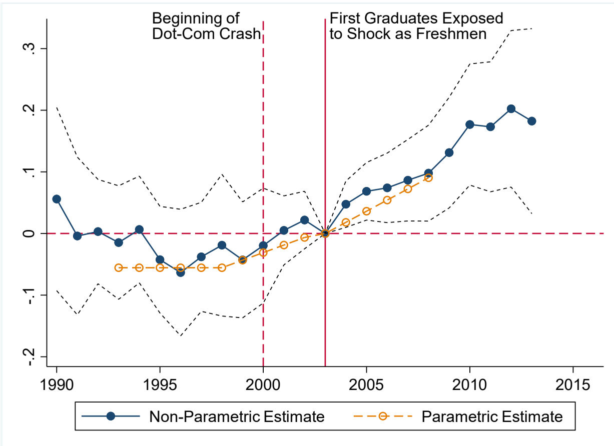
(d) Distance ≤ 15 Miles of Wilmington, DE and the Effect on Share Business Degrees, Relative to 1985



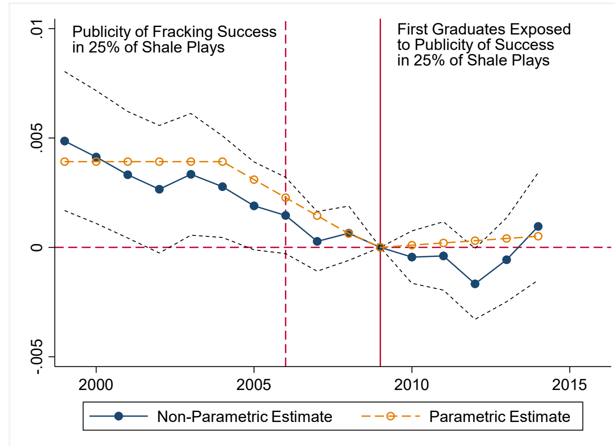
Note: Closed circles show interaction between year fixed effects and university's geographic exposure to the shock (MSA computer employment share in (a), university's county is within the top quartile in terms of cumulative value of new fossil fuel production within 200 miles of the county's centroid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

Figure 4: The Effect of Sectoral Shocks on Sector-Distant Degrees, by University's Geographic Exposure to the Shock

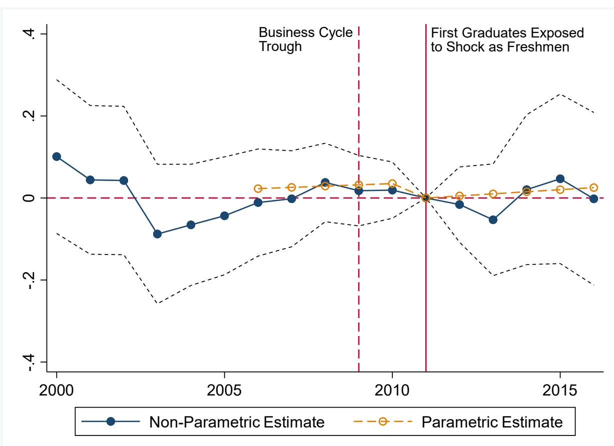
(a) MSA Computer Employment Share and the Effect on Share Sector-Distant Degrees, Relative to 2003



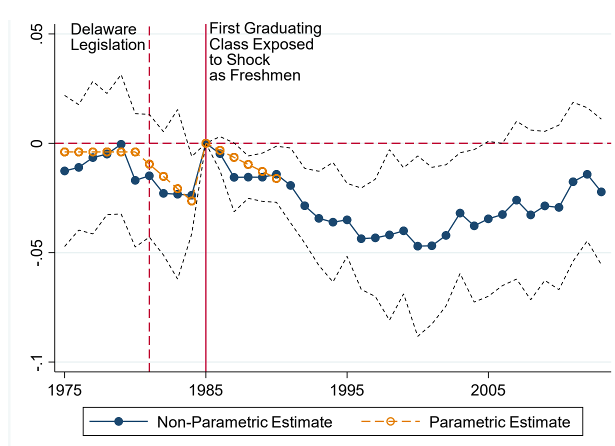
(b) Top Quartile, Cumulative Value of New Fossil Fuel Production within 200 miles, and the Effect on Share Sector-Distant Degrees, Relative to 2009



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



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



Note: See notes to Figure 3 for description of the regressions. Share sector-distant degrees is the total share of degrees awarded in the bottom five majors ranked by likelihood of working in the sector (identified in Table 1).

Table 1: Percentage Working in Industry Conditional on Major, Employed 23-25 Year Olds in the 2009-2017 ACS

	Computer Industry			Oil and Gas Industry			Finance Industry		
	Major	Work in Ind.	Share of all Majors	Major	Work in Ind.	Share of all Majors	Major	Work in Ind.	Share of all Majors
Relevant Majors	Computer Eng.	0.26	0.006	Geology and Earth Sc.	0.048	0.002	Finance	0.33	0.025
	Computer and Info. Sc.	0.26	0.03	Geosciences	0.115	0.0002			
Top 3 Majors by Share in Industry, Not "Relevant"	Management Info. Systems	0.16	0.003	Chemical Eng.	0.029	0.005	Economics	0.2	0.02
	Electrical Eng.	0.11	0.012	Engineering Tech.	0.027	0.005	General Business	0.11	0.035
	Engineering Technologies	0.07	0.005	Operations, Logistics	0.022	0.002	Bus. Admin.	0.1	0.046
	Avg. Share of Major in Industry, excl. relevant, top 3 non-relevant, and bottom 5	0.023	0.74	Avg. Share of Major in Industry, excl. relevant, top 3 non-relevant, and bottom 5	0.004	0.92	Avg. Share of Major in Industry, excl. relevant, top 3 non-relevant, and bottom 5	0.036	0.77
Bottom 5 Majors by Share Working in Industry	Leisure	0.006	0.023	Hospitality	0	0.007	Architecture	0.009	0.006
	Family Sciences	0.005	0.009	Area Studies	0	0.004	Health	0.008	0.071
	Construction Services	0.004	0.003	Anthropology	0	0.006	Chemistry	0.007	0.009
	Health	0.003	0.071	Communic. Technologies	0	0.003	Transportation	0.006	0.002
	Education	0.003	0.082	Int'l Relations	0	0.004	Aerospace Eng.	0.003	0.003
				Philosophy/Religion	0	0.006			
				Criminology	0	0.003			

Notes: Individuals are coded as having the relevant major if either their first or second major is in the relevant grouping. Observations are weighted by the person weight from the ACS. I use the Census general field of degree codes. However, I use the detailed codes for business, social sciences, physical sciences, and engineering, as the sector-relevant majors are classified under the detailed codes in these fields. I use the detailed codes for social sciences to evaluate the extent to which Economics majors enter finance, as this field is potentially much more likely than other social sciences. To focus on degrees that are similarly awarded as those I code as relevant, I limit to majors comprising at least .2% of all degrees awarded, which is the proportion for the oil-and-gas relevant majors.

Table 2: The Effect of Sectoral Shocks on College Majors, Average Across All Universities

		(1)	(2)	(3)	(4)
	Y_{ct}: Share of Majors in	CS/CE	Geology	Finance	Business
(1)	Post	-0.001	0.0001**	-0.0035***	-0.027***
		(0.001)	(0.00007)	(0.0004)	(0.005)
(2)	Post*Years Elapsed	-0.009***	0.0002***	-0.0004**	-0.018***
		(0.0004)	(0.00003)	(0.0002)	(0.002)
(3)	Years Elapsed	0.004***	-0.000001	0.0005***	0.020***
		(0.0002)	(0.00002)	(0.0001)	(0.002)
Impact, relative to t*-1					
(7)	Immediate	0.00346***	0.0001**	-0.00304***	-0.008**
		(.0008)	(.0001)	(.0003)	(.004)
(8)	Medium Run	-0.0192***	0.0012***	-0.00268***	-0.001
		(.0014)	(.0001)	(.0007)	(.005)
	Shock	Dot-Com	Fracking Boom	Financial Crisis	Delaware
	Positive or Negative Shock	Negative	Positive	Negative	Positive
	Post: Year ≥	2003	2009	2011	1985
	Observations	22,200	22,281	15,289	3,381
	R-squared	0.781	0.7553	0.9202	0.882

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Observations are at the university, year level. Standard errors clustered at the university level in parentheses. Each regression includes university fixed effects, and total degrees awarded as a control variable. Post is an indicator for whether the year is greater than or equal to the year in which graduates were freshmen at the shock's onset. Years elapsed equals the difference between the current year and the first year in which graduates were exposed to the shock as freshmen. I measure the effect immediately after the shock (in t*) relative to t*-1 in row (7), and in the medium run in row (8) (in t* + 5 relative to t* -1). Impact in t* relative to t*-1 is β_{Post} - (-1*$\beta_{Years\ Elapsed}$). Impact in t*+ 5 relative to t*-1 is β_{Post} + 5*$\beta_{Post*Years\ Elapsed}$ + 6*$\beta_{Years\ Elapsed}$. Observations are weighted by total degrees awarded. Regressions include years preceding the shock only if they are within ten years of *t**, and years following the shock only if they are within five of *t**. The variable *Years Elapsed* is censored at -5. The regression in column 3 includes only the five years preceding *t* * since there is another recession and recovery between *t* *-10 and *t* *-5.

Table 3: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock

		(1)	(2)	(3)	(4)
	Y_{ct}: Share of Majors in	CS/CE	Geology	Finance	Business
(1)	Post	-0.0001	0.0001	-0.002***	-0.028***
		(0.001)	(0.0001)	(0.001)	(0.005)
(2)	Post*Exposure	-0.015	0.0002	-0.057**	0.008
		(0.027)	(0.0002)	(0.026)	(0.018)
(3)	Post*Exposure*Years Elapsed	-0.068***	0.0002**	-0.018	0.019***
		(0.012)	(0.0001)	(0.015)	(0.006)
(4)	Post*Years Elapsed	-0.007***	0.0002***	0.00005	-0.019***
		-0.0004	(0.00003)	(0.0003)	(0.002)
(5)	Exposure*Years Elapsed	0.033***	0.00002	0.013	-0.008*
		(0.007)	(0.0001)	(0.008)	(0.004)
(6)	Years Elapsed	0.003***	-0.000005	0.0002	0.020***
		-0.0003	(0.00003)	(0.0002)	(0.002)
Differential Impact in Exposed Areas, relative to t*-1					
(7)	Immediate	0.002	0.0002	-0.002**	0.001
		(.002)	(.0002)	(.001)	(.015)
(8)	Medium Run	-0.016***	0.001***	-0.004	0.059**
		(.004)	(.0004)	(.003)	(.025)
	Shock	Dot-Com	Fracking Boom	Financial Crisis	Delaware
	Positive or Negative Shock	Negative	Positive	Negative	Positive
	Exposure	MSA % Computer Employment 2000	Top Quartile New FF Prod. in 200 Miles	MSA % Finance Employment 2000	≤ 15 Miles of Wilm., DE
	Post: Year ≥	2003	2009	2011	1985
	Observations	22,200	22,281	15,289	3,381
	R-squared	0.783	0.7573	0.920	0.882

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

Local Labor Markets and Human Capital Investments

Appendix: For Online Publication

Russell Weinstein*

June 1, 2020

1 Data

1.1 Classifying Computer- and Finance Related Industries to Define Dot-Com Crash and Financial Crisis Exposure

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 likely contained in one of the census codes I have

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

included (potentially "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 likely included in one of the other codes that I have 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, which I list above.

I include the FIRE industries, excluding insurance and real estate, as finance-related industries. This includes the following 2000 census classification codes: Banking; Savings institutions, including credit unions; credit agencies, n.e.c; security, commodity brokerage, and investment companies.

1.2 Classifying Majors in IPEDS/NSF Data

From 2003 through 2013, CIP code 52.08 refers to "Finance and Financial Management Services". From 2000-2002, CIP code 52.08 refers to "Financial Management and Services".

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

I classify business majors as business, management, marketing, and related support services. Starting in 2003, CIP code 52 refers to "Business, Management, Marketing, and Related Support Services". 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.

The Integrated Science and Engineering Resources Data System of the National Science Foundation is used to obtain university-level data on majors for studying Delaware's finance shock. Within this dataset, I use the NCES population of institutions. Prior to 1996, the sample includes all universities accredited at the college

[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.

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. I use the broad (standardized) academic discipline classifications in the data, and study the impact on business and management majors.

To study the impact of the fracking boom, I focus on geology majors. While petroleum engineering degrees are also very relevant for the oil and gas industry, they are generally offered only in fracking-exposed areas. In 2008, the year before graduates were first exposed to publicity of fracking success in 25% of shale plays, only 17 universities awarded petroleum engineering degrees and all but two of these are in states with high levels of new oil and gas production during the fracking boom.

2 Robustness: Impact of University Exposure to Sectoral Shocks

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

The medium-run effects on CS/CE majors are approximately 44% smaller for the top 20 universities and they are not statistically significant from zero. The effects for the non-top 20 universities are statistically significantly negative. The coefficients on $(t \geq t^*)(Exposure)(top20)$ and $(t \geq t^*)(t - t^*)(Exposure)(top20)$ are jointly significant from zero, although neither is significant from zero on its own (Appendix Table A6). Only two of the top 20 universities are in the top quartile of fracking exposure. The effect of local exposure is larger for these top 20 universities, but also statistically significant for non-top 20 universities. For the finance regressions, the $Exposure * top20$ interactions are not jointly significant, and only the immediate effect for non-top 20 universities is statistically significant from zero.[2]

The principal results are robust to $Ln(Majors)$ as the dependent variable, and

[2] Similarly, local exposure may also matter less at research universities. Interestingly, I still see large effects at research/doctoral universities, though there are differences relative to nonresearch/nondoctoral universities. See Appendix Table A8 and Appendix Figure A8.

controlling for $Ln(TotDegrees)$. The effects suggest CS/CE degrees decrease an additional 24% at universities in MSAs with 1990 computer-employment share higher by .1, for graduates five years after those first exposed. Geology degrees increase an additional 17% in top-quartile-exposed areas, for graduates five years after the first treated cohort. Finance degrees decrease an additional 6% at universities in MSAs with finance employment share higher by .05, though this is not statistically significant. Estimates suggest an additional 21% increase in business majors at Wilmington-area universities after Delaware's finance shock, for graduates five years after the first treated cohort (Appendix Table A7).[3]

For the dot-com crash and 2008 financial crisis, I alternatively define exposure as location in an MSA at the 90th percentile or above in the relevant employment share. These most exposed universities experienced greater decreases in the relevant majors, though the magnitudes are slightly smaller, and the effects of the financial crisis are not statistically significant. However, as discussed with the main results, the nonparametric specification is more likely to capture the true effect given the response to this shock begins before t^* (see Appendix Figure A2).

For the fracking boom, I use the cumulative value of new production within 200 miles of the county's centroid from 2004-2014. This is slightly more complicated when using the parametric specification because of the different timing of new production across shale plays.[4] The confidence intervals are much larger on the year*$Exposure$ interactions, and the parametric and nonparametric specifications are less similar. The fracking boom increased the share of geology majors an additional .04 percentage points (17%) if the cumulative value of exposure was higher by 24.5 billion dollars ($p \leq .01$), the difference between the 90th and 10th percentiles.

For Delaware's finance shock, I alternatively define $Exposure_c$ in three ways: distance between university j and Wilmington, an indicator for being within Delaware, and finally distance within 15 miles of Wilmington but only including universities within 100 miles of Wilmington as controls.

All three show Delaware's policy had large local effects on business majors (Appendix Table A2, Appendix Figure A2), though not significant ($p = .118$) when excluding farther universities. Not surprisingly the effect is smallest when using the

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

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

continuous distance measure. This assumes the effects increase linearly in distance, and the impact of increasing distance might be quite small for universities not in the Wilmington area.

2.1 University funding

Following a local demand shock, particular academic programs may experience changes in funding from the university, local/state government, or corporations, and this may explain the change in majors. Credit card companies eventually supported The University of Delaware's business school, though not immediately, and so cannot explain short-run changes in business majors. The Center for Financial Institutions Research and Education was created at the University of Delaware, expected to be in full operation by the Fall of 1988 (seven years after the initial shock) ("College of Business and Economics" 1987). The business school building at the University of Delaware was named MBNA America Hall in October 1997 (16 years after the shock) ("History" 2016).

Other examples of financial firm involvement with Delaware's universities 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),[5] 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). While these funding ties did not cause the initial increase in majors, they are consistent with the finance shock having an effect on business majors at local universities.

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

[5] MBNA was one of the world's largest credit card companies (Epstein 2000) before being acquired by Bank of America in 2006. Headquartered in Delaware, it spun out of one of the original firms moving to Delaware following the FCDA.

References

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

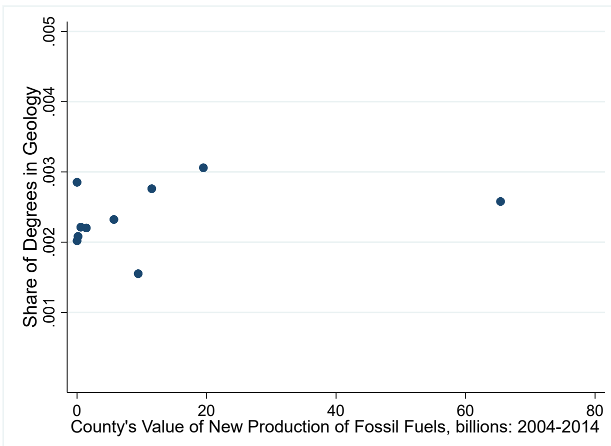
[2] Hecker, Daniel E. (2005): "High-technology employment: a NAICS based update," *Monthly Labor Review*, July.

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

Appendix Figure A1: Share of Degrees in Sector-Relevant Fields by Exposure to Sectoral Shocks

(a) CS/CE Degrees, 2002

(b) Geology Degrees, 2008

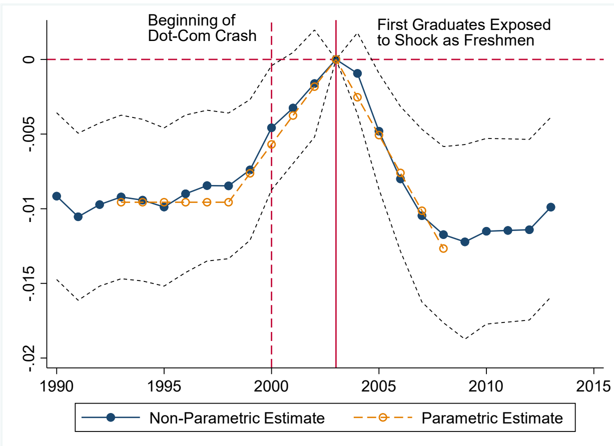


(c) Finance Degrees, 2010

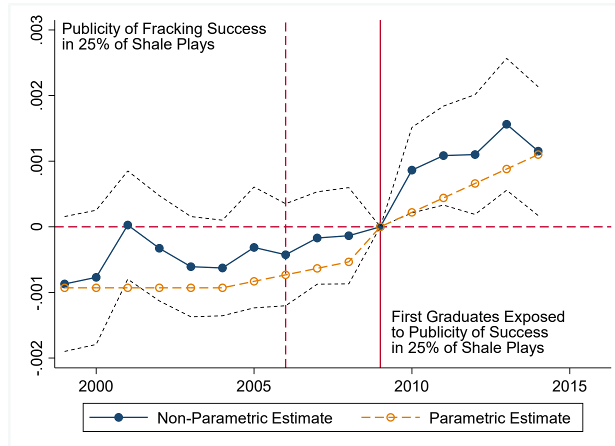
Notes: These figures show binned scatterplots, where the underlying data contain one observation per university. Universities are divided into roughly equally sized bins of exposure, weighting observations by total degrees awarded at the university, implying each bin produces roughly the same number of total degrees. In (a), each point represents the average share of degrees awarded in CS and CE across universities in the bin, weighting observations by total degrees awarded at the university. This weighted average implies each point represents the share of all degrees produced in the bin that are awarded in CS and CE. Plot (b) shows an analogous figure for geology degrees, and plot (c) for finance degrees. In (b) the x-axis is the cumulative value of new production of fossil fuels from 2004-2014 within 200 miles of the county's centroid. Degrees awarded are measured in the year preceding the first year the graduating class was exposed to the shock as freshmen. See text for details.

Appendix Figure A2: The Effect of Sectoral Shocks on College Majors, by University's Geographic Exposure to Shock: Alternative Definitions of Exposure

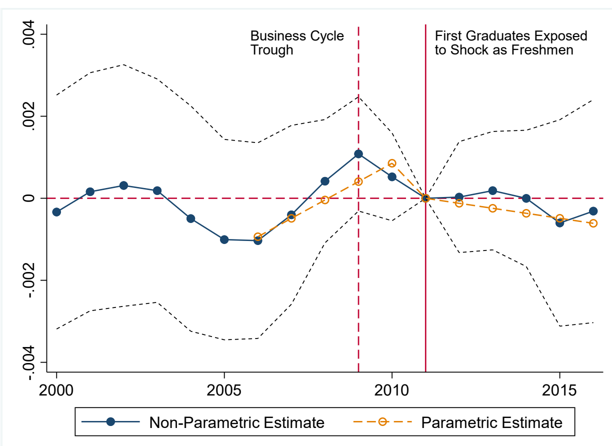
(a) MSA Computer Employment Share ≥ 90th percentile and the Effect on CS/CE Degrees, Relative to 2003



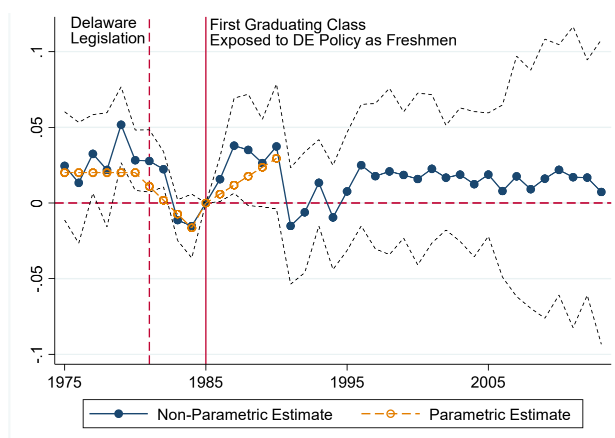
(b) Cumulative Value of New Fossil Fuel Production within 200 miles, and the Effect on Geology Degrees, Relative to 2009



(c) MSA Finance Employment Share ≥ 90th percentile and the Effect on Finance Degrees, Relative to 2011

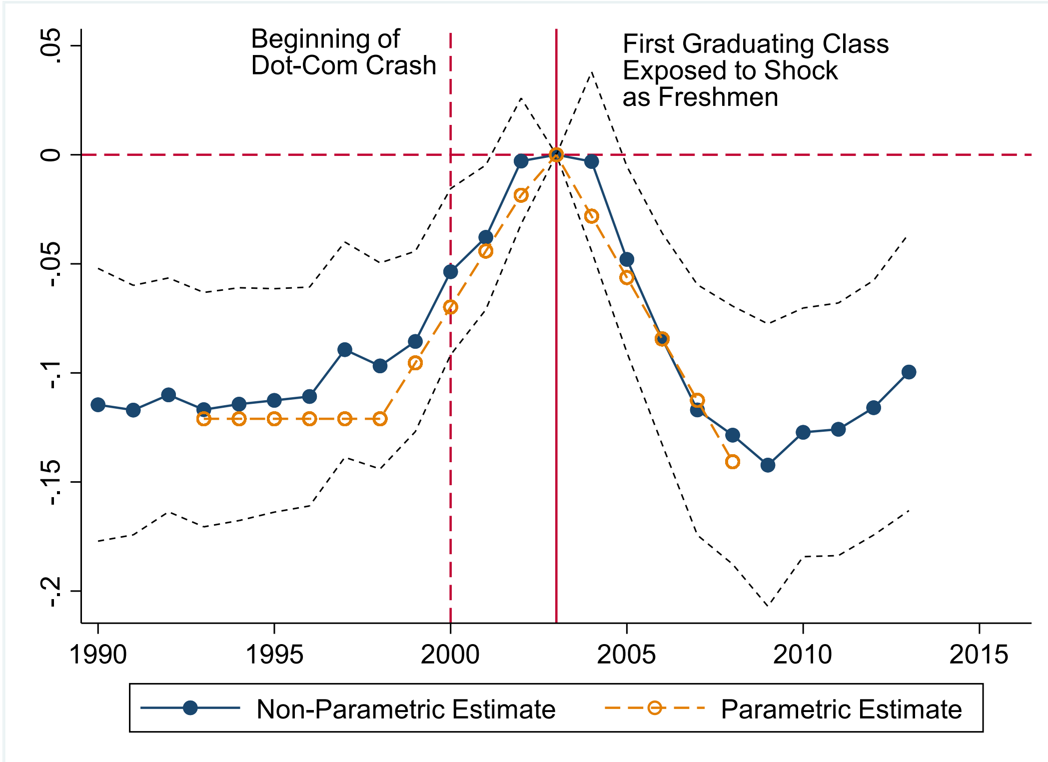


(d) Effect of Being within the State of Delaware on Share Business Degrees, Relative to 1985



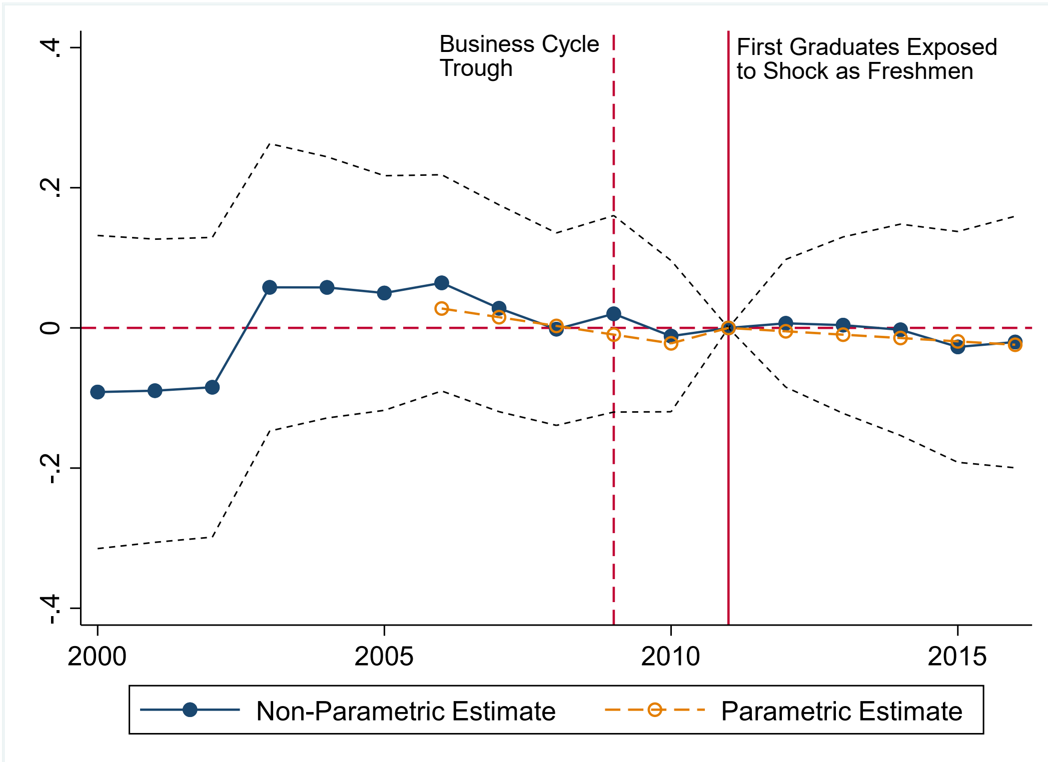
Note: Closed circles show interaction between year fixed effects and university's geographic exposure to the shock (indicator for MSA computer employment share ≥ 90th percentile in (a), cumulative value of new fossil fuel production within 200 miles of the university's county centroid (in hundreds of billions of dollars) from 2004 to 2014 in (b), indicator for MSA finance employment share ≥ 90th percentile in (c), and university in the state of Delaware in (d)). Dotted lines are 95% confidence intervals for these coefficients. These regressions also include year fixed effects, university fixed effects, and total degrees. Open circles show fitted values for the effect of university's exposure to the shock, based on coefficients from the parametric regression (interactions between geographic exposure to the shock, indicators for post shock, and years relative to first treated year). Fitted values are relative to the value in the first treated year. The parametric regressions also include total degrees, university fixed effects, and lower-level interaction terms. Observations are weighted by total degrees awarded.

Appendix Figure A3: Effect of MSA Computer Employment Share on Share Computer Science Degrees, Relative to 2003



Note: Dependent variable here is share of degrees awarded in computer science, rather than computer science and computer engineering (as in Figure 3). Closed circles show interaction between year fixed effects and university's geographic exposure to the shock (MSA computer employment share). Dotted lines are 95% confidence intervals for these coefficients. These regressions also include year fixed effects, university fixed effects, and total degrees. Open circles show fitted values for the effect of university's exposure to the shock, based on coefficients from the parametric regression (interactions between geographic exposure to the shock, indicators for post shock, and years relative to first treated year). Fitted values are relative to the value in the first treated year. The parametric regressions also include total degrees, university fixed effects, and lower-level interaction terms.

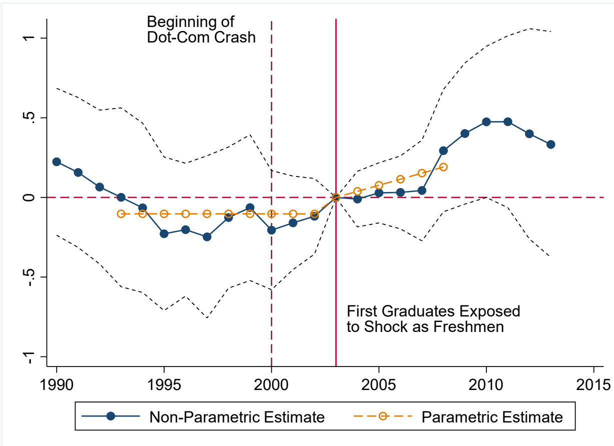
Appendix Figure A4: The Effect of the Financial Crisis on Share Business Degrees, by University's Geographic Exposure to the Shock



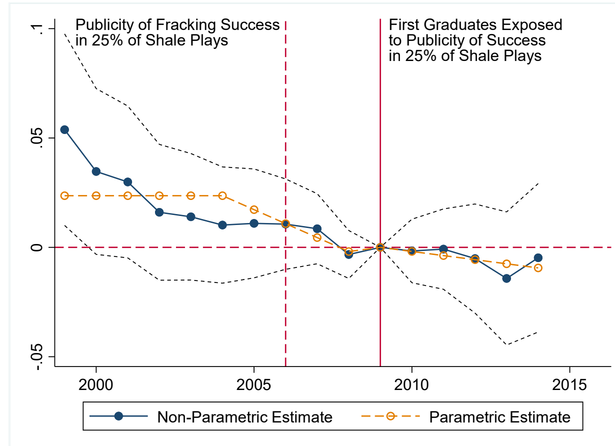
Notes: This plot is similar to Figure 3c, but with share business majors as the dependent variable. See text and Figure 3c for details.

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

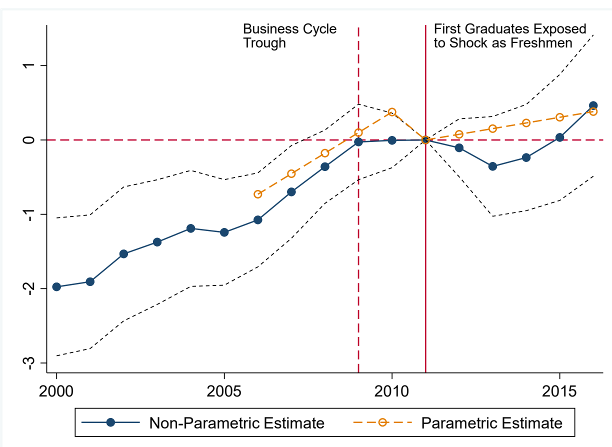
(a) MSA Computer Employment Share and the Effect on Total Degrees, Relative to 2003



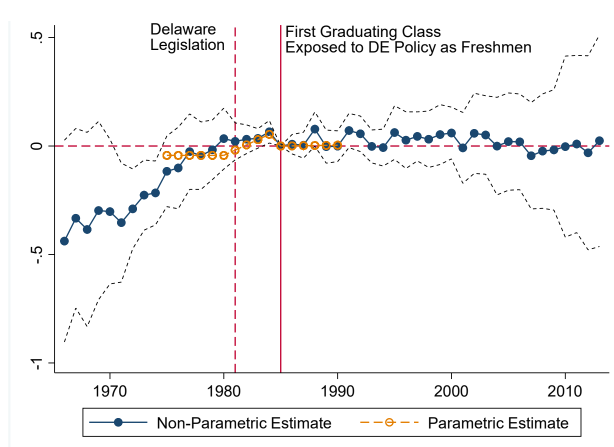
(b) Top Quartile, Cumulative Value of New Fossil Fuel Production within 200 miles, and the Effect on Total Degrees, Relative to 2009



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



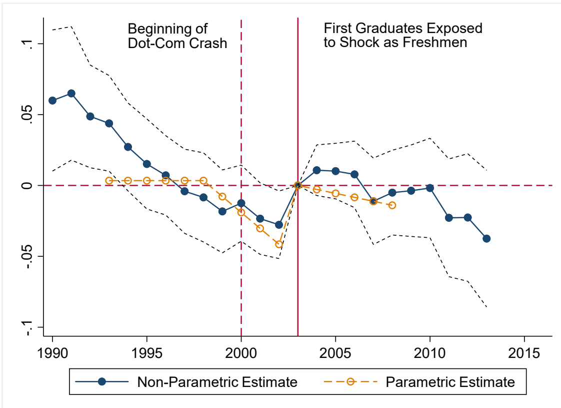
(d) Distance ≤ 15 Miles of Wilmington, DE and the Effect on Total Degrees, Relative to 1985



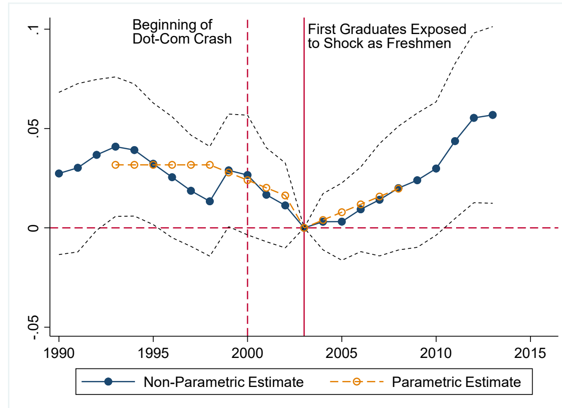
Note: Dependent variable is ln(Total Degrees Awarded by the University). Closed circles show interaction between year fixed effects and university's geographic exposure to the shock (MSA computer employment share in (a), university's county is within the top quartile in terms of cumulative value of new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

Appendix Figure A6: The Effect of the Dot-Com Bust on Sector-Distant Degrees, by University's Geographic Exposure to the Shock

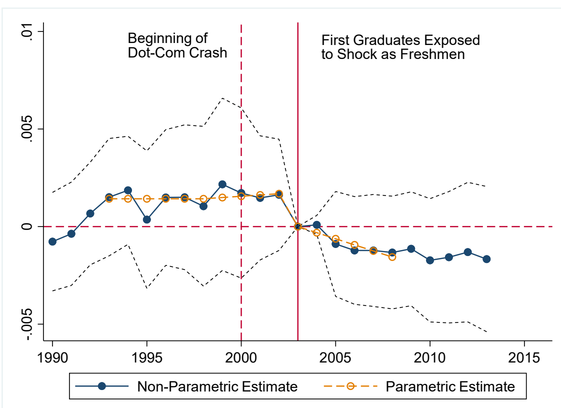
(a) Leisure



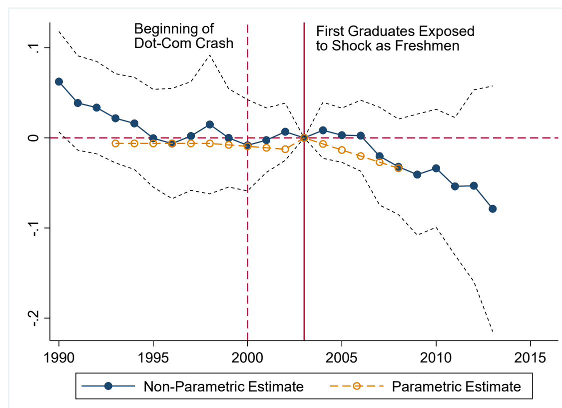
(b) Family Sciences



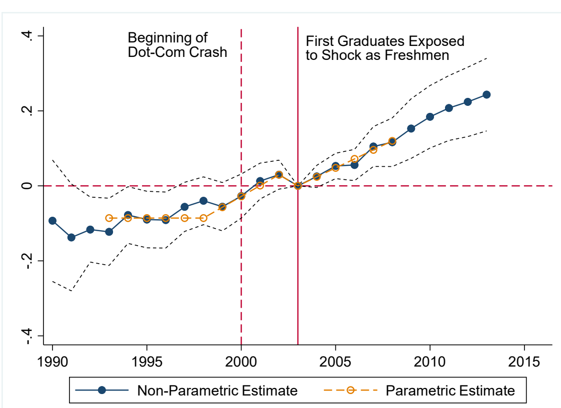
(c) Construction Services



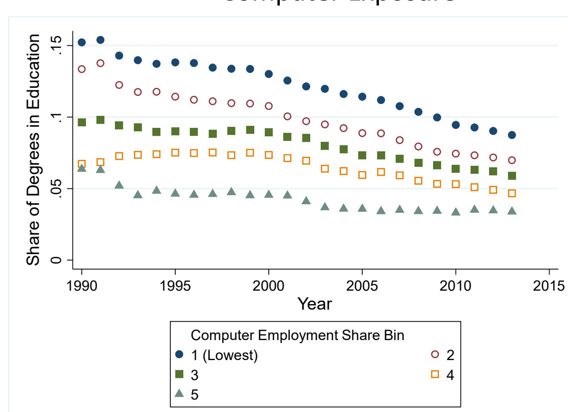
(d) Health



(e) Education



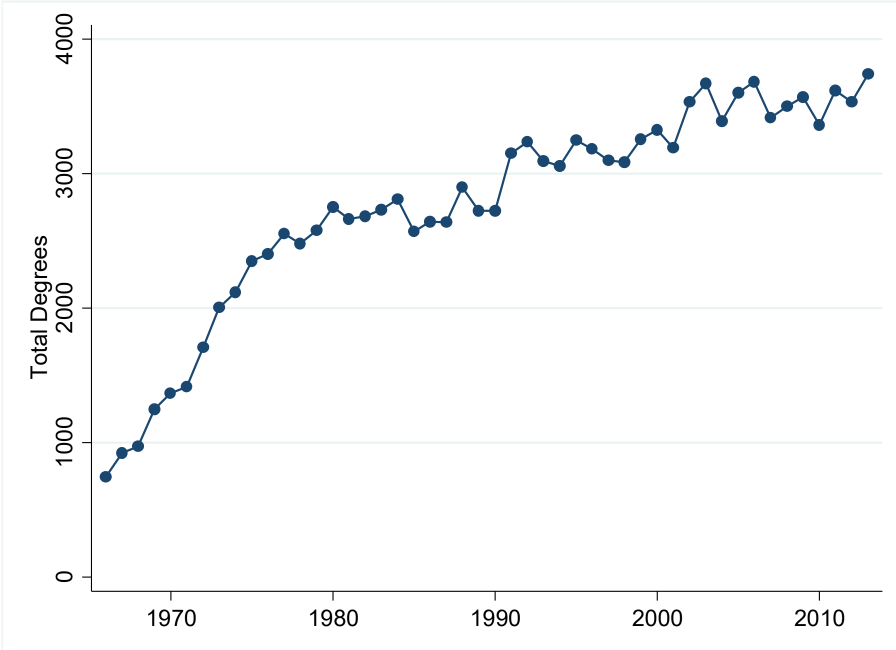
(f) Education Degrees Over Time by Computer Exposure



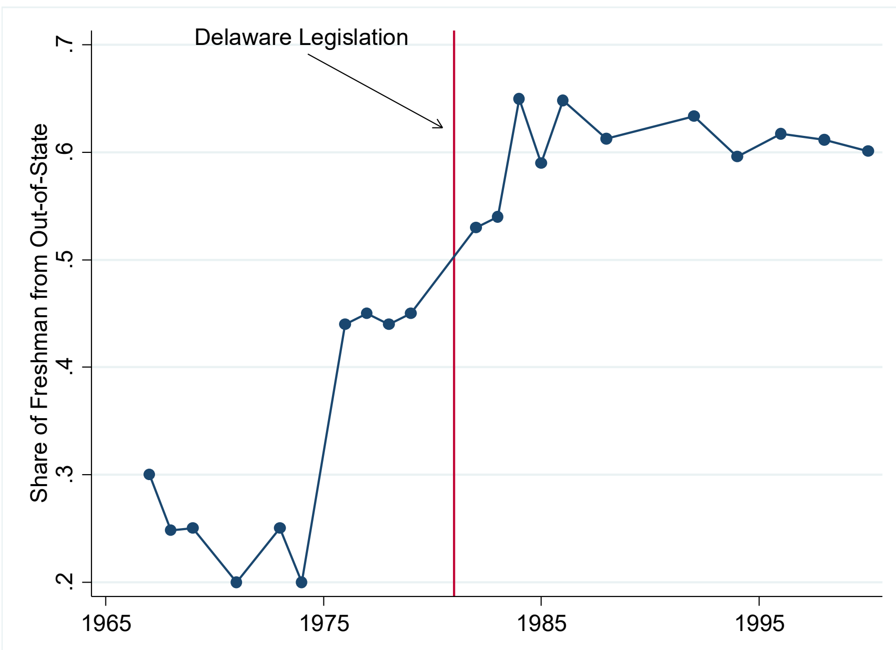
Note: Plots (a) through (e) show separate regressions for each of the bottom five majors ranked by likelihood of working in the computer industry (see Table 1). Closed circles show interaction between year fixed effects and MSA computer employment share. See Figure 3 for description of the regressions. Plot (f) shows binned scatterplots, where the underlying data contain one observation per university and year. Universities are divided into roughly equally sized bins of MSA computer employment share in 2000, weighting observations by total degrees awarded at the university, implying each bin produces roughly the same number of total degrees. Each point in the scatterplot represents the average share of degrees awarded in education across universities in the bin, where observations are weighted by total degrees awarded. See text for details.

Appendix Figure A7: Changes in Enrollment at the University of Delaware

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



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

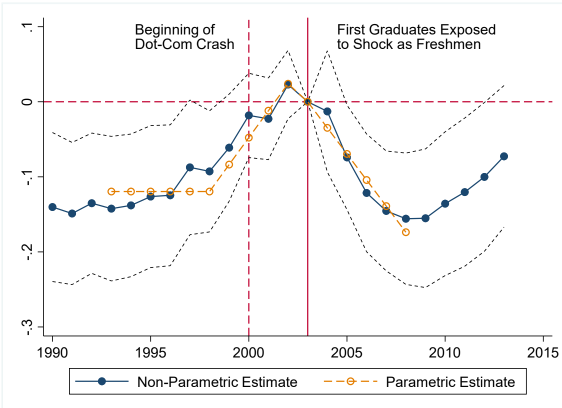


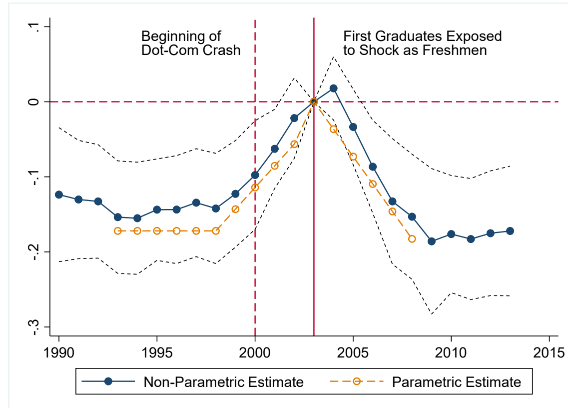
Note: Source for (a) is IPEDS (accessed through the Integrated Science and Engineering Resources Data System of the NSF). Sources for (b) include college guides (Peterson's and the College Board), as well as IPEDS.

Appendix Figure A8: The Effect of Sectoral Shocks on Universities, by Geographic Exposure to the Shock and University Type

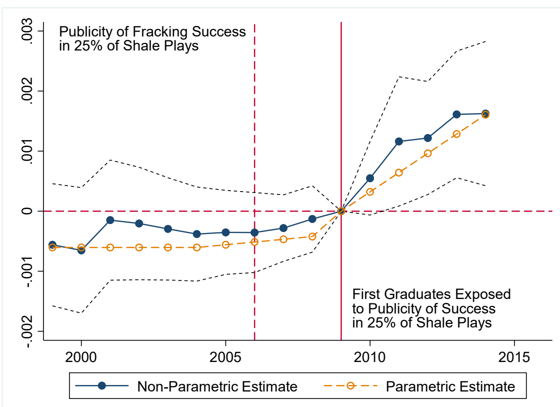
Research/Doctoral Universities | Master's/Baccalaureate Universities

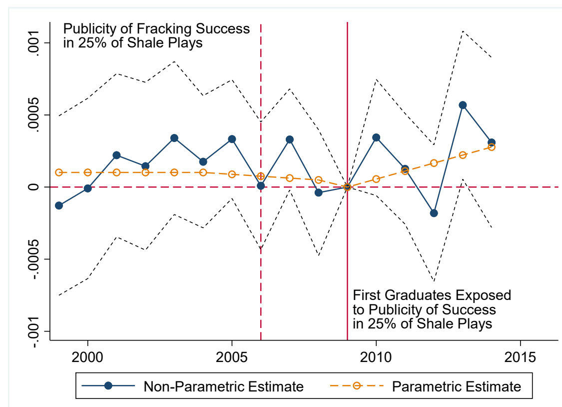
(a) Effect of MSA Computer Employment Share on Share Computer Science and Computer Engineering Degrees, Relative to 2003



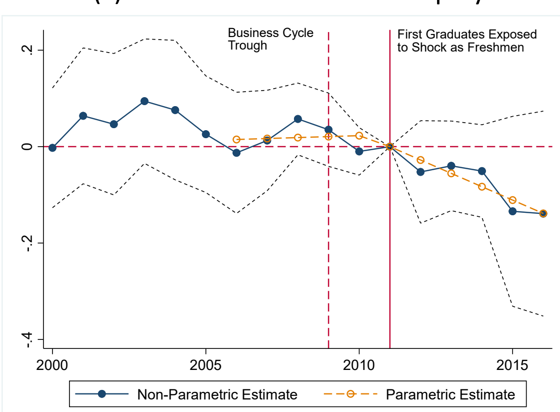


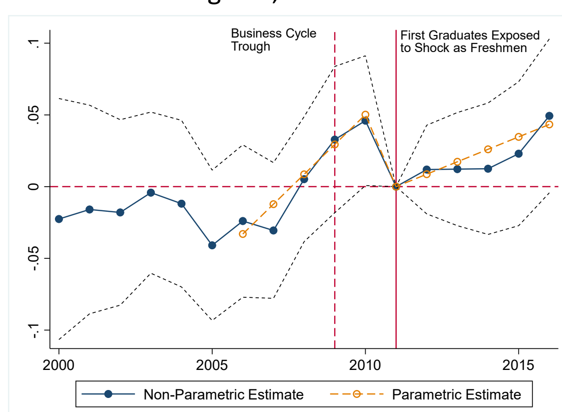
(b) Effect of Fracking Exposure on Share Geology Degrees, Relative to 2009



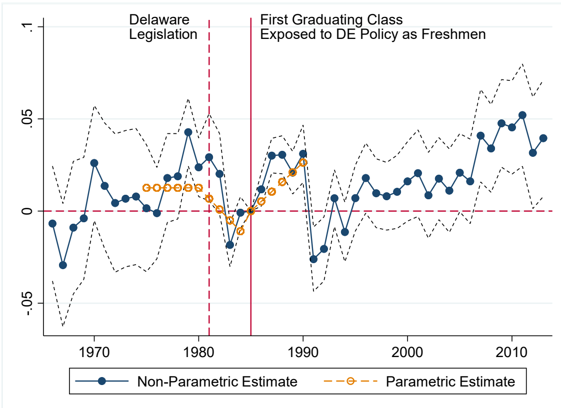


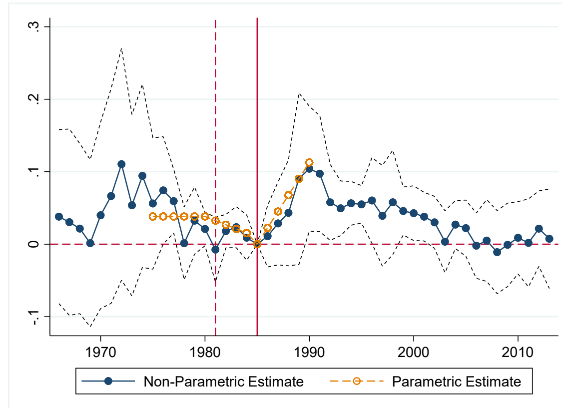
(c) Effect of MSA Finance Employment Share on Share Finance Degrees, Relative to 2011





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



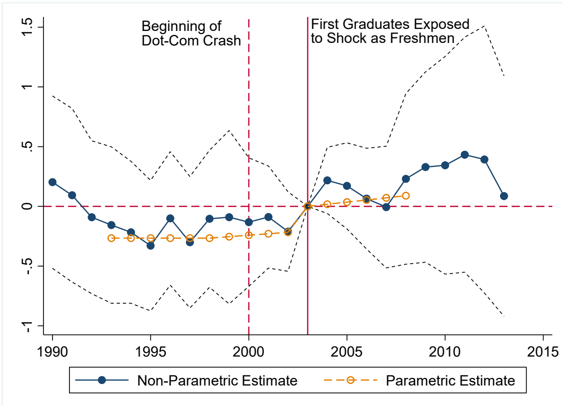


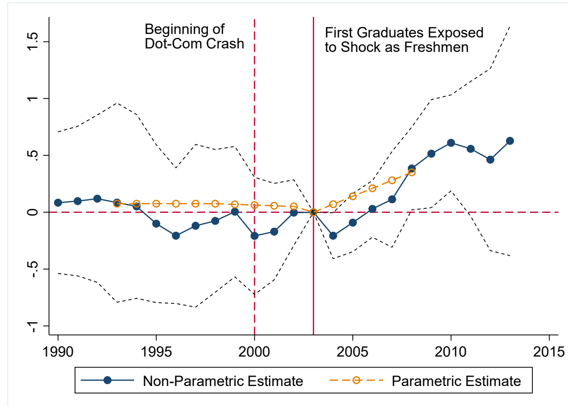
Note: Plots are the same as those described in Figure 3, but with regressions estimated separately for research/doctoral universities and master's/baccalaureate universities (including Master's, Baccalaureate, and Baccalaureate/Associates Colleges). University classifications are based on the 2000 Carnegie rankings.

Appendix Figure A9: The Effect of Sectoral Shocks on Ln(Total Degrees), by University's Geographic Exposure to Shock and University Classification

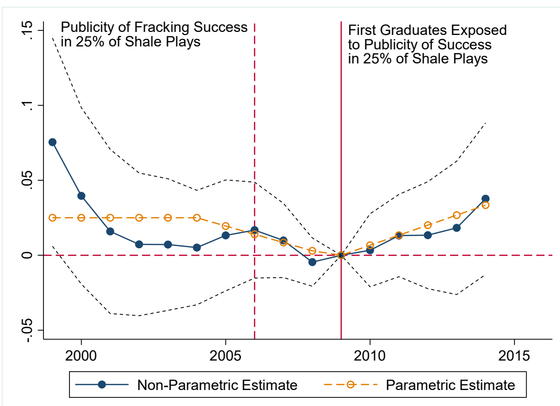
Research/Doctoral Universities | Master's/Baccalaureate Universities

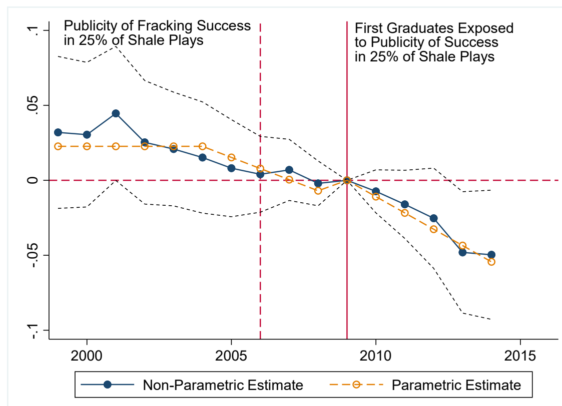
(a) Effect of MSA Computer Employment Share on Total Degrees, Relative to 2003



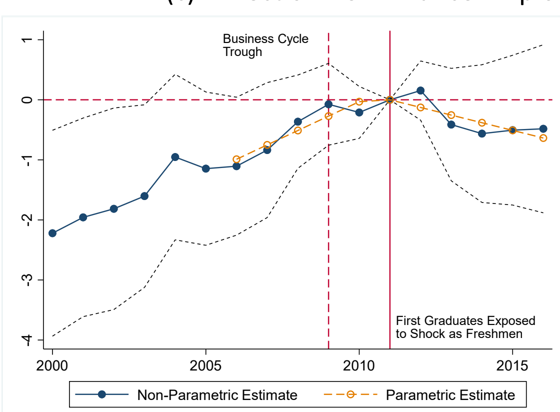


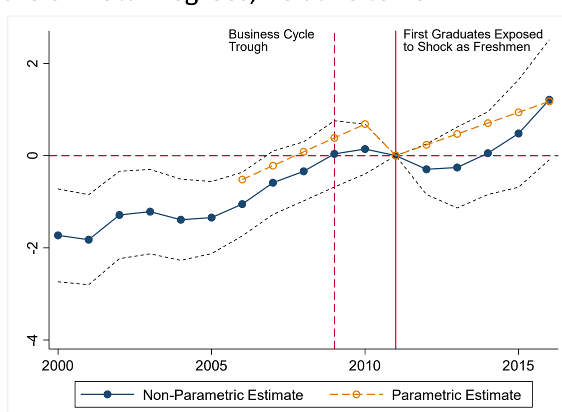
(b) Effect of Fracking Exposure on Total Degrees, Relative to 2009



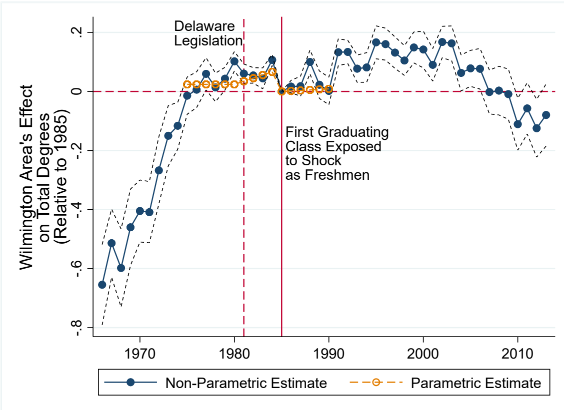


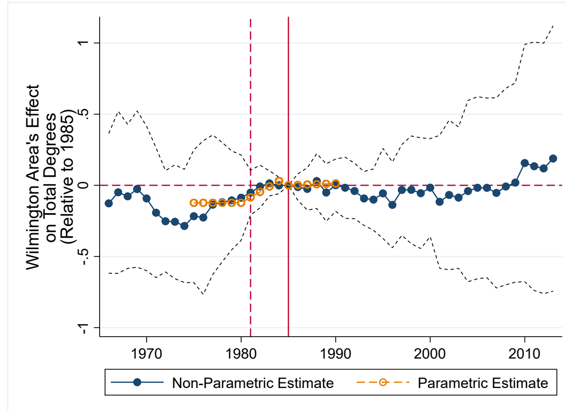
(c) Effect of MSA Finance Employment Share on Total Degrees, Relative to 2011





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

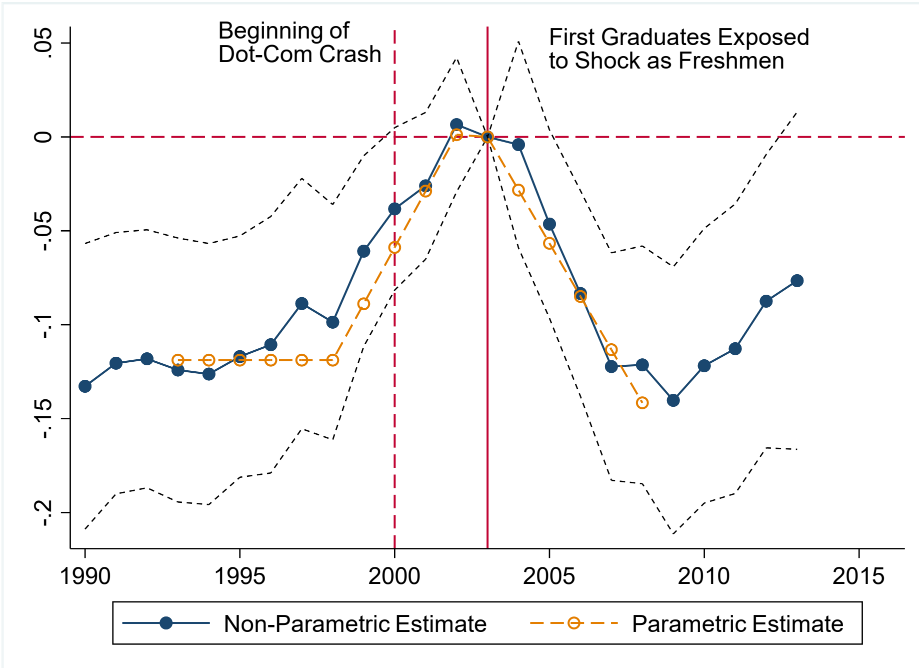




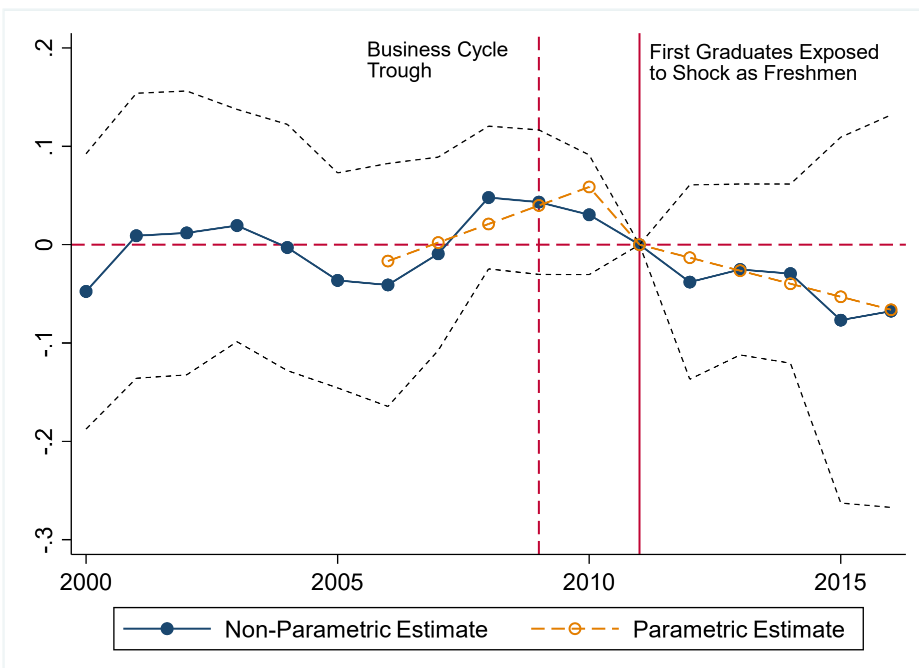
Note: Plots are the same as those described in Appendix Figure A5, but with regressions estimated separately for research/doctoral universities and master's/baccalaureate universities (including Master's, Baccalaureate, and Baccalaureate/Associates Colleges). University classifications are based on the 2000 Carnegie rankings.

Appendix Figure A10: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock, Excluding Universities Outside of MSAs, or with MSAs not represented in the Census

(a) MSA Computer Employment Share and the Effect on Share CS/CE Degrees, Relative to 2003



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



Notes: This figure presents estimates from the same specification as in Figure 3, but excluding universities which are not located in MSAs, or the MSA was not represented in the Census. In Figure 3, I set the MSA employment share for these universities to zero.

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

		(1)	(2)	(3)
	Y_{ct}: Share of Majors in	CS/CE	Geology	Finance
(1)	Post	-0.001	0.0001	-0.0030***
		(0.001)	(0.0001)	(0.0004)
(2)	Post*Alt_Exposure	-0.0001	0.0004	-0.0013
		(0.002)	(0.0004)	(0.0008)
(3)	Post*Alt_Exposure*Years Elapsed	-0.004***	0.0001	-0.0006
		(0.001)	(0.0001)	(0.0005)
(4)	Post*Years Elapsed	-0.007***	0.0002***	-0.0002
		(0.0004)	(0.00003)	(0.0002)
(5)	Alt_Exposure*Years Elapsed	0.002***	0.0001	0.0004
		(0.001)	(0.0001)	(0.0003)
(6)	Years Elapsed	0.003***	-0.00001	0.0003**
		(0.0002)	(0.00003)	(0.0001)
Differential Impact in Exposed Areas, relative to t*-1				
(7)	Immediate	0.002	0.0001	-0.001
		(.0019)	(.0001)	(.0007)
(8)	Medium Run	-0.011***	0.0004***	-0.001
		(.003)	(.0001)	(.002)
	Shock	Dot-Com	Fracking Boom	Financial Crisis
	Observations	22,200	22,281	15,289
	R-squared	0.783	0.7567	0.9203

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Regressions are the same as in Table 3, but with different exposure variables. The variable *Alt_Exposure* is an indicator for MSA computer employment share ≥ 90th percentile in (a), cumulative value of new fossil fuel production within 200 miles of the university's county centroid (in hundreds of billions of dollars) from 2004 to 2014 in (b), and an indicator for MSA finance employment share ≥ 90th percentile in (c). To calculate the effects in rows (7) and (8) I use Alt_Exposure = 1 in columns 1 and 3, and Alt_Exposure = .245 in column (2). See text for details.

Appendix Table A2: The Effect of Delaware's Finance Shock on College Majors by University's Exposure to the Shock, Alternative Definitions of Exposure

	Y_{ct}: Share of Majors in Business	(1)	(2)	(3)
(1)	Post	-0.028***	-0.017**	-0.019***
		(0.005)	(0.008)	(0.007)
(2)	Post*Exposure	0.026***	-0.008	-0.005
		(0.007)	(0.005)	(0.018)
(3)	Post*Exposure*Years Elapsed	0.015***	-0.005**	0.012*
		(0.006)	(0.002)	(0.007)
(4)	Post*Years Elapsed	-0.019***	-0.012***	-0.012***
		(0.002)	(0.004)	(0.003)
(5)	Exposure*Years Elapsed	-0.009**	0.003*	-0.002
		(0.004)	(0.002)	(0.004)
(6)	Years Elapsed	0.020***	0.015***	0.016***
		(0.002)	(0.003)	(0.003)
	Differential Impact in Exposed Areas, relative to t^{*} *-1*			
(7)	Immediate	0.016**	-0.005	-0.008
		(.007)	(.004)	(.015)
(8)	Medium Run	0.046**	-0.012**	0.040
		(.022)	(.005)	(.025)
	Exposure	University in Delaware	Distance to Wilmington (Hundreds of Miles)	Distance ≤ 15 miles, Nonexposed Distance ≤ 100 miles
	Observations	3,381	3,381	1,536
	R-squared	0.882	0.882	0.920

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Regressions are the same as in Table 3, but with different exposure variables. In column 1, this is an indicator for whether the university is located in the state of Delaware. In column 2, this is distance to Wilmington, DE in hundreds of miles. In column 3, this is an indicator for distance within 15 miles, but including in the regression only those universities within 100 miles of Wilmington, DE. To calculate the effects in rows (7) and (8), I use exposure = 1 in columns 1 through 3.

Appendix Table A3: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock

	Y_{ct}: Share of Majors in	CS
(1)	Post	-0.001
		(0.001)
(2)	Post*Exposure	-0.007
		(0.026)
(3)	Post*Exposure*Years Elapsed	-0.054***
		(0.012)
(4)	Post*Years Elapsed	-0.006***
		(0.0004)
(5)	Exposure*Years Elapsed	0.026***
		(0.006)
(6)	Years Elapsed	0.003***
		(0.0002)
Differential Impact in Exposed Areas, relative to t^*-1		
(7)	t^*	0.002
		(.002)
(8)	t^*+5	-0.012***
		(.004)
	Shock	Dot-Com
	Observations	22,200
	R-squared	0.785

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Observations are at the university, year level. Standard errors clustered at the university level in parentheses. This is the same regression reported in Table 3, column 1, but the dependent variable in this table is the share of degrees awarded in computer science, rather than computer science and computer engineering.

Appendix Table A4: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock, Excluding Universities Outside of MSAs, or with MSAs not represented in the Census

		(1)	(2)
	Y_{ct}: Share of Majors in	Computer Science & Computer Engineering	Finance
(1)	Post	0.001	-0.001
		(0.002)	(0.002)
(2)	Post*Exposure	-0.031	-0.077
		(0.031)	(0.051)
(3)	Post*Exposure*Years Elapsed	-0.058***	-0.032
		(0.014)	(0.031)
(4)	Post*Years Elapsed	-0.007***	0.001
		(0.001)	(0.001)
(5)	Exposure*Years Elapsed	0.030***	0.019
		(0.009)	(0.017)
(6)	Years Elapsed	0.003***	-0.00005
		-0.0004	(0.001)
	Differential Impact in Exposed Areas, relative to t^*-1		
(7)	Immediate	-0.0001	-0.003
		(.003)	(.002)
(8)	Medium Run	-0.014***	-0.006
		(.004)	(.006)
	Shock	Dot-Com	Financial Crisis
	Observations	15,035	10,354
	R-squared	0.786	0.924

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table presents estimates from the same specification as in Table 3, but excluding universities which are not located in MSAs, or the MSA was not represented in the Census. In Table 3, I set the MSA employment share for these universities to zero.

Appendix Table A5: The Effect of Sectoral Shocks on Ln(Total Degrees), by University's Exposure to the Shock

	Y_{ct}: Ln(Total Degrees Awarded)	(1)	(2)	(3)	(4)
(1)	Post	0.021***	-0.0539***	0.040***	-0.016*
		(0.006)	(0.0046)	(0.013)	(0.009)
(2)	Post*Exposure	0.103	0.0083	-0.653*	-0.078***
		(0.124)	(0.0091)	(0.370)	(0.026)
(3)	Post*Exposure*Years Elapsed	0.038	0.0045	-0.200	-0.023*
		(0.054)	(0.0048)	(0.147)	(0.013)
(4)	Post*Years Elapsed	-0.006***	-0.0186***	0.007**	0.011**
		(0.003)	(0.0030)	(0.003)	(0.005)
(5)	Exposure*Years Elapsed	-0.0001	-0.0064*	0.277***	0.024
		(0.044)	(0.0035)	(0.089)	(0.016)
(6)	Years Elapsed	0.030***	0.0474***	0.011***	0.005
		(0.002)	(0.0017)	(0.002)	(0.004)
	Differential Impact in Exposed Areas, relative to t^{*} *-1*				
(7)	Immediate	0.010	0.002	-0.019	-0.054***
		(.013)	(.008)	(.016)	(.015)
(8)	Medium Run	0.029	-0.008	0.0003	-0.05
		(.022)	(.018)	(.029)	(.037)
	Shock	Dot-Com	Fracking Boom	Financial Crisis	Delaware
	Observations	22,200	22,281	15,289	3,381
	R-squared	0.986	0.9829	0.988	0.985

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Observations are at the university, year level. Standard errors clustered at the university level in parentheses. Each regression includes university fixed effects. Observations are weighted by total degrees awarded. See notes to Table 3 for definition of variables, years in sample, regression details, and construction of difference-in-difference.

Appendix Table A6: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock and US News Rank

		(1)	(2)	(3)
	Y_{ct}: Share of Majors in	CS/CE	Geology	Finance
(1)	Post	-0.0002	0.0001	-0.002***
		(0.001)	(0.0001)	(0.001)
(2)	Post*Top20	-0.010	-0.0003	-0.002
		(0.008)	(0.0006)	(0.003)
(3)	Post*Exposure	0.001	0.0002	-0.063**
		(0.024)	(0.0002)	(0.027)
(4)	Post*Exposure*Top20	-0.064	0.0019	0.126
		(0.112)	(0.0018)	(0.080)
(5)	Post*Exposure*Years Elapsed	-0.072***	0.0002**	-0.019
		(0.013)	(0.0001)	(0.016)
(6)	Post*Exposure*Years Elapsed*Top20	0.042	0.0006	0.005
		(0.056)	(0.0006)	(0.026)
(7)	Post*Years Elapsed	-0.006***	0.0002***	0.0001
		(0.0004)	(0.00003)	(0.0003)
(8)	Post*Years Elapsed*Top20	-0.003	-0.0002	-0.0001
		(0.003)	(0.0003)	(0.0004)
(9)	Exposure*Years Elapsed	0.033***	0.00003	0.014
		(0.007)	(0.0001)	(0.009)
(10)	Exposure*Years Elapsed*Top20	-0.013	-0.0004*	-0.038
		(0.034)	(0.0002)	(0.032)
(11)	Years Elapsed	0.003***	-0.00002	0.0001
		(0.0002)	(0.00003)	(0.0002)
(12)	Years Elapsed*Top20	0.002	0.0003	0.001
		(0.002)	(0.0002)	(0.001)
	Differential Impact in Exposed Areas, relative to t^{*} *-1*			
	Immediate*,* Non-Top 20 Universities	0.003	0.0002	-0.002**
		(.002)	(.0002)	(.001)
	Immediate, Top 20 Universities	-0.004	0.002	0.002
		(.008)	(.002)	(.002)
	Medium Run, Non-Top 20 Universities	-0.016***	0.001***	-0.004
		(.004)	(.0004)	(.003)
	Medium Run, Top 20 Universities	-0.009	0.004***	-0.007
		(.018)	(.001)	(.005)
	p -value on joint test of Post*Exposure*Top20 coefficients	0.0108	0.0266	0.289
	Shock	Dot-Com	Fracking Boom	Financial Crisis
	Observations	22,200	22,281	15,289
	R-squared	0.783	0.7579	0.921

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table presents coefficients from regressions similar to Table 3, but additionally including the triple interaction between Post, Exposure, Years Elapsed, and Top 20 Ranking in US News, and lower-level interaction terms. I use the US News Rankings of universities in 1999.

Appendix Table A7: The Effect of Sectoral Shocks on Ln(College Majors), by University's Exposure to the Shock

		(1)	(2)	(3)	(4)
	Y_{ct}: Ln(Majors)	CS/CE	Geology	Finance	Business
(1)	Post	-0.019	0.1283***	-0.133***	-0.150***
		(0.027)	(0.0400)	(0.030)	(0.026)
(2)	Post*Exposure	-0.340	0.0422	-0.719	0.107
		(0.549)	(0.0752)	(0.978)	(0.067)
(3)	Post*Exposure*Years Elapsed	-0.868***	-0.0099	-0.592	0.078***
		(0.218)	(0.0279)	(0.702)	(0.021)
(4)	Post*Years Elapsed	-0.245***	0.0990***	0.003	-0.100***
		(0.010)	(0.0145)	(0.015)	(0.011)
(5)	Exposure*Years Elapsed	0.376**	0.0300	0.408	-0.048**
		(0.150)	(0.0244)	(0.304)	(0.019)
(6)	Years Elapsed	0.113***	-0.0256**	0.001	0.104***
		(0.007)	(0.0100)	(0.010)	(0.011)
	Differential Impact in Exposed Areas, relative to t^{*}*-1*				
(7)	Immediate	0.004	0.072	-0.016	0.059
		(.046)	(.062)	(.044)	(.055)
(8)	Medium Run	-0.242***	0.173**	-0.0616	0.212***
		(.078)	(.083)	(.132)	(.052)
	Shock	Dot-Com	Fracking Boom	Financial Crisis	Delaware
	Observations	17,110	6,274	5,705	2,851
	R-squared	0.899	0.7061	0.944	0.927

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table presents coefficients from a regression similar to Table 3, but the dependent variable is Ln(Majors) in the relevant field. Similarly, these regressions include controls for Ln(Total Degrees) rather than Total Degrees.

Appendix Table A8: The Effect of Sectoral Shocks on College Majors, by University's Exposure to the Shock and University Classification

		(1)	(2)	(3)	(4)	(5)	(6)
	Y_{ct}: Share of Majors in	Computer Science and Computer Engineering		Geology		Finance	
(1)	Post	0.001	-0.001	0.0002	0.00003	-0.004***	-0.001*
		(0.002)	(0.001)	(0.0001)	(0.0001)	(0.001)	(0.001)
(2)	Post*Exposure	-0.060	0.028	0.0004	-0.00004	-0.025	-0.071**
		(0.042)	(0.040)	(0.0003)	(0.0002)	(0.039)	(0.036)
(3)	Post*Exposure*Years Elapsed	-0.071***	-0.065***	0.0003**	0.0001	-0.030	-0.012
		(0.020)	(0.016)	(0.0001)	(0.0001)	(0.031)	(0.012)
(4)	Post*Years Elapsed	-0.007***	-0.006***	0.0002***	0.0001***	0.0003	-0.0002
		(0.001)	(0.0005)	(0.0001)	(0.00003)	(0.001)	(0.0003)
(5)	Exposure*Years Elapsed	0.036***	0.029***	0.00005	-0.00001	0.002	0.021**
		(0.012)	(0.009)	(0.0001)	(0.0001)	(0.015)	(0.010)
(6)	Years Elapsed	0.003***	0.003***	-0.00004	0.00004	0.0004	0.00002
		(0.0005)	(0.0003)	-0.00005	(0.00003)	(0.0004)	(0.0002)
	Differential Impact in Exposed Areas, relative to t^*-1						
(7)	Immediate	-0.002	0.006	0.0004	-0.00005	-0.001	-0.003*
		(.004)	(.004)	(.0003)	(.0002)	(.002)	(.001)
(8)	Medium Run	-.02***	-.013**	0.002***	0.0002	-0.008	-0.0003
		(.006)	(.005)	(.0006)	(.0003)	(.006)	(.002)
	Shock	Dot-Com		Fracking Boom		Financial Crisis	
	Universities	Research/ Doctoral	Master's/ Bacc.	Research/ Doctoral	Master's/ Bacc.	Research/ Doctoral	Master's/ Bacc.
	Observations	4,028	18,172	4,034	18,247	2,771	12,518
	R-squared	0.814	0.767	0.7143	0.7788	0.912	0.921

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table presents coefficients from the same specifications as those shown in Table 3, but estimated separately for universities that are classified as research/doctoral and master's/baccalaureate (including Master's, Baccalaureate, and Baccalaureate/Associates Colleges). University classifications are based on the 2000 Carnegie rankings. Standard errors clustered at the university level in parentheses.

Appendix Table A9: The Effect of Sectoral Shocks on Share Sector-Distant Degrees, by University's Exposure to the Shock

	Y_{ct}: Share Sector-Distant Degrees	(1)	(2)	(3)	(4)
(1)	Post	-0.007***	-0.0008	-0.001	-0.009***
		(0.001)	(0.0006)	(0.001)	(0.002)
(2)	Post*Exposure	-0.006	0.0002	-0.038	0.032***
		(0.028)	(0.0009)	(0.046)	(0.012)
(3)	Post*Exposure*Years Elapsed	0.006	0.0009**	0.002	0.002
		(0.012)	(0.0005)	(0.023)	(0.003)
(4)	Post*Years Elapsed	0.005***	-0.0019***	0.002***	-0.012***
		(0.001)	(0.0003)	(0.001)	(0.002)
(5)	Exposure*Years Elapsed	0.012	-0.0008**	0.003	-0.006***
		(0.009)	(0.0003)	(0.015)	(0.002)
(6)	Years Elapsed	-0.003***	0.0015***	0.003***	0.007***
		(0.001)	(0.0002)	(0.0004)	(0.002)
	Differential Impact in Exposed Areas, relative to t^{*}-1				
(7)	Immediate	0.0006	-0.0006	-0.0018	0.026**
		(.003)	(.001)	(.002)	(.011)
(8)	Medium Run	0.001**	-0.0001	-0.0005	0.010
		(.005)	(.001)	(.007)	(.014)
	Shock	Dot-Com	Fracking Boom	Financial Crisis	Delaware
	Observations	22,200	22,281	15,289	3,381
	R-squared	0.923	0.9032	0.913	0.953

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Observations are at the university, year level. Standard errors clustered at the university level in parentheses. Each regression includes university fixed effects. Observations are weighted by total degrees awarded. See notes to Table 3 for definition of variables, sector-distant degrees, years in sample, regression details, and construction of difference-in-difference.