

DISCUSSION PAPER SERIES

IZA DP No. 12614

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## ABSTRACT

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# Industry Fluctuations and College Major Choices: Evidence from an Energy Boom and Bust\*

This paper examines how college students in the United States altered their college major decisions during the energy boom and bust of the 1970s and 1980s. We focus on petroleum engineering and geology, two majors closely related to the energy industry. We find strong evidence that the energy boom increased the prevalence of these two energy-related majors and the energy bust lowered the prevalence of these majors. Effects are particularly strong for young people born in energy intensive states. Thus, college major decisions responded to industry fluctuations with important location-specific effects consistent with frictions to migration and information flows.

**JEL Classification:** I20, J20, J60, R10

**Keywords:** college major, human capital, higher education, energy boom, energy bust

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## 1. Introduction

College students care about a number of factors when choosing their major field of study, but their employment and earning prospects are especially important factors for many (Freeman and Hirsch 2008; Arcidiacono et al. 2012; Altonji et al. 2015; Long et al. 2015). An individual's college major is significantly related to job prospects and earning potential in the labor market (Webber 2014, 2016; Kirkeboen et al. 2016). At the same time, information is imperfect, especially about the future prospects that a given college major would offer (Arcidiacono et al. 2016). Students form expectations about the future, but fluctuations in the demand and supply for various majors are often difficult to predict. Furthermore, some industries are especially volatile. The energy industry is particularly volatile, due to significant fluctuations in energy prices and production technologies. The energy industry also needs many graduates with very specialized skills in science and engineering, and some college majors are strongly tied to the energy industry. During good times, the energy industry is a high-paying industry for college graduates with related skills. During bad times, college graduates with energy related majors likely find it more difficult to find a job using their skills and may end up unemployed or taking a job in a less related field. An important question is whether and how students respond to energy industry fluctuations by altering their college majors. We address this question in this paper using microdata from the American Community Survey (ACS).

The 1970s were a turbulent economic period in the United States, with the nation experiencing high inflation, high unemployment levels, and stagnant economic growth (Barsky and Kilian 2004). These problems aligned with spikes in global oil prices due to supply

restrictions coordinated by the Organization for Petroleum Exporting Countries (OPEC).<sup>1</sup>

However, economic difficulties were not equally spread across the US. The nation was a net importer of oil, but the US did produce much of the oil it consumed. Domestic oil production in the US was concentrated in a few states with extractable oil reserves, and rising global oil prices stimulated domestic oil production in these areas (Kumar 2017). Rising oil prices also increased prices for coal, natural gas, and other energy sources (Black et al. 2005). US energy employment boomed during the 1970s and early 1980s, and this likely increased the demand for college graduates with skills related to energy resource extraction, especially in oil rich states.

The US oil boom did not last forever. Domestic oil production peaked in many parts of the country during the early 1980s and then began to decline. Disagreements among OPEC members led to breakdowns in their collusion, leading to increased global oil supply and falling oil prices. The oil bust of the 1980s reduced US energy production and the US energy industry's demand for labor (Kumar 2017).

The energy boom of the 1970s and the energy bust of the 1980s likely affected the desirability of investing in higher education skills related to the energy industry. We expect that the energy boom would lead to higher wages and better overall employment prospects for energy related majors than prior to the boom, which would lead to more young people choosing energy related majors during the boom, especially in energy rich states. Correspondingly, we expect that the energy bust would result in worsened prospects for energy related majors relative to the boom period and lead many young people to shift away from energy related majors. While these hypotheses have strong intuitive appeal, we know of no prior research that rigorously examines

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<sup>1</sup> Barsky and Kilian (2004) question the conventional wisdom regarding the quantitative importance of oil price shocks for the macroeconomy.

the effects of the energy boom and bust during the 1970s and 1980s on college major decisions.<sup>2</sup> Thus, we intend to fill an important gap in the research literature.

In this study, we examine the effects of the 1970s and 1980s energy boom and bust on the college major choices of college graduates who were likely making college major decisions around this time. We first present illustrative data showing changes over time across cohorts. We focus on two college majors, petroleum engineering and geology.<sup>3</sup> These college majors are strongly related to the energy industry, especially in energy producing states. This analysis indicates sizable changes in the popularity of these majors consistent with our expectations. Specifically, we observe increased rates of majoring in petroleum engineering and geology during the energy boom compared to the pre-boom period. We also observe steep decreases in petroleum engineering and geology majors during the energy bust relative to the energy boom period.

We examine spatial heterogeneity in effects based on the state in which individuals were born. The ACS data do not tell us where an individual went to high school or college, but the state of birth is highly correlated with these and has been used as a proxy in previous literature (Dynarski 2008; Malamud and Wozniak 2012; Orrenius and Zavodny 2015; Sjoquist and Winters 2014, 2015a). State of birth is a useful proxy for our purposes because it is determined long before later economic fluctuations during high school and college that could cause

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<sup>2</sup> After completing our initial draft, we learned that Weinstein's (2019) revised working paper of Weinstein (2017) looks at the effects of the post-2000 energy boom on geology majors using institutional data from the Integrated Postsecondary Education Data System (IPEDS). Our approach is different from Weinstein (2019) in a number of ways that make our studies complementary. We examine an earlier time period and different data sources. We are able to examine effects of an energy bust and not just a boom. We look at both geology and petroleum engineering. We classify individuals based on state of birth. IPEDS degree data do not provide student state of origin, so in-migrants are combined with in-state residents. A relative advantage of the IPEDS data used by Weinstein (2019) is the ability to precisely identify the location of the institution within states. Weinstein (2019) also looks at different shocks to other majors.

<sup>3</sup> We construct the geology major as a combination of three closely related detailed majors in the ACS: geology and earth science, geosciences, and geological and geophysical engineering.

individual location decisions to be endogenously chosen. Students born in energy states are expected to be more strongly affected by energy booms and busts in their college major decisions than students living far away from potential energy jobs. Many students' preferences and expectations for future employment fields may be affected by their current and previous residential locations and location-specific shocks (Orrenius and Zavodny 2015; Ransom and Winters 2019; Weinstein 2019). Students born in energy states may be especially responsive to energy shocks because the energy industry might be a more attractive option and they may have more information about the opportunities available.

To examine geographically disparate effects of energy shocks on college majors, we classify states as either energy states or non-energy states. We conduct a difference-in-differences (DD) analysis that exploits both temporal and spatial differences. As expected, we find that college graduates born in energy states are especially strongly affected by energy shocks in their choice of college major. We note that our DD analysis has some limitations with measurement error in specifying the timing and spatial precision of treatment, so our DD estimates should likely not be interpreted as unbiased causal estimates. However, we argue that the DD approach is likely to attenuate effects toward zero while still providing directionally consistent estimates. Thus, the DD estimates likely underestimate the true effect. Furthermore, the DD effects are qualitatively robust to numerous reasonable alternatives. We also explore the timing of effects via an event-study style analysis. Interestingly, we find that prospective geology majors respond to energy booms and busts more quickly than petroleum engineering majors.

Given the limited previous literature related to this topic, our analysis makes an important contribution to understanding how students make college major decisions in response to

industry-specific shocks. We also contribute to a small literature indicating that college major decisions have an important location-specific element. That is, college major decisions do not just depend on national industry conditions. They strongly depend on local industry conditions because of frictions slowing the flow of people and information across space. These are important insights for understanding human capital investments related to the energy industry, but there are also broader implications for other industries that are geographically localized and require specialized human capital.

## **2. Conceptual Background**

Students interested in higher education face a number of choices including whether to go, when to go, where to go, and what field to study. These choices can have substantial consequences for labor market and other life outcomes (Altonji et al. 2012; Webber 2014, 2016). Economists typically view individual educational decisions as human capital investments with costs and benefits accrued at different times. The costs include tuition and fees, foregone wages, and disutility of effort. The benefits relate to future employment prospects, social status, and the enjoyment that comes from learning interesting and empowering things. The exact costs and benefits of various potential educational investments are uncertain, but individuals form expectations about these based on available information. Rational individuals choose the educational path that offers them the highest expected discounted lifetime utility, but individuals differ in their preferences, endowments, and expectations, so educational choices differ across individuals.

The choice of major field of study is an especially important decision. Prior research indicates that college major completed can have significant effects on wages and income (Altonji

et al. 2015). Many young people are very interested in the employment prospects and potential earnings various majors offer (Blom et al. 2015; Wiswall and Zafar 2015a, b; Ersoy 2018). However, they also care about whether a college major is fun, interesting, and acceptable to parents and peers (Zafar 2011, 2013; Zhan 2015; Liu et al. 2018). They are also discouraged by majors perceived as very difficult with low probabilities of completion. Of course, there are tradeoffs, and some students choose a major that suits them well in some dimensions but less so in others. For example, science and engineering majors often have good employment prospects but are very time-intensive and difficult to complete, leading to high attrition rates (Griffith 2010; Ost 2010; Price 2010; Sjoquist and Winters 2015b; Arcidiacono et al. 2016).

This paper examines individual college major choices for science and engineering majors related to the energy industry. Specifically, we focus on petroleum engineering and geology, the two majors most connected to the energy industry. These majors tend to be financially lucrative for workers employed in the energy industry, but the energy industry is notoriously volatile due to external factors, making energy related majors potentially risky investments. College graduates with energy related majors who enter the labor market during an energy bust will have a hard time finding a job in the energy industry and may have to eventually settle for a less desirable initial job in another industry. Furthermore, aggregate conditions at the time of labor market entry can have persistent effects (Kahn 2010; Oreopoulos et al. 2012; Brunner and Kuhn 2014; Altonji et al. 2016). Graduates entering the workforce during an economic downturn can suffer initially, and the initial wounds can have scarring effects that last for decades.

Young people are potentially sensitive to the fluctuations of turbulent industries like energy when making college major decisions. Some students may be attracted to energy related majors when they expect strong prospects upon graduation but deterred when they expect weaker

energy industry conditions. Of course, young people must start their major before they know what industry conditions will be like upon graduation. Students interested in energy related majors will form expectations based on current and past industry conditions, and these might change abruptly based on sharp changes in energy markets. Picking an energy related major at a bad time may be very costly, and early signs of energy downturns may prompt sharp responses among potential majors, even for those who have already started an energy related major and can switch to another major with some cost.

We also expect the choice of an energy related major to depend on a young person's location history and preferences. While some workers are willing to move across the country for a job, many graduates desire to stay in a familiar area and may choose a major that they think can help them obtain a good job in a place they want to live. Because US energy employment is concentrated in a few states, energy related majors should likely expect a high probability of residing in an energy state if they want to work in the energy industry. Individuals have heterogeneous preferences for different locations, and this may depend on their prior location experiences (Winters 2019). Persons with prior exposure to energy states may highly value the opportunity to live in an energy state, making them more interested in energy majors and more sensitive to energy industry conditions in choosing a college major. Even among individuals with minimal location preferences, past or current residence in an energy state may increase familiarity with the industry and make it a more salient option. Finally, some college majors are unavailable at many colleges and universities. For example, in 1980 only 15 states had any college or university with a bachelor's degree field in petroleum engineering. While any high school graduate could choose an out-of-state college or university based on the availability of a specific major, tuition differentials between in-state and out-of-state students at public

institutions and the financial and psychological costs of moving long distances from home make petroleum engineering a more viable major for students from states with it as an in-state option. Because we cannot observe an individual's full migration history, we cannot offer strong evidence on very specific mechanisms, but we do believe that frictions to the flow of people and information are important. Thus, we expect spatially heterogeneous effects in the responsiveness of choosing energy related majors to energy shocks.

Our study also relates to previous literature examining the effects of energy industry conditions on the amount of education completed. In particular, regional energy booms have been found to reduce the average years of schooling for individuals in energy-rich areas (Black et al. 2005; Cascio and Narayan 2015; Kumar 2017; Rickman et al. 2017).<sup>4</sup> Local energy booms appear to increase the opportunity cost of education because a young person can drop out of school and take a lucrative job in the energy industry without high levels of formal education. This higher opportunity cost during energy booms can reduce high school completion, college attendance, and college completion, especially among young people at the margins of completing more education vs. working in the energy industry. Of course, some young people are infra-marginal. Some would never go to college, and others would attend and graduate college even if the opportunity cost were substantially higher. Our analysis focuses on people who graduate college and examines the extent to which they alter their college majors in response to energy booms and busts. This complements previous literature on the effects of energy industry conditions on the years of schooling completed but also explores new questions that are

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<sup>4</sup> Some researchers suggest that the longer run effects on educational attainment are less negative than the short run effects (Emery et al. 2012). This suggests that energy booms may alter the timing of formal schooling, with many dropouts returning to school after an energy boom ends.

important for the energy industry and have implications for college major investments more broadly.

### **3. Data**

The primary data for our analysis are from the American Community Survey (ACS) and obtained via IPUMS (Ruggles et al. 2019).<sup>5</sup> The ACS is an annual survey of one percent of the US population that collects individual information on demographics, education, income, employment, and other characteristics. Our summary statistics and regression analyses use individual survey weights provided in the ACS. We pool the 2009-2017 years of the ACS to form a larger sample to increase estimate precision. The ACS first collected information on college major in 2009 and continued to do so in each year up to 2017, the most recent year of data available at the time of our analysis. The college major question asks individuals with a bachelor's degree or higher to report their major field of study for their bachelor's degree. The ACS does not ask about field of study for graduate degrees or for persons not completing a bachelor's degree.

The ACS does not provide information on where a person went to high school or college. Following previous literature, we proxy for these based on state of birth (Dynarski 2008; Malamud and Wozniak 2012; Orrenius and Zavodny 2015; Sjoquist and Winters 2014, 2015a). Sjoquist and Winters (2014) find that more than three-fourths of high-school attendees reside in their birth-state, so we view state of birth as a good though imperfect proxy.

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<sup>5</sup> Our analysis also utilizes data from the 1980 decennial census 5% PUMS, also obtained from IPUMS, in order to classify states as energy states and non-energy states as discussed below.

Our main analytic sample is restricted to persons with a bachelor’s degree or higher and born in the US. Our main results further limit the sample to graduates whose major field of study was in science, technology, engineering, and mathematics (STEM), so that we are capturing movements between energy majors and other STEM fields. However, we also estimate regressions that expand the sample to all individuals regardless of education level or broad college major. We also limit our sample based on the year an individual reached age 18, based on the assumption that initial college major decisions were typically made around age 18. Our full sample includes persons whose year age 18 is between 1960 and 2000, but our main analysis focuses on a narrower range of cohorts.

#### 4. Methods and Models

Following previous literature, we estimate linear probability models (LPM) with a difference-in-differences (DID) framework. The main regression models follow specifications below:

$$EnergyMajor_{ist} = \beta After_t + \gamma EnergyState_s + \delta After_t \times EnergyState_s + \theta X_{ist} + u_{ist} \quad (1)$$

$$EnergyMajor_{ist} = \delta After_t \times EnergyState_s + \theta X_{ist} + \pi_s + \tau_t + u_{ist} \quad (2)$$

$$EnergyMajor_{ist} = \delta After_t \times EnergyState_s + \theta X_{ist} + \pi_s + \varphi_{st} + u_{ist} \quad (3)$$

In equation (1),  $EnergyMajor_{ist}$  is a dummy dependent variable for a specific energy major of interest; we separately examine majors in petroleum engineering and geology.  $After_t$

is a dummy variable to indicate either an energy boom or energy bust, depending on the model; we construct this binary variable to classify individuals as being exposed to a specific energy shock period based on the year they reached age 18. Specifically, we define an individual as exposed to an energy boom if they reached age 18 during 1972-1981. Similarly, an individual is exposed to an energy bust if they reached age 18 in years 1982-1991.<sup>6</sup>  $EnergyState_s$  is a dummy that defines energy states based on an individual's state of birth. We use 1980 census data to calculate the oil and gas industry share of total employment in each state; six states, Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming, had more than two percent of their total employment in the oil and gas industry. We define these six states as energy states for our main analysis. In robustness checks, we modify the threshold for energy states and show the results are qualitatively robust.  $\delta$  is the DID estimator capturing the effect of the interaction between  $After_t$  and  $EnergyState_s$ . It estimates the effect of the treatment (energy boom or bust) on the treated group (energy states) while netting out permanent differences via the  $EnergyState_s$  dummy and the time change in the dependent variable experienced in non-energy states via the  $After_t$  dummy.  $X_{ist}$  is a set of control variables including dummies for sex and race.

In addition, three categories of fixed effects are included in alternative specifications. In equation (2),  $\pi_s$  is a set of birth-state fixed effects, which captures time-invariant differences across birth states. Their inclusion controls for long-run differences across birth-states.  $\tau_t$  is a set of year-age-18 fixed effects, which captures time-variant nationwide factors unique to each year-age-18 cohort. In equation (3), in addition to  $\pi_s$ , the birth-state fixed effects, we include a

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<sup>6</sup> In robustness checks, we change the definitions of the energy boom and bust periods to alternative years.

full set of census birth-region $\times$ year-age-18 fixed effects,  $\varphi_{st}$ .<sup>7</sup> The  $\varphi_{st}$  amount to a set of year-age-18 cohort fixed effects for each region-of-birth, which means that identifying variation comes from variation across cohorts born in the same region and year (while netting out birth-state fixed effects). Region-wide shocks are absorbed by these fixed effects. Notice that the detailed sets of fixed effects in equations (2) and (3) are perfectly collinear with the singular dummy variables  $After_t$  and  $EnergyState_s$  in equation (1), so these are excluded from equations (2) and (3). However, the interaction term,  $After_t * EnergyState_s$ , is still included and its coefficient,  $\delta$ , gives the DID estimator.

The model in equation (3) is our preferred specification, but we also report results for equations (1) and (2) as robustness checks. Equation (1) is also useful for assessing long-run differences between energy states and non-energy states and for examining temporal changes in non-energy states corresponding to energy boom and energy bust periods.

Providing unbiased causal estimates via DID requires several identifying conditions. First, the DID estimator assumes that the treatment group (energy states) and the control group (non-energy states) are on parallel trends prior to the treatment and would have continued on parallel trends in the absence of treatment. We offer evidence on this later. Second, the DID estimator assumes that the control group receives no treatment. However, this is violated if persons from non-energy states altered their college majors in response to national energy booms or busts. This is likely to occur in part because our discrete classification of energy and non-energy states hides the fact that there is some moderate energy production in non-energy states. It also may occur if persons from non-energy states respond to energy industry shocks by altering plans to migrate to energy states to work in the energy industry. Third, an unbiased DID

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<sup>7</sup> The four US Census regions are the Northeast, Midwest, South, and West.

estimate requires year age 18 to accurately measure the timing of treatment, so that cohorts age 18 before the energy boom (or bust) are unaffected by the relevant treatment. This can be violated if some people made college major decisions at an age other than 18 around the time the treatment began. It is also violated if we misspecify the timing of the treatment, which is quite possible with energy shock effects on education decisions because industry changes are not always sharp and it may take time for young people to update their information.

Difficulty in specifying the timing and spatial scope of treatment is unavoidable, and we cannot be confident that the DID estimator provides unbiased causal estimates for our setting. However, we argue that the primary issue is that treatment is measured with error. Some of the measurement error is likely random and will thus tend to attenuate coefficient estimates toward zero. Additionally, some measurement error likely results because non-energy states receive some treatment, while the DID assumes they receive zero treatment. This measurement error is not random, but it is likely to attenuate the DID coefficient toward zero because the DID estimator essentially subtracts out the pre- and post-treatment period difference in the control states from the pre- and post-treatment period difference in the treatment states. In other words, differencing out an actual treatment effect for the control group will cause the DID estimator to understate the treatment effect for the treatment group. Thus, measurement error prevents DID from providing unbiased estimates, but the estimates should be directionally consistent. That is, the true effect is likely larger than what the DID coefficient estimate will suggest.

Inferences in DID estimation are also complicated when the number of treatment groups is small. Our main estimates use six treatment states. We report clustered standard errors and results from two alternative inferences procedures suggested by Cameron et al. (2008) and Ferman and Pinto (2019). Cameron et al. (2008) suggest a wild cluster bootstrap procedure for

DID applications with few groups; we implement their procedure using the Stata `boottest` program developed by Roodman et al. (2019) to obtain p-values for our DID coefficient estimates. Ferman and Pinto (2019) develop an alternative inference method for DID with few treated groups and heteroskedastic errors, e.g., due to differing group sizes; we apply their procedure also to obtain p-values for our DID coefficient estimates.

## **5. Empirical Evidence**

### **5.1 Descriptive Evidence**

Before proceeding to regression results, we first present some descriptive evidence. Figure 1 shows the trend in real oil prices during our time period. Oil prices abruptly increased in 1973 and again in 1979 due to OPEC supply restrictions. However, signs of an oil glut emerged and prices started falling in 1982. Figure 2 shows real oil and gas GDP per capita separately for energy states and non-energy states. Energy prices altered oil and gas production values and provided sizable economic shocks to oil and gas states. These shocks likely altered the desirability of energy-related majors, especially in energy states.

Figure 3 illustrates the time trend across cohorts for petroleum engineering majors as a percentage of all STEM majors separately for energy states and non-energy states. Petroleum engineering is a relatively small major, which likely drives some of the year-to-year volatility in the figure. However, the overall pattern is clear. There was an increase in petroleum engineering majors in energy states during the 1970s and a sharp drop during the 1980s. The increase was from less than one percent during the 1960s to more than two percent during the late 1970s and early 1980s. The share fell below one percent in the mid-1980s and remained below one percent for the rest of the period. There is also evidence of a corresponding boom and

bust for petroleum engineering majors from non-energy states, but it is much smaller in magnitude.

Figure 4 provides a similar illustration for geology majors as a share of all STEM majors separately for energy and non-energy states. The pattern is similar to petroleum engineering majors, but there are a few things to note. First, the share of geology majors during most of the 1960s was similar between energy states and non-energy states. Second, the geology peak in energy states occurred in 1978, three years earlier than for petroleum engineering. Third, the share of geology majors was similar in energy and non-energy states during the late 1980s and 1990s.

Table 1 reports sub-sample means for the petroleum engineering and geology dummy dependent variables separately by treatment period for energy states and non-energy states. The treatment periods are based on year age 18 and divided into three groups: 1962-1971, 1972-1981, and 1982-1991. The first period is considered the pre-treatment, the second period is the energy boom, and the third is the energy bust. Table 1 also reports the differences over time for both energy and non-energy states, the differences between state groups for each time period, and the difference-in-differences (DID) estimates based on sub-sample means. A few things warrant emphasis. First, the shares of petroleum engineering and geology majors are higher in energy states than non-energy states in all three periods, but the difference for geology majors is trivially small for 1982-1991. Second, the shares of petroleum engineering and geology majors increased between the pre-boom and boom periods for both groups of states and then fell between the boom and bust periods for both groups of states. Third, the magnitudes of time changes were much larger for energy states, so that the DID estimates in the bottom right corner are positive during the boom and negative during the bust.

## 5.2 Main DID Regression Results

Table 2 presents petroleum engineering DID regression results for the three specifications. Panel A examines the effect of the energy boom relative to the pre-boom period. The coefficient on the Energy Boom\*Energy State interaction term gives the DID estimate. It is positive and statistically significant in all three columns with very similar magnitudes across the columns that are also similar to the corresponding simple DID estimate in Table 1.<sup>8</sup> Column 3 is the preferred specification and yields a coefficient of 0.0085, which is 93 percent of the pre-boom mean in energy states. This supports our hypothesis that the energy boom increased the likelihood that students from energy states completed bachelor's degrees in petroleum engineering.

Column 1 in Panel A also provides further insights. First, the significant positive coefficient on the Energy State dummy indicates that persons born in energy states and age 18 during the pre-boom period were also more likely to major in petroleum engineering than their pre-boom counterparts born in non-energy states. Additionally, the significant positive coefficient on the Energy Boom period dummy indicates that students in the non-energy states exhibited an increased likelihood of completing degrees in petroleum engineering between the pre-boom and boom periods. If this increase for non-energy states is due to the energy shock and not unrelated factors, then the DID estimates will understate the total effect of the energy boom in energy states.

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<sup>8</sup> The three inference procedures give similar results in Table 2 and most of the remaining tables. The Ferman and Pinto method is not applicable (N/A) for our Column 1 specifications that exclude birth state fixed effects and year-age-18 fixed effects.

Panel B examines the effect of the energy bust relative to the energy boom period. The Energy Bust\*Energy State interaction term gives the DID estimate. It is negative and statistically significant in all three columns with very similar magnitudes. The estimated DID effect of the bust is also larger than the DID effect of the boom, and the magnitude corresponds to 119 percent of the pre-boom mean in energy states. Thus, the energy bust reduced the prevalence of petroleum engineering majors and more than wiped out the increase during the boom. Column 1 in Panel B also shows a significant positive coefficient for the Energy State dummy and a significant negative coefficient for the Energy Bust period dummy. The latter suggests that persons born in non-energy states were also partially treated by the bust and shifted away from petroleum engineering in response.

Table 3 reports DID regression results for geology. The overall patterns are the same as for petroleum engineering. The interaction term estimates are significantly positive for the boom and significantly negative for the bust.<sup>9</sup> The positive interaction effect of 0.0091 in Column 3 of Panel A corresponds to about 27 percent of the pre-boom mean in energy states. The negative interaction effect of -0.0152 in Column 3 of Panel B is larger than the positive interaction effect and corresponds to 45 percent of the pre-boom mean in energy states. The uninteracted boom and bust terms in Column 1 are also significantly positive and negative, respectively, again suggesting treatment of the control group. One notable difference for geology is that the uninteracted bust effect of -0.0131 is quite large in magnitude. Significant effects on the non-energy states again imply that DID estimates may understate the true effect in energy states.

### **5.3 Additional Analysis**

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<sup>9</sup> The wild cluster bootstrap p-values in Columns 1 and 2 of Panel A exceed 0.05 but are still below 0.10.

We next provide additional analysis intended to gauge the sensitivity of the qualitative results to alternative specifications. Table 4 expands the sample from only STEM graduates to all persons regardless of education level and type, though still restricting the sample to individuals born in the US and the year-age-18 criteria. For brevity, we just report the equation (3) specification, which includes the full set of fixed effects. Because we are adding non-STEM graduates and non-bachelor's degree graduates to the sample, the absolute magnitudes of coefficients shrink. Petroleum engineering and geology are both STEM majors, so adding non-STEM graduates and non-bachelor's graduates to the sample adds only individuals with zeros for the dependent variables and substantially lowers the sample means. Thus, we present absolute magnitudes and also scaled results for which the dependent variables are divided by the pre-boom means in energy states. In Panel A, the interaction term has coefficients of 0.00046 and 0.00047 for petroleum engineering and geology majors, respectively. The scaled results indicate that this is 99 percent of the pre-boom mean in energy states for petroleum engineering and 27 percent of the pre-boom mean in energy states for geology. In Panel B, the interaction term has significant negative coefficients of -0.00056 and -0.00084 for petroleum engineering and geology majors, respectively. The scaled results report that these magnitudes are 120 percent and 49 percent of the pre-boom means in energy states for petroleum engineering and geology, respectively. These relative magnitudes for Table 4 are quite comparable to corresponding relative magnitudes in Tables 2 and 3. Thus, limiting the main sample to STEM graduates is not distorting the main conclusions. The rest of the results in this paper use the STEM graduates sample unless stated otherwise.

Table 5 examines an alternative measure of treatment. Instead of using a binary variable to divide states into energy and non-energy states, Table 5 employs a continuous treatment

measure based on the 1980 energy share in the state. More specifically, we compute the 1980 share of oil and gas employment relative to total employment in each state and interact that with an Energy Boom dummy variable in Panel A. We interact the continuous treatment measure with the Energy Bust dummy in Panel B. Results in Table 5 include the full set of fixed effects similar to Column 3 in Tables 2 and 3. Every state with positive oil and gas employment is now assigned a treatment with the “dosage” increasing with the energy share of employment in 1980. The coefficient magnitudes in Table 5 are not directly comparable to previous tables, but the qualitative implications are very similar. The increased prevalence of petroleum engineering and geology majors during the energy boom period is increasing with the energy share; i.e., states with higher shares of oil and gas employment in 1980 experienced larger increases in both of these energy majors. Similarly, the decreased prevalence of both energy majors during the bust was higher in states with higher oil and gas employment shares in 1980. While this is not the preferred approach, it is reassuring that the results are qualitatively robust to this alternative.<sup>10</sup>

One limitation of our DID analysis is that we cannot precisely identify the timing of the treatment. Young people make college major decisions at various ages, but we do not observe when individuals entered college, chose their major, changed their major, or completed college. It is also unclear how quickly students making college major decisions update their expectations in response to industry fluctuations. Table 6 provides an alternative approach to the simple DID regressions in which we group year-age-18 cohorts into four-year intervals and interact dummies for these intervals with the Energy State dummy. We limit the sample for this analysis to cohorts

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<sup>10</sup> In Appendix Table results, we also show that the main DID results are qualitatively robust to altering the group of energy states by changing the threshold for energy state classification to one percent or three percent of employment. Similarly, we also confirm in results not shown that the main results are qualitatively robust to excluding states with moderate oil and gas employment (between one and two percent in 1980) from the control group. We also estimated separate effects for the moderate oil and gas states and found them to be in the same direction as the main effects but smaller in magnitude as expected given the weaker treatment dosage.

age 18 in 1962-1995, and we make 1962-1971 the pre-treatment time period. We include birth-state fixed effects and birth-region×year-age-18 fixed effects. The interaction terms provide treatment effect estimates for changes over time relative to 1962-1971 in energy states relative to non-energy states. Table 6 indicates that the effect timing differed significantly for petroleum engineering and geology. The 1972-1975 interaction term is significantly positive for geology, but the coefficient for petroleum engineering is relatively small and not significant at conventional levels using two of the three inference methods. The 1976-1979 interaction term is significantly positive for both energy majors. The 1980-1983 interaction term is significantly positive for petroleum engineering but not for geology. The remaining interaction term coefficients are consistently negative for both petroleum engineering and geology; these negative effects are always significant for petroleum engineering but only marginally significant for geology during 1988-1991 and 1992-1995. Thus, the difference in timing is that geology majors responded more quickly to changing conditions than petroleum engineering.

We also estimated similar regressions using single cohort-year dummy interactions with the Energy State dummy. Results are presented in Figure 5 with the interaction term coefficients indicated as dots and confidence intervals based on clustered standard errors illustrated with lines around the dots. The sample is again cohorts age 18 in 1962-1995, and we again make 1962-1971 the pre-treatment time period. Birth-state fixed effects and birth-region×year-age-18 fixed effects are again included. Year-to-year variations are often noisy, and single-year aberrations are difficult to interpret. Still, the basic patterns are notable. For petroleum engineering, the first meaningful positive effect is observed for the 1974 year-age-18 cohort, but we see a large and significant positive effect for geology for the 1972 year-age-18 cohort. The coefficients for petroleum engineering stayed positive until the 1983 cohort, but the effects for geology became

much smaller by the 1981 cohort. Again, year-to-year noise hinders precise timing, but Figure 5 provides suggestive evidence that decisions to major in geology changed more quickly than decisions to major in petroleum engineering.

The quicker responsiveness for geology relative to petroleum engineering likely results from some combination of curriculum flexibility and supply elasticity. Petroleum engineering is typically a very structured program and it is not available at most colleges and universities in the US. Students starting out in other STEM fields or at institutions not offering petroleum engineering cannot easily switch into petroleum engineering as upper classmen. Similarly, some petroleum engineering programs may be slow to expand capacity when student demand increases. While geology has curriculum structure too, it is generally easier to switch into geology after starting coursework in a related STEM field. Geology major programs are also more widely available across colleges and universities, allowing a change of major without having to change one's college or university.

## **6. Conclusion**

College major fields of study have important consequences for individuals, employers, and aggregate economies. Many employers need workers with specialized skills acquired from closely related college majors. However, there are also some risks to students who invest in very specific skills that are tied to a specific industry. These risks are amplified if the related industry has highly variable labor demand. Such is the case for the energy industry. The energy industry needs some workers with very specialized skills in science and engineering, but the energy industry is especially volatile. The US energy industry experienced a boom in the 1970s and a

bust in the 1980s with sizable effects on state and local areas with energy resources that greatly altered the demand for energy related skills.

This paper examines the effect of the energy boom and bust of the 1970s and 1980s on the college major choices of college graduates who were traditional college age during these shocks. Consistent with expectations, we find strong evidence that the energy boom encouraged more young people to choose energy related majors in petroleum engineering and geology, and the effects are especially concentrated among young people born in energy states. Similarly, we find that the energy bust substantially and sharply reduced the likelihood of young people majoring in energy related fields. Our main results are qualitatively robust to a number of alternatives. We also find evidence that decisions to major in geology respond more quickly to energy shocks than decisions to major in petroleum engineering.

Our results strongly indicate that young people respond to industry-specific employment conditions when making college major decisions. This is an intuitive result with strong implications for the energy industry, but it also has implications for other industries with similar labor conditions. We also emphasize that the energy boom and bust effects we find for petroleum engineering and geology majors are strongly concentrated among graduates born in energy states. This indicates an important location-specific element to college major decisions. Young people do not just make college major decisions based on national-level factors. There appear to be frictions in the flow of people and information that make college students particularly sensitive to local economic conditions. These findings increase understanding of how young people make college major decisions.

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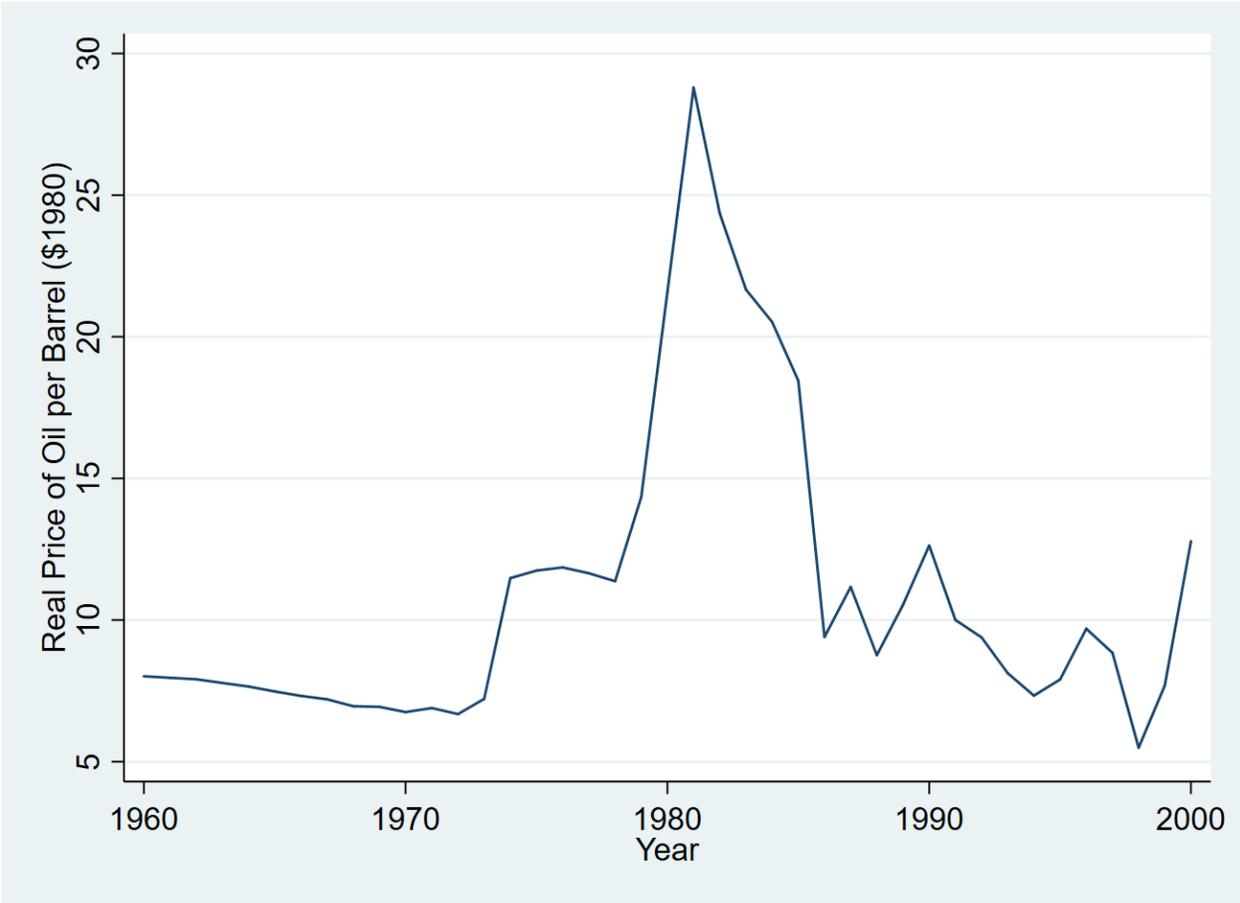
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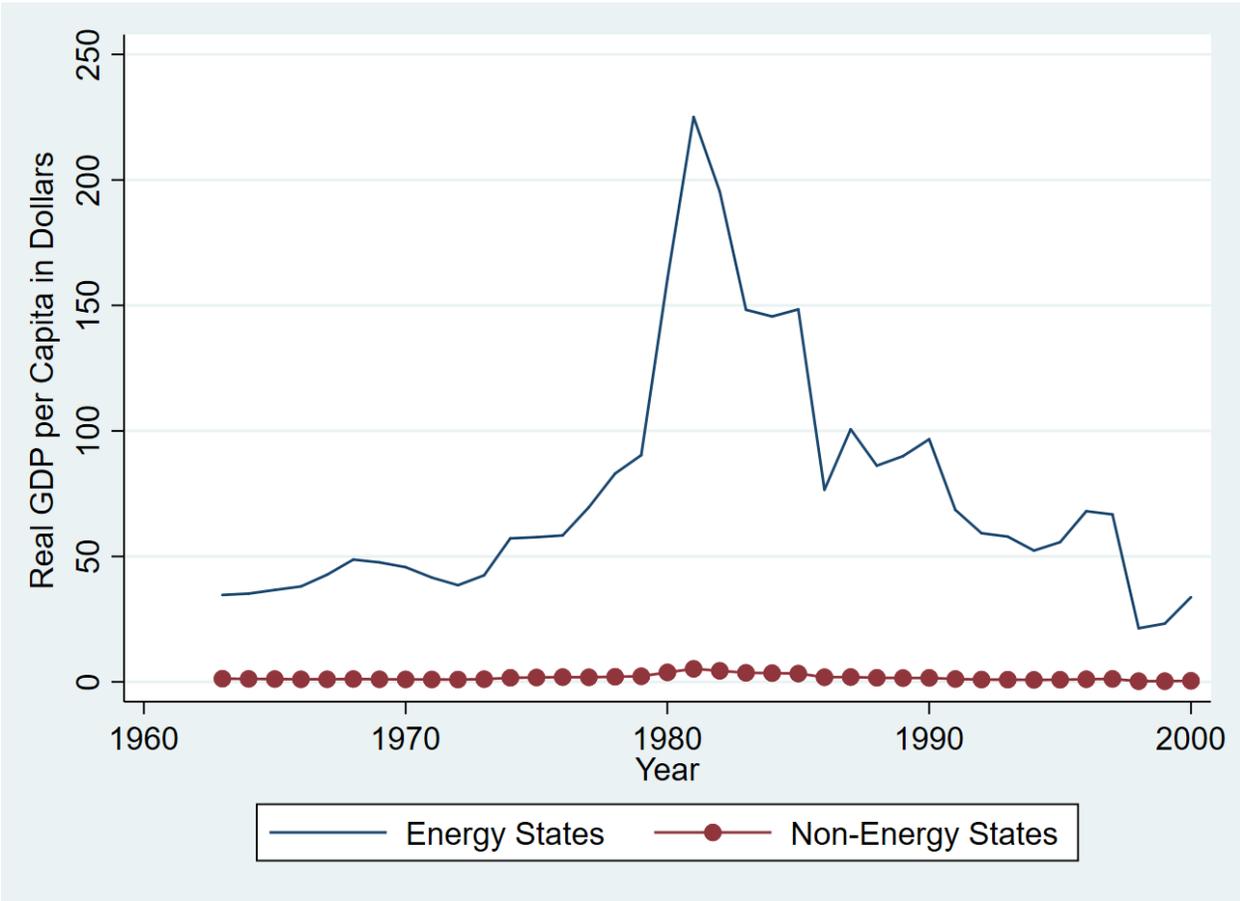
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**Figure 1: Real Price of Oil per Barrel (\$1980)**



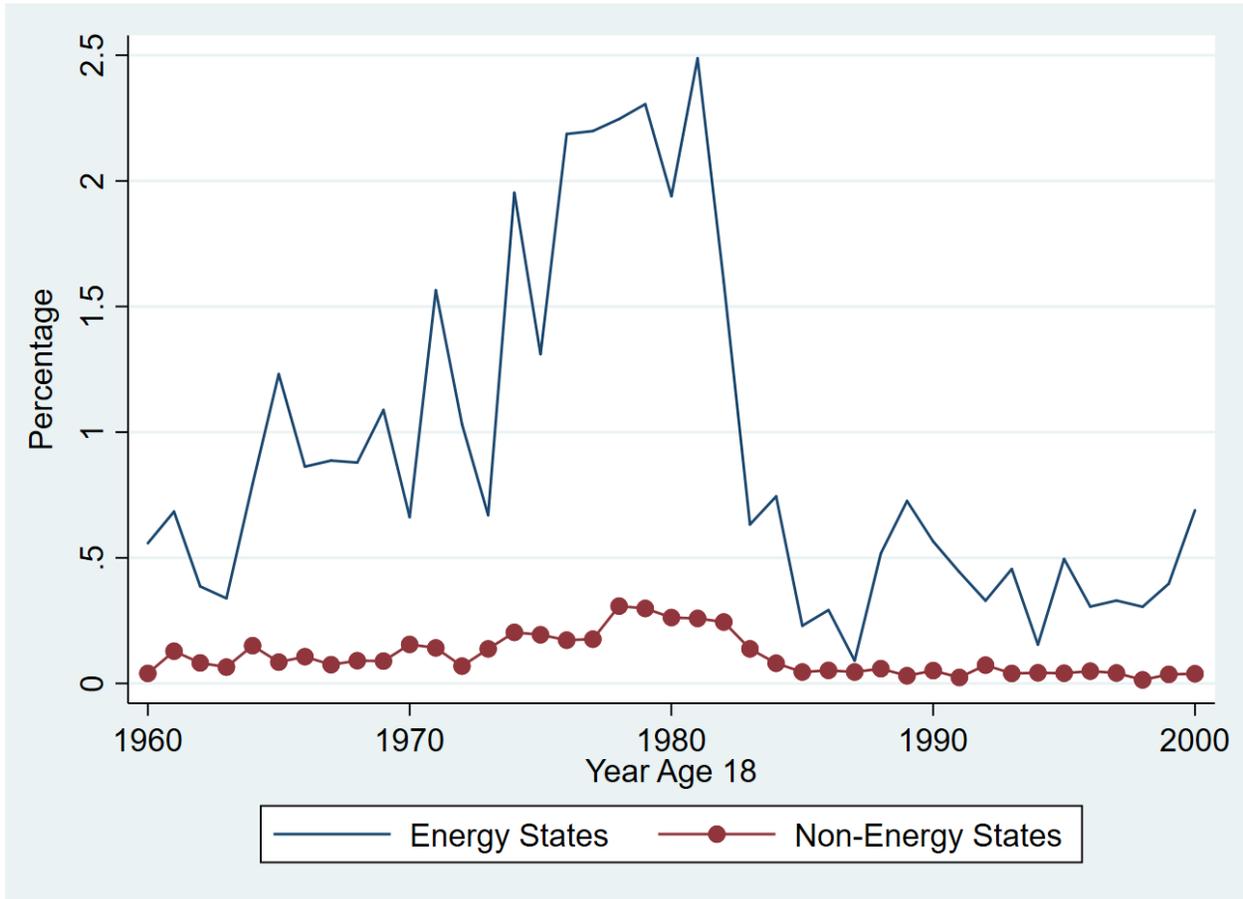
Source: US Energy Information Administration

**Figure 2: Real Oil & Gas GDP per Capita for Energy States and Non-Energy States**



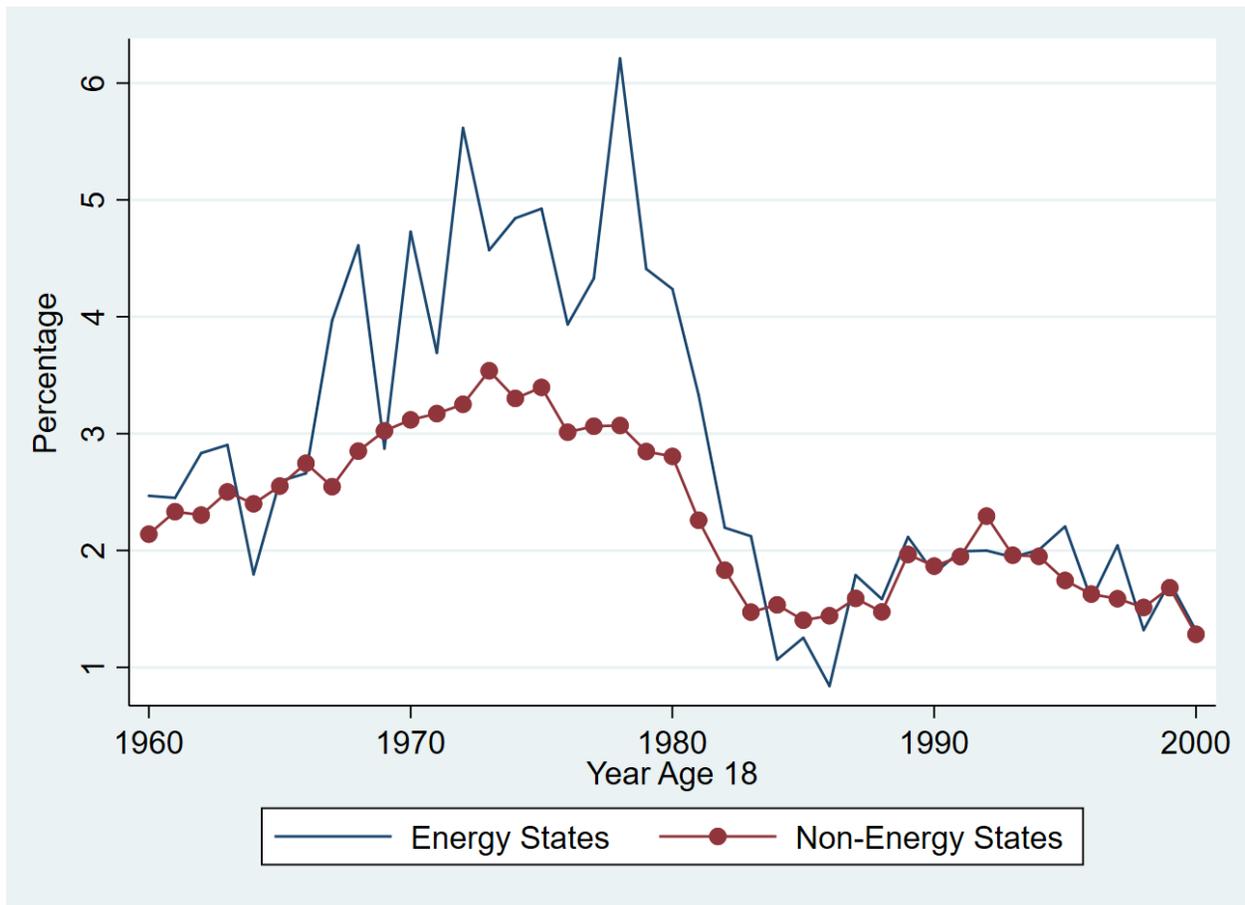
*Source:* Author computations based on data from the US Bureau of Economic Analysis. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming, and are defined as those with oil and gas industry employment more than 2% of total employment in 1980.

**Figure 3: Petroleum Engineering Percentage of STEM Majors for Energy and Non-Energy States**



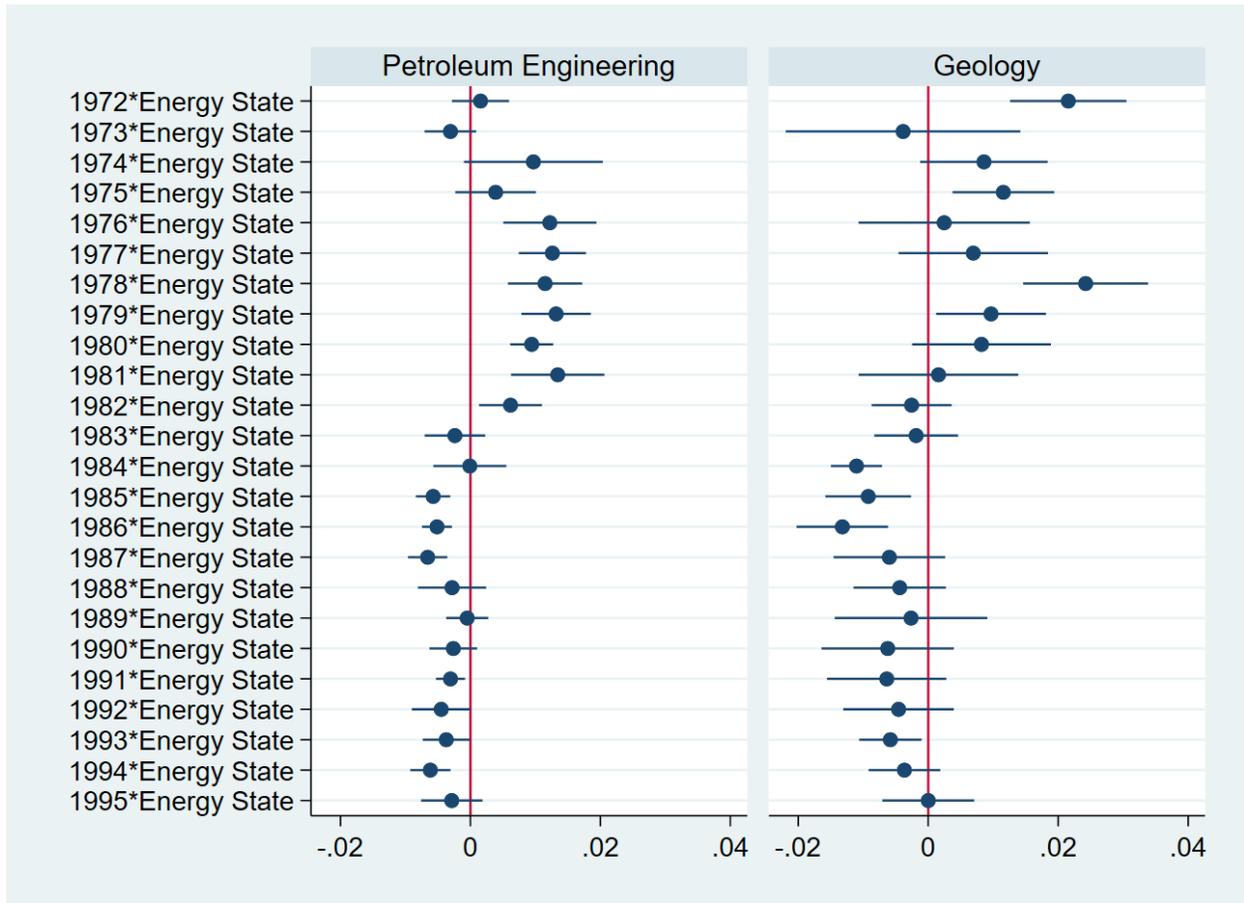
Notes: Based on author computations using the American Community Survey (ACS) for the sample of college graduates with a STEM major. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming.

**Figure 4: Geology Percentage of STEM Majors for Energy and Non-Energy States**



Notes: Based on author computations using the American Community Survey (ACS) for the sample of college graduates with a STEM major. Geology is defined to include geology, geosciences, and geology engineering. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming.

**Figure 5: One-Year Treatment for Petroleum Engineering and Geology**



Notes: Plotted points are regression coefficient estimates for single-year treatment variables defined by interactions between dummy variables for year age 18 and Energy State. The horizontal bars report 95% confidence intervals based on standard errors clustered by birth state. The sample includes college graduates with a STEM major and age 18 in years 1962-1995. The regressions include birth state fixed effects, birth-region×year-age-18 fixed effects, and individual controls for gender and race. Cohorts age 18 in 1962-1971 are defined as pre-treatment cohorts. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming.

**Table 1: Sub-Sample Means and Difference-in-Differences**

	(1) 1962-1971	(2) 1972-1981	(3) 1982-1991	(2)-(1)	(3)-(2)
<u>Energy States</u>					
Petro. Engineering	0.0091	0.0185	0.0060	0.0094	-0.0125
Geology	0.0337	0.0464	0.0170	0.0127	-0.0294
N	15,506	19,332	17,202		
<u>Non-Energy States</u>					
Petro. Engineering	0.0011	0.0021	0.0008	0.0010	-0.0013
Geology	0.0276	0.0303	0.0166	0.0027	-0.0137
N	157,616	206,914	185,342		
<u>Energy States - Non-Energy States</u>				<u>DID(Boom)</u>	<u>DID(Bust)</u>
Petro. Engineering	0.0080	0.0164	0.0052	0.0084***	-0.0112***
Geology	0.0061	0.0161	0.0004	0.0100***	-0.0157***

*Notes:* The sample includes college graduates with a STEM major and age 18 in years 1962-1991. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming. Cohorts are split by year age 18; 1962-1971 is defined as pre-energy boom; 1972-1981 is defined as energy boom; 1982-1991 is defined as energy bust. Geology is defined to include geology, geosciences, and geology engineering. \*\*\*  $p < 0.01$ .

**Table 2: Effects on Petroleum Engineering**

	(1)	(2)	(3)
<u>Panel A: Energy Boom Effects</u>			
Energy Boom	0.0014*** (0.0003)		
Energy State	0.0083*** (0.0012)		
Energy Boom*Energy State	0.0083*** (0.0014)	0.0087*** (0.0015)	0.0085*** (0.0016)
Wild Cluster p-value	0.0005	0.0020	<0.0001
Ferman & Pinto p-value	N/A	0.0246	<0.0001
N	399,368	399,368	399,368
<u>Panel B: Energy Bust Effects</u>			
Energy Bust	-0.0012*** (0.0002)		
Energy State	0.0166*** (0.0014)		
Energy Bust*Energy State	-0.0112*** (0.0018)	-0.0111*** (0.0018)	-0.0108*** (0.0019)
Wild Cluster p-value	0.0005	0.0005	<0.0001
Ferman & Pinto p-value	N/A	0.0273	<0.0001
N	428,790	428,790	428,790
Birth state fixed effects	No	Yes	Yes
Year age 18 fixed effects	No	Yes	Yes
Region*Year age 18 FE	No	No	Yes

*Notes:* The sample includes college graduates with a STEM major. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming. Dependent variable is a dummy for petroleum engineering. Estimates are obtained via linear probability model. Regressions also include controls for gender and race. Panel A includes cohorts age 18 in 1962-1981. Panel B includes cohorts age 18 in 1972-1991. 1962-1971 is the pre-energy boom period; energy boom cohorts are those age 18 in 1972-1981; energy bust cohorts are those age 18 in 1982-1991. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. Ferman & Pinto p-values are based on Ferman and Pinto (2019).

**Table 3: Effects on Geology**

	(1)	(2)	(3)
<u>Panel A: Energy Boom Effects</u>			
Energy Boom	0.0034*** (0.0007)		
Energy State	0.0071*** (0.0022)		
Energy Boom*Energy State	0.0100*** (0.0026)	0.0099*** (0.0025)	0.0091*** (0.0029)
Wild Cluster p-value	0.0995	0.0805	0.0305
Ferman & Pinto p-value	N/A	0.0066	0.0230
N	399,368	399,368	399,368
<u>Panel B: Energy Bust Effects</u>			
Energy Bust	-0.0131*** (0.0007)		
Energy State	0.0170*** (0.0018)		
Energy Bust*Energy State	-0.0153*** (0.0020)	-0.0152*** (0.0020)	-0.0152*** (0.0025)
Wild Cluster p-value	0.0120	0.0150	0.0010
Ferman & Pinto p-value	N/A	0.0098	<0.0001
N	428,790	428,790	428,790
Birth state fixed effects	No	Yes	Yes
Year age 18 fixed effects	No	Yes	Yes
Region*Year age 18 FE	No	No	Yes

*Notes:* The sample includes college graduates with a STEM major. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming. Dependent variable is a dummy for geology, defined as the sum of geology, geosciences, and geology engineering. Estimates are obtained via linear probability model. Regressions also include controls for gender and race. Panel A includes cohorts age 18 in 1962-1981. Panel B includes cohorts age 18 in 1972-1991. 1962-1971 is the pre-energy boom period; energy boom cohorts are those age 18 in 1972-1981; energy bust cohorts are those age 18 in 1982-1991. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. Ferman & Pinto p-values are based on Ferman and Pinto (2019).

**Table 4: Effects on Energy Degrees Unconditional on Education Level or Type**

	Petroleum Engineering	Geology
<u>Panel A: Energy Boom Effects</u>		
Energy Boom*Energy State	0.00046*** (0.00010)	0.00047*** (0.00016)
Wild Cluster p-value	<0.0001	0.0220
Ferman & Pinto p-value	<0.0001	0.0213
Mean Adjusted Coefficient	0.985*** (0.207)	0.274*** (0.094)
N	6,629,827	6,629,827
<u>Panel B: Energy Bust Effects</u>		
Energy Bust*Energy State	-0.00056*** (0.00011)	-0.00084*** (0.00012)
Wild Cluster p-value	<0.0001	0.0005
Ferman & Pinto p-value	<0.0001	<0.0001
Mean Adjusted Coefficient	-1.198*** (0.237)	-0.491*** (0.071)
N	6,515,378	6,515,378
Energy State Pre-Boom Mean	0.00046	0.00171

*Notes:* Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming. Estimates are obtained via linear probability model regressions that include birth state fixed effects, birth-region×year-age-18 fixed effects, and individual controls for gender and race; this corresponds to column (3) in Tables 2 and 3. Panel A includes cohorts age 18 in 1962-1981. Panel B includes cohorts age 18 in 1972-1991. 1962-1971 is the pre-energy boom period; energy boom cohorts are those age 18 in 1972-1981; energy bust cohorts are those age 18 in 1982-1991. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. The Ferman & Pinto p-values are based on Ferman and Pinto (2019). The sample is not restricted based on education level or college major, and non-graduates are assigned to the zero category for the dependent variables. This results in much larger sample sizes and smaller sample means. Energy state pre-boom period sample means for the dependent variables are reported at the bottom of the table. The mean adjusted coefficient and standard error in parentheses are computed by dividing the dependent variable by its energy state pre-boom mean and estimating the regression using the rescaled dependent variable.

**Table 5: Using Continuous Treatment via 1980 Energy Share**

	Petroleum Engineering	Geology
<u>Panel A: Energy Boom Effects</u>		
Energy Boom*Energyshare1980	0.262*** (0.056)	0.271*** (0.071)
N	399,368	399,368
<u>Panel B: Energy Bust Effects</u>		
Energy Bust*Energyshare1980	-0.340*** (0.044)	-0.466*** (0.077)
N	428,790	428,790

*Notes:* The sample includes college graduates with a STEM major. Estimates are obtained via linear probability model regressions that include birth state fixed effects, birth-region×year-age-18 fixed effects, and individual controls for gender and race; this corresponds to column (3) in Tables 2 and 3. Panel A includes cohorts age 18 in 1962-1981. Panel B includes cohorts age 18 in 1972-1991. 1962-1971 is the pre-energy boom period; energy boom cohorts are those age 18 in 1972-1981; energy bust cohorts are those age 18 in 1982-1991. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Energyshare1980 is the share of employment in oil and gas for all 51 states (including DC) in 1980.

**Table 6: Using 4-Year Interval Treatments**

	Petroleum Engineering	Geology
1972-1975*Energy State	0.0028 (0.0025)	0.0093*** (0.0031)
Wild Cluster p-value	0.2571	0.0165
Ferman & Pinto p-value	0.0425	0.0170
1976-1979*Energy State	0.0121*** (0.0011)	0.0110*** (0.0028)
Wild Cluster p-value	<0.0001	0.0360
Ferman & Pinto p-value	<0.0001	0.0211
1980-1983*Energy State	0.0064*** (0.0016)	0.0014 (0.0035)
Wild Cluster p-value	0.0025	0.7029
Ferman & Pinto p-value	<0.0001	0.3324
1984-1987*Energy State	-0.0047*** (0.0014)	-0.0098*** (0.0025)
Wild Cluster p-value	0.0235	0.0130
Ferman & Pinto p-value	<0.0001	<0.0001
1988-1991*Energy State	-0.0025** (0.0011)	-0.0049* (0.0026)
Wild Cluster p-value	0.0040	0.3407
Ferman & Pinto p-value	<0.0001	0.0568
1992-1995*Energy State	-0.0046*** (0.0009)	-0.0034* (0.0018)
Wild Cluster p-value	0.0050	0.0845
Ferman & Pinto p-value	<0.0001	0.1524
N	679,766	679,766

*Notes:* The sample includes college graduates with a STEM major and age 18 in years 1962-1995. Cohorts age 18 in 1962-1971 are defined as pre-treatment cohorts. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming. Estimates are obtained via linear probability model regressions that include birth state fixed effects, birth-region×year-age-18 fixed effects, and individual controls for gender and race; this corresponds to column (3) in Tables 2 and 3. Standard errors in parentheses are clustered by birth state. \*  $p < 0.1$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. Ferman & Pinto p-values are based on Ferman and Pinto (2019).

## **Appendix A**

**Table A1: Petroleum Engineering Results Defining Energy States Using 1% Threshold**

	(1)	(2)	(3)
<u>Panel A: Energy Boom Effects</u>			
Energy Boom	0.0011*** (0.0003)		
Energy State	0.0066*** (0.0013)		
Energy Boom*Energy State	0.0074*** (0.0012)	0.0076*** (0.0013)	0.0073*** (0.0013)
Wild Cluster p-value	<0.0001	0.0010	<0.0001
Ferman & Pinto p-value	N/A	0.0265	<0.0001
N	399,368	399,368	399,368
<u>Panel B: Energy Bust Effects</u>			
Energy Bust	-0.0009*** (0.0002)		
Energy State	0.0140*** (0.0018)		
Energy Bust*Energy State	-0.0094*** (0.0015)	-0.0094*** (0.0015)	-0.0091*** (0.0015)
Wild Cluster p-value	<0.0001	<0.0001	<0.0001
Ferman & Pinto p-value	N/A	0.0171	<0.0001
N	428,790	428,790	428,790
Birth state fixed effects	No	Yes	Yes
Year age 18 fixed effects	No	Yes	Yes
Region*Year age 18 FE	No	No	Yes

*Notes:* The sample includes college graduates with a STEM major. Energy states include Alaska, Colorado, Kansas, Louisiana, Mississippi, Montana, New Mexico, North Dakota, Oklahoma, Texas, and Wyoming, and are defined as those with oil and gas industry employment more than 1% of total employment in 1980. Estimates are obtained via linear probability model. Regressions also include controls for gender and race. Panel A includes cohorts age 18 in 1962-1981. Panel B includes cohorts age 18 in 1972-1991. 1962-1971 is the pre-energy boom period; energy boom cohorts are those age 18 in 1972-1981; energy bust cohorts are those age 18 in 1982-1991. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. Ferman & Pinto p-values are based on Ferman and Pinto (2019).

**Table A2: Geology Results Defining Energy States Using 1% Threshold**

	(1)	(2)	(3)
<u>Panel A: Energy Boom Effects</u>			
Energy Boom	0.0032*** (0.0008)		
Energy State	0.0088*** (0.0025)		
Energy Boom*Energy State	0.0084*** (0.0021)	0.0079*** (0.0021)	0.0077*** (0.0021)
Wild Cluster p-value	0.0150	0.0125	0.0005
Ferman & Pinto p-value	N/A	0.0077	0.0232
N	399,368	399,368	399,368
<u>Panel B: Energy Bust Effects</u>			
Energy Bust	-0.0124*** (0.0006)		
Energy State	0.0171*** (0.0021)		
Energy Bust*Energy State	-0.0153*** (0.0018)	-0.0154*** (0.0019)	-0.0150*** (0.0020)
Wild Cluster p-value	<0.0001	0.0025	0.0005
Ferman & Pinto p-value	N/A	0.0334	<0.0001
N	428,790	428,790	428,790
Birth state fixed effects	No	Yes	Yes
Year age 18 fixed effects	No	Yes	Yes
Region*Year age 18 FE	No	No	Yes

*Notes:* The sample includes college graduates with a STEM major. Energy states include Alaska, Colorado, Kansas, Louisiana, Mississippi, Montana, New Mexico, North Dakota, Oklahoma, Texas, and Wyoming, and are defined as those with oil and gas industry employment more than 1% of total employment in 1980. Estimates are obtained via linear probability model. Regressions also include controls for gender and race. Panel A includes cohorts age 18 in 1962-1981. Panel B includes cohorts age 18 in 1972-1991. 1962-1971 is the pre-energy boom period; energy boom cohorts are those age 18 in 1972-1981; energy bust cohorts are those age 18 in 1982-1991. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. Ferman & Pinto p-values are based on Ferman and Pinto (2019).

**Table A3: Petroleum Engineering Results Defining Energy States Using 3% Threshold**

	(1)	(2)	(3)
<u>Panel A: Energy Boom Effects</u>			
Energy Boom	0.0014*** (0.0003)		
Energy State	0.0089*** (0.0011)		
Energy Boom*Energy State	0.0089*** (0.0016)	0.0089*** (0.0017)	0.0090*** (0.0019)
Wild Cluster p-value	0.0025	0.0040	0.0005
Ferman & Pinto p-value	N/A	0.0225	<0.0001
N	399,368	399,368	399,368
<u>Panel B: Energy Bust Effects</u>			
Energy Bust	-0.0012*** (0.0002)		
Energy State	0.0177*** (0.0016)		
Energy Bust*Energy State	-0.0123*** (0.0022)	-0.0122*** (0.0022)	-0.0123*** (0.0022)
Wild Cluster p-value	<0.0001	<0.0001	<0.0001
Ferman & Pinto p-value	N/A	0.0214	<0.0001
N	428,790	428,790	428,790
Birth state fixed effects	No	Yes	Yes
Year age 18 fixed effects	No	Yes	Yes
Region*Year age 18 FE	No	No	Yes

*Notes:* The sample includes college graduates with a STEM major. Energy states include Louisiana, Oklahoma, Texas, and Wyoming, and are defined as those with oil and gas industry employment more than 3% of total employment in 1980. Estimates are obtained via linear probability model. Regressions also include controls for gender and race. Panel A includes cohorts age 18 in 1962-1981. Panel B includes cohorts age 18 in 1972-1991. 1962-1971 is the pre-energy boom period; energy boom cohorts are those age 18 in 1972-1981; energy bust cohorts are those age 18 in 1982-1991. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. Ferman & Pinto p-values are based on Ferman and Pinto (2019).

**Table A4: Geology Results Defining Energy States Using 3% Threshold**

	(1)	(2)	(3)
<u>Panel A: Energy Boom Effects</u>			
Energy Boom	0.0034*** (0.0007)		
Energy State	0.0064*** (0.0024)		
Energy Boom*Energy State	0.0115*** (0.0027)	0.0112*** (0.0026)	0.0104*** (0.0031)
Wild Cluster p-value	0.0360	0.0320	0.0170
Ferman & Pinto p-value	N/A	0.0051	0.0240
N	399,368	399,368	399,368
<u>Panel B: Energy Bust Effects</u>			
Energy Bust	-0.0132*** (0.0007)		
Energy State	0.0178*** (0.0017)		
Energy Bust*Energy State	-0.0162*** (0.0020)	-0.0161*** (0.0020)	-0.0168*** (0.0024)
Wild Cluster p-value	0.0040	0.0030	0.0020
Ferman & Pinto p-value	N/A	0.0024	<0.0001
N	428,790	428,790	428,790
Birth state fixed effects	No	Yes	Yes
Year age 18 fixed effects	No	Yes	Yes
Region*Year age 18 FE	No	No	Yes

*Notes:* The sample includes college graduates with a STEM major. Energy states include Louisiana, Oklahoma, Texas, and Wyoming, and are defined as those with oil and gas industry employment more than 3% of total employment in 1980. Estimates are obtained via linear probability model. Regressions also include controls for gender and race. Panel A includes cohorts age 18 in 1962-1981. Panel B includes cohorts age 18 in 1972-1991. 1962-1971 is the pre-energy boom period; energy boom cohorts are those age 18 in 1972-1981; energy bust cohorts are those age 18 in 1982-1991. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. Ferman & Pinto p-values are based on Ferman and Pinto (2019).

**Table A5: Effects on Energy Majors Using Alternative Treatments Periods**

	Petroleum Engineering	Geology
<b>Panel A: Energy Boom Effects 1971-1980</b>		
Energy Boom*Energy State	0.0088*** (0.0012)	0.0094*** (0.0023)
Wild Cluster p-value	<0.0001	0.0355
Ferman & Pinto p-value	<0.0001	<0.0001
N	388,915	388,915
<b>Panel B: Energy Bust Effects 1981-1990</b>		
Energy Bust*Energy State	-0.0084*** (0.0019)	-0.0141*** (0.0024)
Wild Cluster p-value	0.0010	0.0045
Ferman & Pinto p-value	<0.0001	<0.0001
N	430,340	430,340
<b>Panel C: Energy Boom Effects 1973-1982</b>		
Energy Boom*Energy State	0.0083*** (0.0012)	0.0041 (0.0029)
Wild Cluster p-value	<0.0001	0.1676
Ferman & Pinto p-value	<0.0001	0.0476
N	409,978	409,978
<b>Panel D: Energy Bust Effects 1983-1992</b>		
Energy Bust*Energy State	-0.0123*** (0.0019)	-0.0131*** (0.0023)
Wild Cluster p-value	<0.0001	<0.0001
Ferman & Pinto p-value	<0.0001	<0.0001
N	427,102	427,102

*Notes:* The sample includes college graduates with a STEM major. Energy states include Alaska, Louisiana, New Mexico, Oklahoma, Texas, and Wyoming. Estimates are obtained via linear probability model regressions that include birth state fixed effects, birth-region×year-age-18 fixed effects, and individual controls for gender and race; this corresponds to column (3) in Tables 2 and 3. For Panel A, the boom treatment cohorts are age 18 in 1971-1980 and cohorts age 18 in 1961-1970 are the pre-treatment control group. For Panel B, the bust treatment cohorts are age 18 in 1981-1990 and cohorts age 18 in 1971-1980 are the omitted comparison group. For Panel C, the boom treatment cohorts are age 18 in 1973-1982 and cohorts age 18 in 1963-1972 are the pre-treatment control group. For Panel D, the bust treatment cohorts are age 18 in 1983-1992 and cohorts age 18 in 1973-1982 are the omitted comparison group. Standard errors in parentheses are clustered by birth state. \*\*\*  $p < 0.01$  based on clustered standard errors. Wild cluster bootstrap p-values are based on the Cameron et al. (2008) method. The Ferman & Pinto p-values are based on Ferman and Pinto (2019).