Do Universities Improve Local Economic Resilience?*

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Abstract

We use a novel identification strategy to investigate whether regional universities make their local economies more resilient to adverse economic shocks. Our strategy is based on state governments assigning normal schools (to train teachers) and insane asylums to counties between 1840 and 1930. Normal schools later became much larger regional universities while asylum properties mostly continue as small state-owned psychiatric health facilities. Because site selection criteria were similar for these two types of institutions, comparing counties assigned a normal school versus an insane asylum identifies the effect of a regional university. We find that having a university roughly offset the manufacturing decline in counties with a high initial manufacturing share, and we attribute this resilience primarily to a spending channel.

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Local economies are routinely subject to adverse changes that can lead to employment losses and lower incomes. As such, economists and policymakers are interested in factors that make a local economy more resilient, hoping to avoid those negative consequences (Lin, 2012; Martin, 2012; Wolman et al., 2017; Bartik, 2018). Significant attention is paid to the presence of a university (Hartt, Zwick and Revington, 2019; Maxim and Muro, 2020). For example, Pittsburgh's well-known universities are sometimes credited with the city's resilience to the Rust Belt decline (Andes et al., 2017).[1]

Using a novel identification strategy, we investigate whether a regional university makes the local economy more resilient. Our strategy utilizes the placement of normal schools and insane asylums in the late 19th and early 20th century. We argue and show that state governments assigned these institutions to counties using similar criteria. Most normal schools grew into regional universities that were a large part of the local economy, while most insane asylums were converted into hospitals and stayed small.

The social reform movements of the 19th century included expanding education and advocating better care for those with mental illness. As a product of the education movement, local governments established community schools, creating widespread demand for qualified teachers. To meet this demand, many states established normal schools to train teachers according to the "norm" for good teaching (Labaree, 2008). At the same time, the "moral treatment" movement advocated more compassionate care for those with mental illnesses, with the objective of facilitating recovery. Many states constructed insane asylums. The locations of both normal schools and insane asylums were political decisions, and both institutions required proximity and ease of access to population centers. The states also needed locations with sufficient property and desired locations with natural beauty in order to achieve each institution's goals (Humphreys, 1923; Kirkbride, 1854). Further, states often choose locations for multiple normal schools as well as multiple asylums.[2]

[1]This gets discussed in the press as well, with titles such as "The Mystery of Pittsburgh: How Some Shrinking Cities are Thriving in the New Economy" and "From Rustbelt to Brainbelt." (Henderson, 2018; The Economist, 2020).

[2]This contrasts with states choosing only one location for the capital or flagship university.

In the early 20th Century, normal schools and insane asylums were similar in size relative to county population. But in the mid-20th Century, most normal schools converted to regional state colleges and universities and grew to where students were a large share of the county population. These universities typically focus on undergraduate education and are not as research intensive as flagship state schools. In contrast to the normal schools, asylums never grew large, and most of the asylum properties continue as state-owned psychiatric health facilities.

This history allows us to identify the effects of universities by comparing the resilience of counties which were assigned normal schools versus counties that were assigned asylums. Our identification assumption is that the asylum counties are a good counterfactual for what would have happened in the normal counties had the normal schools not turned into regional universities. The historical evidence we provide about the assignment of the two provides evidence that the two counties were selected on similar observable and unobservable criteria. We also assume that the presence of an insane asylum does not have direct effects on resilience. This seems plausible because we document that they have remained at about the same (small) size since the early 20th century.

We consider several types of resilience, which we think are of general interest to economists and policymakers. In the main text, we focus on resilience to the manufacturing decline. Since U.S. manufacturing employment's peak in the 1970s, there have been large declines, first concentrated in the Rust Belt, but geographically broad since 2000. This has led to consternation about adverse impacts on local economies (Autor, Dorn and Hanson, 2013; Pierce and Schott, 2016). We find that normal counties with similar exposure to manufacturing before a large decline have more resilient economies, losing less employment, income, and population during and following the decline. In fact, the resilience is roughly one-for-one, so every job lost due to manufacturing in asylum counties is not lost in normal counties. We see similar effects when we look at population and earnings changes.

For robustness, we also consider resilience to mining employment decline and resilience to the business cycle. In Appendix B, we find that normal schools do increase resilience of the local economy to the mining employment decline beginning in 1981, although the magnitude is closer to two-thirds than one-for-one. And in Appendix C, we compare how normal counties and asylum counties fare in recessions since 1980. While the immediate impact of the recession is similar in normal and asylum counties, we find that by the second year after a business cycle peak, impacts on employment and income are less severe in normal counties.

Based on these distinct measures, we conclude that regional universities make the local economy more resilient. We then consider the mechanisms through which this resilience occurs. We find evidence of this direct spending mechanism, with university employment and spending expanding more in response to the bad shock in normal counties compared to asylum counties. One possibility is that state universities expand in bad economic times due to increased demand from unemployed workers. State budget allocations to universities may also remain relatively constant when there are negative economic shocks, and this may improve the local economy's resilience. When we decompose the resilience by sector, we find that much of the resilience is explained by non-tradable sectors, such as retail. Using typical values of multipliers found in the literature, university spending growth can explain a majority of the resilience.

Of course, there are other channels through which universities may affect resilience, such as increasing the skills of local workers or creating innovation spillovers to firms, either local firms or firms who move because of the university. Because the regional universities we consider are not intensive research universities, and because we find small effects of having a normal school on the age profile and on the education level of locals, these channels seem less likely to occur compared to other settings. In Appendix D, we do look for evidence on whether universities improve resilience through their effect on upskilling in the local market, but we do not find conclusive evidence of this channel.

Our empirical strategy identifies the effect of universities that were converted from normal schools. These are not among the largest or most research intensive universities. However, this treatment effect is particularly policy-relevant. A state is unlikely to start or close a flagship research university, but might a regional university. Further, regional universities are more heavily reliant on state budgets, and so the value of these universities is annually policy-relevant.[3]

COVID-19 has provided an example of the policy relevance of regional universities.[4] Current regional university consolidation and program reduction discussions are ongoing in Pennsylvania and Wisconsin, and in April 2020, the Chancellor of the Vermont State Colleges proposed permanently closing three campuses due to additional COVID-19 losses (he resigned soon afterwards due to backlash) (Seltzer, 2020; Quinton, 2020). Many universities have laid off or furloughed staff. These decisions may have implications for how the local markets adjust to future economic shocks.

Although we primarily focus on regional universities, we complement our main analysis by adjusting our empirical strategy to examine resilience in counties with public research universities.[5] Counties with public research universities are not statistically-differentially resilient to manufacturing decline, though the point estimate would suggest they are modestly more resilient.

Our paper contributes to an important and growing literature studying the relationship between universities and local economic growth. Many of these papers focus on the relationship between universities and innovation, while others consider the effect on growth more broadly (Aghion et al., 2009; Andrews, 2020; Cantoni and Yuchtman, 2014; Feng and Valero,

[3]In 2013, the average state appropriation to non-selective four-year public universities was 26.2 percent of the average total spending at these universities. This reliance on state appropriations is much lower among selective public universities. For 35 selective four-year public universities, this was 18.9% (Deming and Walters, 2017).

[4]An important consideration regarding external validity is that our paper studies resilience to manufacturing declines and recessions, neither of which had direct negative effects on universities. In fact, enrollment is known to grow during times of economic decline. Thus, our results do not speak to resilience to shocks that negatively affect universities, such as the COVID-19 pandemic.

[5]We note the important caveat that we have only 56 research university counties, and that assignment of these may have differed as there is commonly only one per state. Nonetheless, we look at the differential resilience between these research universities' counties and asylum counties.

2020; Hausmann, 2020; Kantor and Whalley, 2014, 2019; Valero and Reenen, 2019).[6]

We make two contributions to this literature. First, none of these papers consider whether universities improve resilience to negative economic shocks. Most related to our work is Glaeser and Saiz (2004), which shows a relationship between resilience to negative shocks and share with a bachelor's degree, and Feyrer, Sacerdote and Stern (2007), which does not see this relationship among Rust Belt counties. We find only a weak correlation between having a regional university and the share with a bachelor's degree, meaning that we are interested in different attributes of a location that might affect resilience. While we consider a higher-educated workforce as a channel through which universities might affect resilience, the channel we find most evidence for is a spending channel.

Second, we present a novel identification strategy to address the endogenous location decisions of universities. We compare counties with universities to counties that received asylums. This strategy contrasts with some of the other identification strategies used in this literature, including comparing to runners-up locations (Andrews, 2020), using budgetary shocks (Aghion et al., 2009; Kantor and Whalley, 2014), and legislative changes incentivizing university research (Hausmann, 2020).

Our identification strategy is similar to Andrews (2020), and we view the two strategies as complementary, especially given our different outcomes of interest. One of the biggest differences is that we identify the effects of different types of universities. Although his sample includes roughly 10 normal schools, it is primarily research-intensive universities. In contrast, our sample includes very few R2 universities and no R1 universities. This is particularly important given Andrews (2020) focus on patents and our focus on resilience. Second, while our sample is not hand-matched, it is larger. We have over 200 normal schools counties and nearly 130 asylum counties, giving us more statistical power. Finally, all counties in our control group are given a similarly-sized state institution, an asylum.We identify the effect of the normal school growing into a large regional university. Andrews

[6]Moretti (2004) studies the relationship between the supply of college graduates and wages, using the presence of a land-grant institution as an instrument.

(2020) is also interested in the effect of universities relative to counties with a "consolation prize," but has only 27 counties in his sample for this exercise.

Our paper proceeds as follow. In Section 1, we discuss the historical placement of normal schools and asylums that leads to our empirical strategy. We then show that while normal schools' placement was highly selected, there is no reason to suspect it was differently selected than the placement of insane asylums. We describe the effect of normal school assignment on recent enrollment, education levels, and industry composition in Section 2. We investigate the resilience of local labor markets in response to manufacturing declines in Section 3, and with respect to other shocks in Appendices B and C. We consider the mechanisms through which universities improve resilience in Section 4. Section 5 concludes.

1 Normal Schools and Asylums: History and Identification Strategy

During the early and middle part of the 19th century there was strong support for the establishment of public institutions aimed at social improvement and reform. This included development of normal schools, as well as asylums for the mentally ill (Grob, 2008). In this section we describe these institutions, as well as qualitative historical evidence suggesting very similar site selection criteria. In the following section, we show quantitative evidence supporting our identification assumption.

Demand for teachers grew rapidly in the early to mid 19th Century, as local communities began operating elementary and eventually secondary schools (Labaree, 2008). This demand was met was through the establishment of state normal schools to train teachers. The first state normal school was opened in 1839, and by 1930 the number had reached 209 (Ogren, 2005). State governments typically established multiple normal schools across the state.

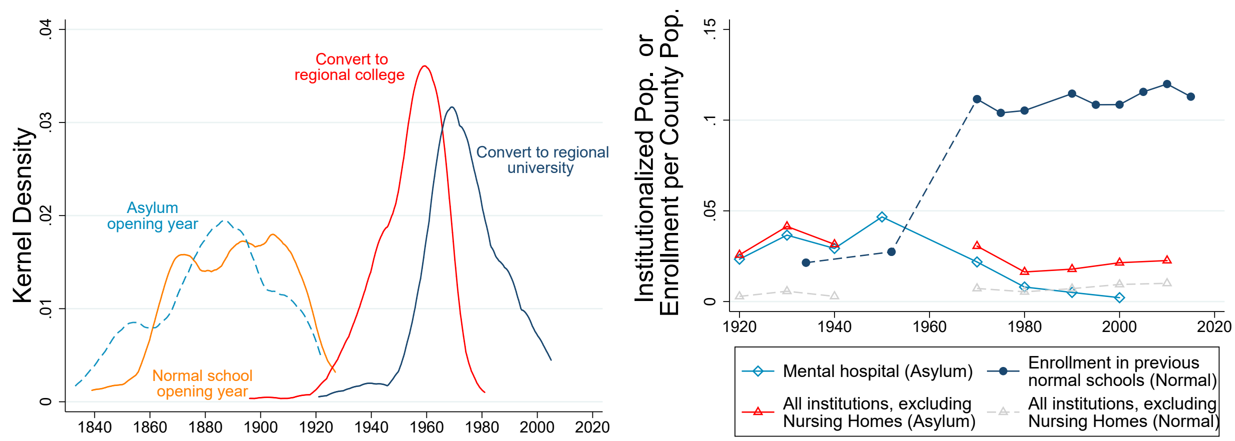
In *The Factors Operating in the Location of State Normal Schools*, Humphreys (1923) argued that political considerations were the most important factor determining normal school locations. Other factors included demand for instruction (e.g. the local population), geographic accessibility, financial and land donations, location of existing schools, and natural beauty. As of 1923, about half of normal schools in the United States had been located directly by the state legislature. The other locations were chosen by commissions authorized by the legislature (Humphreys, 1923).

We focus on normal schools because they evolved to become important state universities. By the early 20th Century, legislatures began changing some normal schools to teachers colleges, allowing them to grant bachelor's degrees. These colleges broadened, reducing teacher education to a smaller component. Through the 1950s many state legislatures renamed teachers colleges as state colleges. From the 1950s through the 1970s, many obtained university status (Labaree, 2008). For example, Southern Illinios University, Northern Illinois University, Eastern Illinois University, and Western Illinois University all started as normal schools. The distribution of opening years and years in which they were converted to state colleges, can be seen in Figure 1a.

The evolution from normal school to regional university was correlated with large enrollment increases (Figure 1b). We digitize historical university-level enrollment data in the 1933-1934 academic year using the *Biennial Survey of Education, 1932-1934* (Foster et al., 1937), and in 1952 using *American Universities and Colleges, Sixth Edition* (American Council on Education, 1952).[7] In 1934, normal school enrollment was about 2 percent of the county's population. By 1970, enrollment in universities that began as normal schools was well over 10 percent of county population, and has been relatively constant since.

We now describe the history of state insane asylums, and why asylum counties are a good control group for normal school counties. The establishment of state insane asylums accelerated in the 1830s, as part of a movement to provide therapeutic and compassionate care that would facilitate recovery (Grob, 2008). Many of these state asylums were built

[7]Total university enrollments in 1970 and 1975 are collected from *Higher Education General Information Survey (HEGIS)* (United States Department of Education. National Center for Education Statistics., 1998, 1999). Total enrollments from 1980 to 2015 are collected from IPEDS (U.S. Department of Education, National Center for Education Statistics, 2020).



(a) Asylum and Normal School Opening Years (b) Asylum and Normal School Size Over Time

Figure 1: **History of Normal Schools and Insane Asylums.** Figure (a) shows opening years for normal schools and asylums. We use an Epanechnikov kernel with a five-year bandwidth for density estimation. The year in which previous normal schools convert to state colleges and state universities is defined to be the year that the school's name changes to college and university respectively. Figure (b) shows average enrollment in normal schools (or in colleges that had been normal schools) per county population in normal counties. We also show average institutionalized population per county population for both normal and asylum counties. Enrollment in Maine and Vermont is missing in 1952; however, using a balanced sample yields a similar figure.

according to the Kirkbride architectural plan, which stressed the importance of picturesque environments, large natural spaces for recreation, and stately buildings.[8] This plan also stressed that asylums be close to population centers and have roads and railroads connected to patients' home cities (Kirkbride, 1854).

These goals resulted in institutions with buildings and grounds quite similar to normal schools. This history meant that site selection criteria was similar, both institutions were desired by local communities, and both were sources of pride at the time they were built.

Importantly, a given state was often choosing locations for normal schools and insane asylums around the same time, as can be seen in Figure 1a. Indeed, Humphreys (1923) shows that location decisions for these two types of institutions were sometimes considered con-

[8]Thomas Kirkbride, the developer of this plan, believed that good architecture was critical for curing mental illness (Yanni, 2007).

currently, and were relevant for political negotiations.[9] Further, states were often choosing locations for several normal schools and several asylums.[10]

Both location decisions depended on a county's political influence, proximity to population and routes of transportation, as well as an attractive natural environment. Both were large state investments, that would come with jobs and economic opportunity. In addition to collecting historical enrollment data for normal schools, we also collect data on historical population in insane asylums to compare the size of these two types of institutions. This represents another test that these institutions were expected to provide similar advantages to their counties, and may have required similar political influence.[11] Figure 1b shows that in the early 20th Century, enrollment at normal schools and population in asylums were similar relative to county population.

An article from the *Kankakee Gazette*, from when the city was assigned an asylum, helps illustrate these points.[12] Written in August 1877, the article is titled "Got It: Knew We Would—Couldn't Be Otherwise!: The Eastern Insane Asylum Located at Kankakee." Reflecting the desirability of insane asylums, it says "Our citizens received the news in a spirit of jubilee, and on Friday evening there was a bonfire, band music... and speeches..." The article also reflects the importance of scenery, describing the place for the asylum as "just outside of the city limits on the south side of the river—a desirable location," and details the 351 acres that will be contributed to the asylum. The article describes one of the benefits for the city is that "the construction of a $200,000 building will give employment

[9]For roughly one third of the states in our sample, asylums and normal schools opened within six years, and for more than half of the states they opened within eleven. The average difference between the opening dates of the first asylum and the first normal school within the same state was approximately 16 years.

[10]For 29 of the 49 states in our sample, they established more than one normal school and more than one asylum.

[11]We collect historical data on population in insane asylums at the county level from various sources. We obtain institutional population by institution type from the decennial censuses of 1920 through 1940 using 100% counts from IPUMS (Ruggles et al., 2021). Because 100% counts are not available in 1950, we instead collected asylum-level resident population data using a 1950 publication of The Council of State Governments (Council of State Governments, 1950).

[12]We thank the Abraham Lincoln Presidential Library and Museum for scanning the microfilm for us during the pandemic.

to laborers..."[13] The article lists the other finalists for the asylum: "Decatur, Bloomington, Champaign, Urbana, Danville, Paxton, and Pontiac," showing that it was a political process that mainly considered small population centers. Of note, Illinois State, originally a normal school, is in Bloomington.[14] Finally, the article also discusses the importance of political influence, crediting "the great services of Messrs. Bonfeid and Taylor, our representatives in the upper and lower houses of the legislature."[15]

Many of the asylum properties continue to be owned by the state, and continue as psychiatric health facilities. Others have been acquired by universities or are used as correctional facilities (Hoopes, 2015). While the size of the institutionalized population fell from 1950 to 1980 during the deinstitutionalization movement, average institutionalized persons per population in asylum counties was still nearly double that of normal counties in 2010. As Figure 1b shows, the per capita population in non-nursing home institutions has fallen only modestly. Hence, when we compare normal counties to asylum counties, we are comparing counties that were assigned a modestly-sized institution between 1840 and 1930. However,

[13]The article also mentions other advantages: "In addition to the advantages which an institution of the size of the new asylum must confer upon the place of its location to a greater or less extent, the impression which exists abroad to a certain degree that Kankakee is a low marshy place, now stands refuted in the most public manner."

[14]Technically, the college is in Normal, Illinois, but Bloomington-Normal is a single metro area and both are in McLean County. In fact, Normal used to be known as "North Bloomington," and the name Normal is taken from "Illinois State Normal School," the original name of Illinois State.

[15]Asylums were desired generally, not only in Kankakee. When the Western Illinois Insane Asylum was awarded, a newspaper article in a rival town had a headline "Rock Island Got It... The New Insane Asylum to be Located at the East Moline Site—Monmouth Made a Good Fight but Failed to Get It" (Warren County Democrat, 1895).

It was common to allege that other places only won asylums because of shady political dealings, which reflects that cities and towns wanted the asylums. For example, when Anna was awarded the Southern Illinois Insane Asylum, a rival town's newspaper ran a story with the subheadlines "Is There Anything Rotten in the State of Denmark?—And Several Other Very Blunt Questions" alleging that Anna was chosen over rival Jonesboro to benefit corrupt politicians (The Cairo Evening Bulletin, 1869). And after the Northern Illinois Insane Asylum was awarded to Elgin, a rival town's newspaper attributed it to "obvious partiality shown by the commissioners in favor of Elgin, even justifying suspicions of corruption... in further view of the palpable fact that the location at Elgin comes short in several very important particulars..." (Ottawa Free Trader, 1869).

Once the asylums were awarded, newspapers were eager to have them built. In Alton, Illinois, a newspaper headline declared they were "In a Hurry for Insane Hospital" (Alton Evening Telegraph, 1915). Finally, newspapers also thought there were benefits years later. During the era of deinstitutionalization, the Dixon State Hospital was described as "A Vital Force in the Economic and Social Life in Dixon" (Dixon Evening Telegraph, 1951).

while the normal schools grew dramatically, the asylums remained modestly-sized and the properties were converted to correctional facilities or more-modern mental health facilities. Furthermore, as can be seen in Figure 1b, much of the conversion happened prior to the period we study, which starts around 1980.

1.1 Need for and Validity of Empirical Strategy

In this section, we show the importance and validity of our identification strategy. Consistent with our description above, we show normal schools were not randomly assigned; however, they were chosen based on the same criteria as insane asylums. We also show that in the more recent time period we study, the geographic advantages enjoyed by counties with normal schools are similar in counties with asylums.

Classification of Normal School and Asylum Counties

Our historical data on normal schools come from Ogren (2005), which includes the school's location, opening year, and years corresponding to name changes.[16] There were 209 normal schools across 204 counties, opened between 1839 and 1930, with median opening year of 1891 (Figure 1a).

We digitize data on asylums' geographic locations and opening years from the 1923 special census of "institutions of mental disease" (Furbush et al., 1926). Our identification comes from states randomly choosing some counties to receive normal schools and some to receive asylums, around the same time. Thus we exclude five asylums that were established before 1830. This yields a sample of 160 asylums from 151 counties.[17]

For the counties that had both normal schools and asylums, we define these as normal counties. There were 25 such counties, out of the 204 counties with normal schools. This

[16] Using the city and state of the normal school, we identified the county using StatsAmerica (Indiana Business Research Center, 2020).

[17] The opening years and locations were extracted from Table 64 and Table 104 of the book. Seventeen of these asylums did not have opening years in the 1923 Census. We obtained these opening years from government websites or other open sources. Sources for each missing opening year are available upon request.

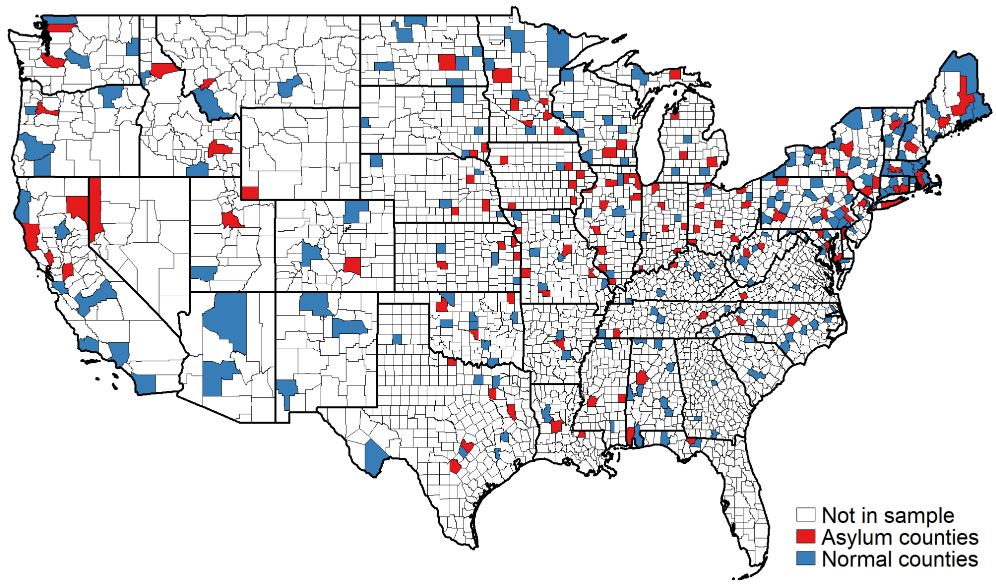


Figure 2: Locations of Normal Schools and Asylums

yields a total of 204 normal counties and 126 asylum counties. Figure 2 shows the geographic distribution of normal and asylum counties in our sample.

Balance on 1840 and Geographic Characteristics

We start by comparing normal school counties to all other counties, based on geographic variables and county characteristics in 1840, before almost all of the normal school locations were chosen. As the above discussion makes clear, normal school counties were chosen by state legislatures and commissions, raising concerns they were placed in counties that have persistent economic advantages.

Panel A of Table 1 explores whether normal counties have significant geographic advantages over a typical county. We test whether they are closer to big cities, based on the following quantity, inspired by a gravity model:

$$\log \text{Nearby Population}_i = \log \sum_{j \neq i} \frac{\text{Population}_j}{\text{Distance}_{ij}}$$

where i is the county of interest and j is summed over all other counties. The quantity is

Table 1: Covariate Balance: Normal School, Asylum, and All Other Counties

	(1)	(2)	(3)	(4)	(5)
	Variable Means			Difference in Means With State FE	
	Normal	Asylum	All others	(1) - (2)	(1) - (3)
Panel A: Geographic Characteristics					
Log Nearby Population	13.02	13.31	11.75	-0.21	0.97***
	(1.29)	(1.41)	(1.28)	(0.17)	(0.08)
Within 150 miles of State Capital	0.48	0.52	0.42	-0.11*	-0.02
	(0.5)	(0.5)	(0.49)	(0.06)	(0.03)
Log Water Coverage	5.06	5.20	4.49	-0.25*	0.11
	(1.69)	(1.63)	(1.82)	(0.15)	(0.1)
Panel B: Characteristics in 1840					
Log Population	9.71	9.51	8.99	-0.02	0.27***
	(1.38)	(1.59)	(1.22)	(0.13)	(0.08)
Insane and Idiot Share	0.08	0.08	0.08	0.00	-0.01
	(0.07)	(0.08)	(0.1)	(0.01)	(0.01)
Log Manufacturing Capital Stock	12.02	11.87	10.51	-0.18	0.49***
	(2.07)	(2.07)	(1.86)	(0.19)	(0.14)
Urban Share	6.72	9.22	1.40	-3.15	2.71**
	(16.13)	(20.31)	(8.11)	(2.56)	(1.15)
Sectoral Employment Share					
Agriculture	73.94	68.65	82.47	5.16	-1.57
	(21.3)	(23.51)	(20.39)	(3.22)	(1.47)
Commerce	2.97	3.82	2.48	-0.69	0.09
	(5.42)	(5.22)	(5.03)	(0.78)	(0.18)
Learned Professions and Engineers	2.25	4.20	2.00	-1.85	0.12
	(3.51)	(11.16)	(4.05)	(1.42)	(0.12)
Manufacturing	17.38	19.51	10.53	-1.94	2.19*
	(14.44)	(15.66)	(12.85)	(1.66)	(1.31)
Mining	0.73	0.79	0.60	-0.21	0.04
	(4.02)	(1.74)	(2.49)	(0.19)	(0.28)
Non-ocean Navigation	1.30	2.24	1.24	-0.81**	-0.15
	(3.32)	(5.71)	(3.95)	(0.39)	(0.16)
Ocean Navigation	1.43	0.79	0.68	0.33	-0.73*
	(7.01)	(2.17)	(5.05)	(0.76)	(0.43)

Notes: This table shows summary statistics for normal, asylum and all other counties. Nearby population is based on 1980 population and a gravity model. Columns (1) through (3) show variable means and standard deviations in parentheses. Column (4) and column (5) display estimates from regressing each variable on the normal county indicator with state fixed effects. Column (4) contains normal and asylum counties and column (5) contains normal and all other counties. In columns (4) and (5) we report standard errors clustered at the state level in parentheses. Sample sizes vary across variables due to missing data for some counties. For the variables in Panel A, there are 204 normal counties and 126 asylum counties. For log nearby population there are 2776 other counties, while for the other two variables in Panel A there are 2779 other counties (the three additional counties are counties that were renamed after 1980 or did not exist in 1980). We are missing many counties in Panel B as their current states were not yet states in 1840, and so data were not available. For log population, insane and idiot share, and urban share, there are 145 normal counties, 92 asylum counties, and 1729 other counties. For Log Manufacturing Capital Stock there are 137 normal counties, 89 asylum counties, and 1581 other counties. For all sectoral employment shares there are 143 normal counties, 90 asylum counties, and 1677 other counties. See text for details.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

large if nearby counties have lots of population. We measure this quantity in 1980.

The point estimates, comparing column (1) to (3), suggest normal school counties are significantly closer to big cities than a typical county, and regression analysis with state fixed effects in column (5) confirms this. This is consistent with historical descriptions of the criteria. However, asylum counties appear to be comparable to normal counties. While the average normal county is closer to the state capital and has more water coverage than the average county (columns 1 and 3), this appears accounted for by being in different states (column 5). Importantly, asylum counties do not appear to differ from normal counties on either measure.

In Panel B, we find that the locations of normal schools were highly selected based on their 1840 characteristics. For these variables we are restricted to states in the east, as many western states were not yet states at this point.[18] Normal counties had significantly larger populations than all other counties, were more urban, had more manufacturing, and had less agriculture. All of these are consistent with proximity to population centers being an important criteria for the placement of normal schools. However, despite these advantages relative to the average county, normal counties and asylum counties look very similar.

Table 1 underscores the need for a strong control group for normal school counties, and shows that asylum counties are a strong control group as they enjoyed the same advantages.

2 Normal Schools' Effects on Local Economies

History suggests normal school counties should have a higher probability of having a regional university. In this section, we show this is indeed true, and we look at the other effects of normal schools on the 1980 labor market. While we are primarily interested in whether a regional university causes a local economy to be more resilient, these effects give important context.

[18]States with available data include Minnesota, Missouri, Arkansas, Louisiana, parts of Iowa, and everything east of the Mississippi River.

2.1 Effect on University Presence and Enrollment

In Table 2, we look at the effect of normal school assignment on the county's higher education sector. We estimate regressions with state fixed effects, and an indicator for having been assigned a normal school. The sample is composed of the counties that were assigned either a normal school or an asylum. We interpret the coefficient on the normal county indicator as the causal impact of having a normal school on y. All the y variables are measured in 1980, but patterns are similar in 2000 or 2015.

The first row shows the effect of having a normal school on someday having a normal school that turns into a regional college or university. Mechanically, asylum counties zero such colleges. The effect is 0.93, implying the vast majority of normal schools did turn into regional universities.[19] Some asylum counties do have four-year public colleges, and the second row shows the average number in an asylum county is 0.44. This average is higher by 0.69 colleges in normal counties. In the third and fourth rows, we see that other types of colleges are potentially crowded out by regional colleges, including four-year private colleges and two-year colleges. These are not statistically significant, although if you add them all together, the point estimate on total number of colleges is close to zero.

Because there is no difference in the total number of colleges, we might think the effect of having been assigned a normal school is small. However, regional universities created from normal schools are much larger in size than other universities.

Using university-level enrollment data from the Integrated Postsecondary Education Data System (IPEDS), enrollment at all Title-IV-eligible universities located in asylum counties is equivalent to roughly 5 percent of the county population. In a normal county, this is higher by more than 8 percentage points—two and a half times larger than in asylum counties. Most of this difference is driven by full-time enrollment which is seen in the next row. Similarly, the number of degrees awarded is more than three times as high in normal counties compared

[19] Throughout the paper, we report the reduced-form effect of having a normal school. Thus, if there is a positive effect of regional universities and we wished to interpret the coefficients as the effect of having a regional university, we will obtain a slight underestimate.

Table 2: The County-Level Higher Education Sector in 1980

	(1) Variable Means Normal	(2) Asylum	(3) Difference in Means With State FE (1) - (2)
Has regional college formerly normal school	0.91	0.00	0.93***
	(0.28)	(00)	(0.02)
Total public four-year colleges	1.11	0.44	0.69***
	(0.67)	(0.88)	(0.12)
Total private four-year colleges	1.39	1.94	-0.45
	(3.27)	(4.62)	(0.53)
Total two-year colleges	0.97	1.16	-0.22
	(2.17)	(2.17)	(0.31)
Enrollment as % of population	11.72	4.56	8.41***
	(9.23)	(5.51)	(1.59)
Full-time enrollment as % of population	8.52	2.97	6.48***
	(7.4)	(4.34)	(1.26)
Total degrees awarded as % of population	3.04	0.93	2.47***
	(2.77)	(1.41)	(0.5)
Bachelor's degrees awarded as % of population	1.43	0.39	1.23***
	(1.38)	(0.69)	(0.25)
% Population over 25 with Bachelor's degree	16.57	15.02	2.04**
	(4.79)	(6.1)	(0.86)
% Population over 25 with some college degree	15.40	15.01	0.57
	(3.89)	(3.97)	(0.35)

Notes: Columns (1) and (2) show means and standard deviations in parentheses. Column (1) includes 204 normal counties, and column (2) includes 126 asylum counties. Data are from IPUMS and IPEDS. Column (3) displays coefficients from regressing each variable on the normal county indicator with state fixed effects. Regressions in column 3 consist of 204 normal counties and 126 asylum counties, and we present standard errors clustered at the state level in parentheses.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

to asylum counties, and that is at least partially driven by bachelor's degrees. This table shows that having been assigned a normal school greatly increases the likelihood of having a large university in the county.

Based on the 1987 Carnegie classification of Institutions of Higher Education, none of the regional universities converted from normal schools were Research I, and less than 2 percent were Research II institutions. Nearly 83 percent were listed as Comprehensive I or II, which are universities that are committed to graduate education through the master's degree (but not through the doctorate degree). Thus, these are not the highest research intensity universities, but they do offer graduate education.

As a final measure of education, we use U.S. Census data to look at the share of the

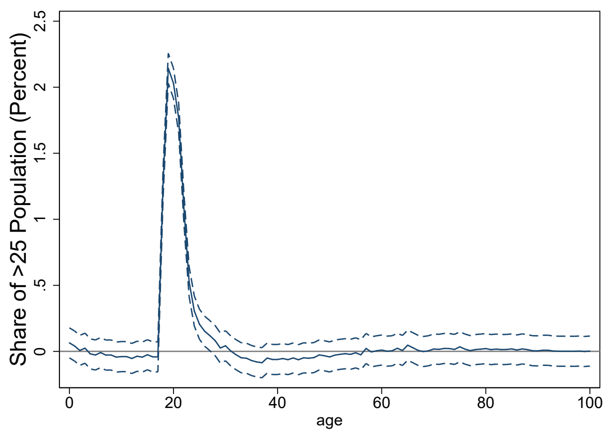


Figure 3: **Difference in Age Distribution in Asylum and Normal Counties, 1980.** Each point represents the coefficient on normal county from the regression of age share on normal counties with state fixed effects. Dashed lines are 95 percent confidence intervals, based on standard errors clustered at the state level. Age share is defined as the population of a specific age divided by the total population over 25 years old. Population by age data is from NHGIS.

population over 25 that has a bachelor's degree in 1980. We find an additional 2 percent of the population has a bachelor's degree. However, this is not much larger than the number of bachelor's degrees awarded in every year. This suggests students are not staying in the county after graduation.

Consistent with students leaving after graduation, normal school counties have a much larger share of 18 to 23 year olds (of the over 25 population), but the rest of the age distribution looks indistinguishable (Figure 3).[20]

2.2 Effect on Population, Earnings, and Local Industry Mix

Finally, we analyze the effect of normal school assignment on local economic characteristics (Table 3). In 1980, near the starting point of our sample for much of our analysis, asylum counties have larger population, greater employment, and higher average earnings per job, though only the latter is statistically significant. In addition, despite the normal schools

[20]We consider the population of each age as a share of the over 25 population. For each age, we regress the age share (as a fraction of the 25+ population) on an indicator for normal counties and state fixed effects, using our sample of normal and asylum counties. Figures from years 1970, 1990, 2000, and 2010—shown in Appendix Figure A8—exhibit similar patterns.

Table 3: County Characteristics in 1980

	(1)	(2)	(3)
	Variable Means		Difference in Means With State FE
	Normal	Asylum	(1) - (2)
Total population (1,000 ppl)	226.05	266.76	-26.28
	(601.44)	(560.22)	(80.55)
% Population growth 1950 to 1980	51.66	50.07	-0.13
	(65.51)	(72.6)	(9.89)
Total employment (1,000 ppl)	119.70	151.42	-21.32
	(342.4)	(359.61)	(51.34)
% of manufacturing employment	16.45	17.67	-1.49*
	(8.69)	(8.26)	(0.82)
% of retail employment	16.31	15.49	1.13***
	(2.58)	(2.82)	(0.31)
Average earning per job ($1,000)	13.23	14.06	-0.52*
	(2.69)	(2.67)	(0.28)
Per capita personal transfer receipts	1,211.60	1,224.76	-25.48
	(245.82)	(299.63)	(41.74)
Per capita UI compensations	74.74	83.49	-0.22
	(47.5)	(53.87)	(4.37)

Notes: This table shows summary statistics for normal and asylum counties using 1980 BEA data. Columns 1 and 2 show means and standard deviations in parentheses. Column 3 shows estimates from regressing each variable on a normal county indicator, with state fixed effects. For county population and employment, we also use log total population and log total employment as dependent variables, and the estimates are not significantly different from 0 (coefficient and standard error for log total population are 0.19 and 0.17, and coefficient and standard error for log employment are -0.20 and 0.19). For each variable in the table except percent retail employment, the regression consists of 200 normal counties and 126 asylum counties. For percent retail employment, the regression consists of 199 normal and 126 asylum counties. In column 3 we present standard errors clustered at the state level in parentheses.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

growing in size from 1950-1980, we do not see faster population growth in normal counties compared to asylum counties during this time period.

There are also few differences in sectoral composition between normal and asylum counties. We look at major industry categories based on SIC codes in 1980 using data from the Bureau of Economic Analysis. These cover most industry-county combinations, although there are some missing values. For presentation purposes, we show only industries for which the industry share differs by more than 0.5 percent between normal and asylum counties, or is statistically different.

The most statistically significant difference is that the share employed in retail trade is roughly 1.1 percentage points higher in normal counties relative to asylum counties. This is intuitive, as retail stores might serve a large student body. We also find a smaller manufacturing share.[21]

All industries, including NAICS industries in 2001, are available in Appendix Tables A5 and A6. Of note, health care, which shows up in the NAICS classification, does not have a statistically significant difference, which is important because it shows asylums do not seem to have a large lasting effect. We find no significant differences in per capita transfers using BEA data.

Overall, in this section we find that while normal schools have a large effect on the higher education presence in a county, there is little evidence that students stay around after graduating. Further, the conversion of normal schools to regional universities did not have a large effect on the local economy, when looking at growth from 1950-1980 and comparing to asylum counties. While there were large enrollment increases in normal counties, this was a period of national economic growth. Both normal and asylum counties are positively selected, and we do not see that the growth of the regional universities led to differential population growth. This may not be surprising given our focus on regional universities, which are less research intensive. As a result, we would expect them to be less likely to create economies with more agglomerative forces relative to other positively selected counties.

3 Resilience to Manufacturing Declines

In this section we analyze the impact of exposure to manufacturing shocks, and whether this differs for normal counties relative to asylum counties. We focus on two episodes of pronounced manufacturing declines: declines in the rust belt starting around 1980 and national

[21] In 2001, we see a similar pattern, with normal counties having a higher share employed in retail trade, and accommodation and food services, which was not its own category in 1980. Interestingly, we see a smaller share employed in wholesale trade. Though not statistically significant, we do see more government and less manufacturing employment.

declines starting in the year 2000.[22]

Using our sample of normal and asylum counties, we estimate:

$$y_i = \beta_1 \text{Normal}_i + \beta_2 \text{Mfg Exposure}_i + \beta_3 \text{Normal}_i \times \text{Mfg Exposure}_i + \alpha_{st} + X_i\gamma + \epsilon_{it} \quad (1)$$

where y_i measures long-run percentage growth of various outcomes, including employment, population, wages, and government transfers; α_{st} is a state fixed effect; and X_i includes controls.

We estimate separate specifications for the Rust Belt and national manufacturing declines. For the Rust Belt shock, Mfg Exposure$_i$ is the 1978 share of county employment in manufacturing, the year manufacturing employment peaked in the U.S. and before a period of permanent decline in the rust-belt states.[23] We limit this analysis to rust-belt states, which is particularly important given differences in manufacturing trends across regions (see Figure 4). Following Alder, Lagakos and Ohanian (2019), we define rust-belt states as Illinois, Indiana, Michigan, New York, Ohio, Pennsylvania, West Virginia, and Wisconsin. Non-rust-belt counties experience large manufacturing declines especially starting in 2000. If we included these non-rust-belt counties, the 1978 manufacturing share may not capture exposure to the large declines starting in 2000.

For the national manufacturing declines starting in 2000, Mfg Exposure$_i$ is the share employed in manufacturing in the year 2000. Because all census regions experience this shock (see Figure 4), for these specifications we look at normal and asylum counties throughout the U.S. and growth from 2000-2018.

The coefficient β_2, which we expect to be negative, measures the impact of additional manufacturing exposure in asylum counties. The coefficient β_3 measures the differential

[22] In Appendices B and C, we consider two other types of resilience. First, we look at whether regional universities make local economies resilient to the decline in mining employment after 1981. We also look at whether regional universities cause local economies to be resilient to the business cycle.

[23] Rust-belt states did experience declines in manufacturing employment following the 1969 and 1973 recessions, but there were important recoveries afterwards. By 1978, manufacturing employment in rust belt states was 91 percent of 1969 manufacturing employment after dropping to 84 percent in 1975.

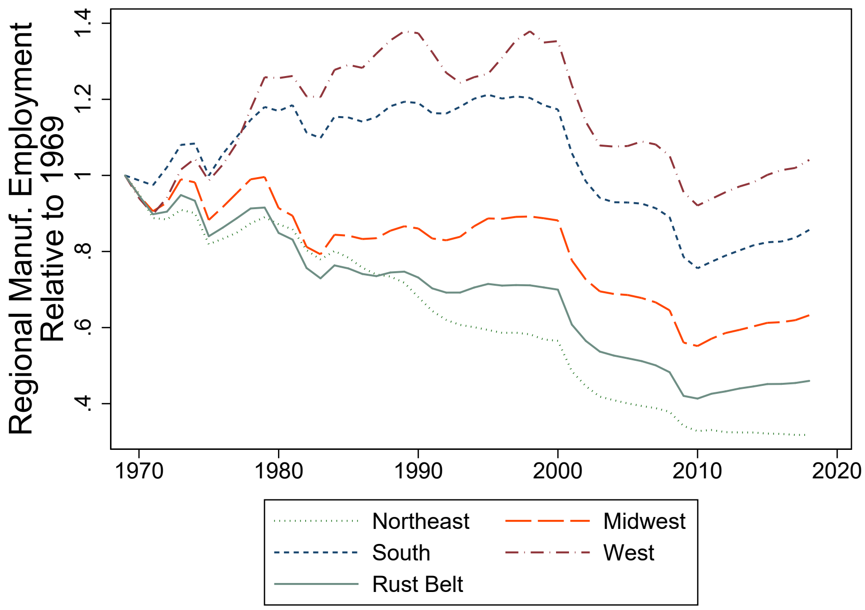


Figure 4: Manufacturing Employment by Census Region, Relative to 1969

impact of manufacturing exposure in normal counties. We are interested in whether $\beta_3 > 0$, implying that universities helped mitigate the negative impact of manufacturing exposure.

To improve precision, we include controls for log population in 1950 and log population in 1980 when studying the acceleration of manufacturing declines in 2000. For the rust belt regression we use log population in 1950 and in 1978 given we study growth from 1978 to 2018. If growth is persistent, then including the controls will reduce the standard error. Given that we argue normal versus asylum county assignment is as good as random, we do not expect that these controls would affect the point estimates. We show evidence of this in the tables to come.

3.1 Effects of Exposure to the Rust-belt Manufacturing Shock

Figure 5 shows increasing the 1978 share employed in manufacturing has a differentially positive (less negative) effect on log employment in normal relative to asylum counties in the same state, starting just after U.S. manufacturing reaches its peak in 1978. We show coefficients on the interaction between year indicator, an indicator for whether the county

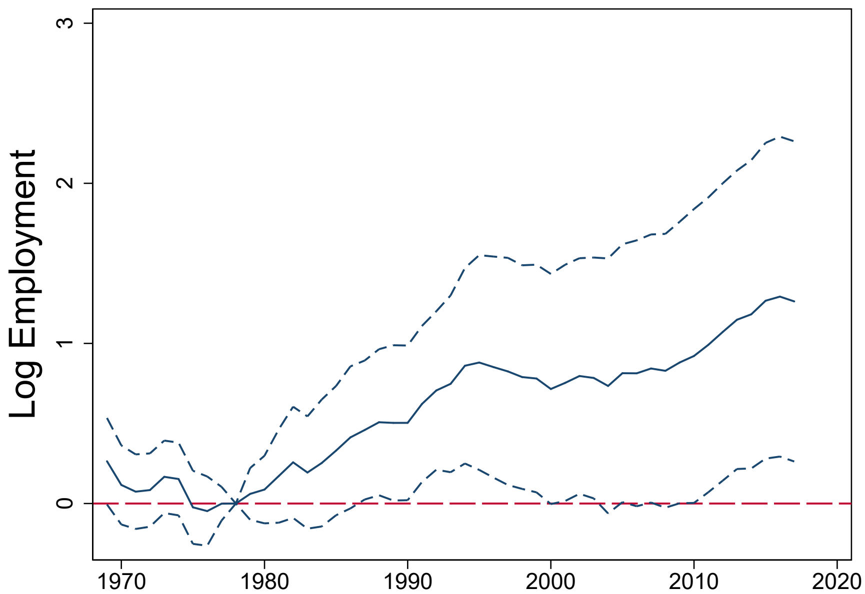


Figure 5: **Differential Effect of 1978 Manufacturing Exposure on Normal Counties Relative to Asylum Counties in Rust-Belt States.** Effects are relative to 1978, and include county and state-year fixed effects, and interactions between year fixed effects and ln(population, 1950), and separately ln(population, 1978). This plot shows coefficients on the interaction between the year indicator, whether the county had a normal school, and 1978 share employed in manufacturing. Dotted lines are 95 percent confidence intervals, with standard errors clustered at the county level.

has a normal school, and share employed in manufacturing in 1978. The regression includes lower-level terms, as well as county and state-year fixed effects. The differential effect of exposure in normal counties continues to grow through the mid 1990s, at which point it remains large and flat, before growing again around the Great Recession. Appendix Figure A11 shows similar plots for the other outcome variables.

Table 4 shows the results from specification (1). We find that regional universities helped make counties more resilient to negative manufacturing shocks. Column 1 shows that among asylum counties in rust-belt states, increasing 1978 manufacturing share by 10 percentage points is associated with 1978-2018 percent employment growth lower by 24 percentage points. However, the effect of exposure is statistically significantly smaller among normal counties. Strikingly, the magnitude suggests no negative impact of exposure. Including state fixed effects implies the differential effect of exposure in normal counties is not statistically

Table 4: The Rust-belt Shock and Differential Changes from 1978-2018 in Normal Counties

Y = % Growth	Employment	Empl.	Empl.	Population	Earnings per Job	Per Capita Transfers
Manufacturing Share, 1978	-2.426**	-1.992**	-2.374***	-1.122**	-5.489***	8.787***
	(0.977)	(0.937)	(0.552)	(0.545)	(1.536)	(2.308)
Normal*Mfg. Share, 1978	2.527**	1.692	1.967***	1.167*	4.446***	-7.759**
	(1.132)	(1.136)	(0.726)	(0.656)	(1.561)	(3.227)
Observations	103	103	103	103	103	103
R-Squared	0.078	0.219	0.543	0.426	0.326	0.524
State FE	N	Y	Y	Y	Y	Y
Control for 1950-1978 Pop. Growth	N	N	Y	Y	Y	Y

Notes: Robust standard errors in parentheses. Dependent variable is $(Y_t/Y_{t-1})-1$. Columns that control for 1950-1978 population growth include controls for Ln(Population, 1950) and Ln(Population, 1978).
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

significant, though the magnitude is still quite large.

Controlling for population growth from 1950-1978 leads to an R-squared value that is over two and a half times as large, and a substantial reduction in the standard error. The point estimate increases modestly, but the increased significance is driven by the reduction in the standard error.[24]

We similarly see that the effect of manufacturing exposure on population growth is less negative in normal counties. Increasing 1978 manufacturing share by 10 percentage points is associated with 1978-2018 percent growth in average earnings that is lower by 55 percentage points. Among normal counties the impact of manufacturing exposure is statistically significantly less negative.

Among asylum counties, higher manufacturing exposure in 1978 is associated with higher percent growth in per capita government transfers. However, among normal counties this impact of manufacturing exposure is statistically significantly smaller, and again implies the impact of exposure is close to zero. These effects appear to be concentrated in retirement transfer receipts and income maintenance benefits, although the latter is not statistically significant.[25] The differentially smaller growth in transfers in high-manufacturing normal

[24] Appendix Table A10 shows that adding additional county-level control variables measured in 1980 or pre-1980 leads to a very similar coefficient, statistically significant at the 5 percent level, and a 17 percent increase in the R-squared.

[25] Retirement transfer receipts are largely social security. Income maintenance includes Supplemental

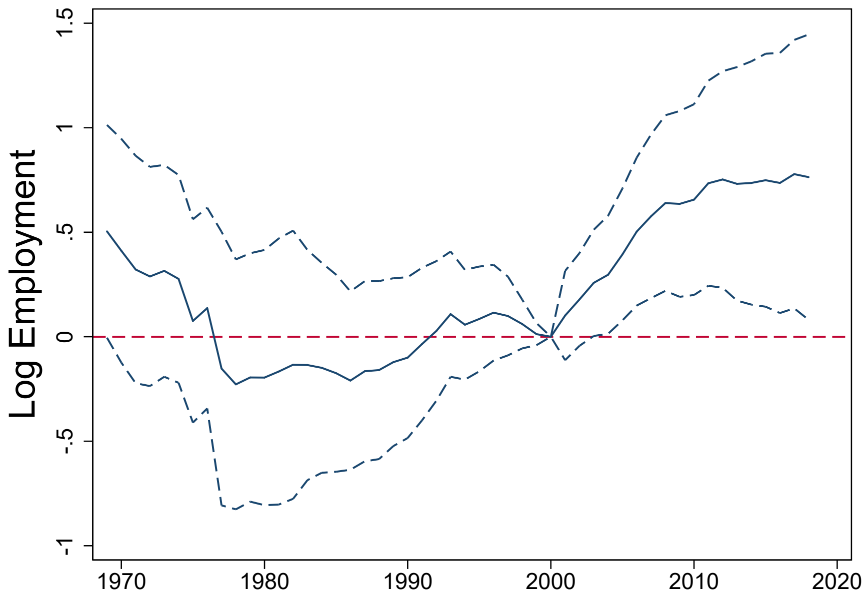


Figure 6: **Differential Effect of 2000 Manufacturing Exposure on Normal Counties Relative to Asylum Counties.** Effects are relative to 2000, and include county and state-year fixed effects, and interactions between year fixed effects and ln(population, 1950), and separately ln(population, 1980). This plot shows coefficients on the interaction between the year indicator, whether the county had a normal school, and 2000 share employed in manufacturing. Dotted lines are 95% confidence intervals, with standard errors clustered at the state level.

relative to asylum counties suggests government funding for education may reduce the need for government funding in other areas.

3.2 Effects of Exposure to Manufacturing Declines Starting in 2000

Figure 6 shows increasing 2000 share employed in manufacturing has a differentially positive (less negative) effect on log employment in normal relative to asylum counties, starting just after the national manufacturing declines of 2000. This differential effect of exposure continues to grow through 2018. We also see that this difference is increasing surrounding the 1990 recession, when manufacturing declined considerably. In this case, we are not concerned about whether the trends are parallel before 2000 because we know that there were manufacturing declines prior to 2000. Appendix Figure A12 shows similar plots for the

Security Income, the Earned Income Tax Credit, Supplemental Nutritional Assistance, and other programs.

Table 5: 2000 Manufacturing Shock and Differential 2000-2018 Changes in Normal Counties

Y = % Growth	Empl.	Empl.	Empl.	Population	Earnings per Job	Per Capita Transfers
Manufacturing Share, 2000	-1.498***	-1.397***	-1.192***	-0.599**	-0.666***	0.563**
	(0.384)	(0.446)	(0.426)	(0.264)	(0.127)	(0.242)
Normal*Mfg. Share, 2000	0.920*	1.088**	0.994**	0.595*	0.294	-0.230
	(0.486)	(0.520)	(0.486)	(0.346)	(0.228)	(0.300)
Observations	325	320	320	320	320	320
R-Squared	0.056	0.311	0.378	0.475	0.467	0.563
State FE	N	Y	Y	Y	Y	Y
Control for 1950-1980 Pop. Growth	N	N	Y	Y	Y	Y

Notes: Standard errors clustered at the state level in parentheses. Dependent variable is $Y_t/Y_{t-1} - 1$. Columns that include controls for 1950-1980 population growth include Ln(Population, 1950) and Ln(Population, 1980) as additional control variables. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

other outcome variables.

Column 1 of Table 5 shows that among asylum counties, increasing 2000 manufacturing share by 10 percentage points is associated with 2000-2018 percent employment growth lower by 15 percentage points. However, among normal counties that effect is statistically significantly smaller, by 9.2 percentage points. The results are slightly larger and significant at the 5 percent level when including state fixed effects, and similar when including controls for 1950-1980 population growth.[26]

In asylum counties, higher manufacturing exposure is correlated with lower growth in earnings per job and higher growth in per capita government transfers. While the point estimates suggest these changes are less adverse in normal counties, they are not precisely estimated.

3.3 Robustness

Our first robustness check is to look at the entire country starting in 1978. U.S. manufacturing employment peaked in 1978, and declined over the following decades, with accelerated declines in the 2000s. As an additional specification we analyze 1978 manufacturing exposure

[26] Appendix Table A10 shows that including additional county-level controls measured in 1980 or pre-1980 yields a very similar coefficient, statistically significant at the 5% level, and a 26% increase in the R-squared. We again see similar results for population growth.

and growth from 1978-2018 in all counties. This specification may capture additional declines over this longer time period, rather than limiting our analysis to 2000-2018. Appendix Table A9 shows that when looking at all counties, the differential effect of 1978 manufacturing exposure on employment, population, and average earnings per job growth from 1978-2018 was statistically significantly less negative in normal counties than in asylum counties. The estimated effect on per capita personal current transfer receipts was also more negative in normal counties, but in this case the result is not statistically significant.[27]

A second robustness check uses a discrete measure of manufacturing intensity instead of the continuous one. Appendix Tables A13 and A14 show similar patterns using an indicator for above median manufacturing share in 1978 and 2000 respectively, though the effects are less precisely estimated and not statistically significant.

Another robustness check controls for variables that might otherwise lead to omitted variable bias. Two potential sources of resilience that have been highlighted in the literature are proximity to large population centers, and share of individuals with a bachelor's degree. It is possible that normal counties are closer to larger population centers, and that they have a higher share of individuals with a bachelor's degree, and that this explains resilience to manufacturing rather than the university. Appendix Table A16 shows results including interactions between the indicator for normal county and log nearby population in 1980 based on a gravity model, as well as 1980 share of individuals with a bachelor's degree. For the rust belt shock, including these interactions leads to approximately a 10 percent decline in the coefficient on the interaction between normal county and manufacturing exposure, and the effect remains significant at the 5 percent level. For the 2000 manufacturing decline, including these interactions also leads to about a 10 percent decline in the magnitude, but the standard error increases and the coefficient is no longer significant. For both shocks, the coefficients are not significant on the interaction between manufacturing exposure and share with a bachelor's degree, and log nearby population. In the mechanisms section we

[27]Appendix Table A12 shows the results by transfer component.

will further discuss the role of upskilling and education in resilience.

Comparing Identification to a Matching Strategy

As an alternative to our control group of asylum counties, we use a matching procedure to identify control counties. We use nearest neighbor matching on 1920 population, as well as propensity score matching with the following variables used to predict likelihood of being assigned a normal school: 1920 population, 1920 urban population share, and 1920 manufacturing employment as a share of population. The matching procedure and results are described in detail in Appendix Table A18. For the Rust Belt shock, the results are similar to our main results. However, for the 2000 manufacturing decline, the negative effect of manufacturing exposure in the control counties using the matches is substantially smaller than the negative effect of exposure in the asylum counties. As a result, the differential effect is smaller in normal counties, and not precisely estimated.

These matching results suggest selection on unobservables for asylum counties relative to other counties observationally similar to normal counties in 1920. Given our qualitative and quantitative evidence that selection was similar for normal and asylum counties, this suggests the matched control group yields biased effects and further underscores the importance of our identification strategy.

Differential Effect in Counties with Research Universities

Almost none of the universities converted from normal schools are designated as research universities in recent years. Thus, our main identification strategy does not allow us to identify whether research universities improve resilience, for example through spillovers, innovation, and entrepreneurship. However, as an additional exercise we estimate differential effects of manufacturing exposure in counties with public research universities, established between 1830 and 1930. This allows us to estimate a specification relying on similar identification assumptions as equation (1). We compare counties that were assigned state universities that were research universities by 1987, to counties that were assigned state normal schools, to counties that were assigned state asylums, all during the period from roughly 1830 to 1930.

We believe the identification assumptions for research universities may be less likely to hold than for normal schools. Most importantly, in many cases there is only one research university per state, and so the selection into becoming a research county may have been quite different than for becoming a normal or asylum county, for which multiple counties were often chosen across the state. We also have limited power to identify an effect, as our regressions include only 56 research university counties, compared to 204 normal school counties.

We estimate (1), and include an additional interaction between manufacturing exposure and an indicator for having a public R1 or R2 university established between 1830 and 1930. We use the 1987 Carnegie Classifications. Because we are estimating the effect of manufacturing exposure in research university counties, we need more than one research university county per state if we include state fixed effects. Only about one third of states have more than one research university based on our definition. As a result, we instead include census division fixed effects, and include our additional county level control variables.[28]

The point estimates suggest manufacturing exposure in 2000 is substantially less negative in research counties than in asylum counties, though this is not statistically significant (Appendix Table A17). The magnitude is about 20 percent larger than the differential effect in normal counties, but this difference is also not statistically significant. The research output of the university does not appear to dramatically further contribute to resilience. As we will discuss, this is consistent with our findings in the mechanisms section to follow.[29]

[28]This specification yields similar results to our main specification in Table 5 if we include only normal and asylum counties (Appendix Table A17).

[29]We present the results for rust belt states for completeness, but there are only 12 research university counties in this specification.

4 Spending Mechanism

We have shown that universities make their economies more resilient, and now we ask why. In this section, we consider whether university growth and spending is resilient to adverse shocks, and whether this growth has direct and indirect effects on the economy. We find support for this channel, explaining a significant fraction of the resilience.

In Appendix D, we consider whether universities increase skills in the local market, and this improves resilience. There are several reasons to expect this channel may not be that large. First, the universities do not seem to attract young people as we showed in Figure 3. Second, having a university has only a modest effect on the education level of the county (Table 2). Finally, these universities are less research-intensive (none are R1 and less than 2 percent are R2) so many of the spillovers identified by the literature may not be operative. In the appendix, we look to see if there is a differential effect on the age profile or the education levels in response to the manufacturing shock.

4.1 University Spending in Response to Manufacturing Shocks

Universities in normal counties are large state universities, and so the demand and budget for these universities may be more resilient to adverse shocks. As a result, direct spending by the universities may be more resilient, increasing the local market's resilience.

We obtain data on university spending from IPEDS, which includes wages and benefits, and operational expenses, but excludes capital outlays such as construction.[30] Because our objective is to understand the impact of university spending on the local economy, we focus on universities whose enrollment is not predominantly distance education. At universities where most students are pursuing online degrees, university staff and spending may be much less concentrated in the local market.[31]

[30]Operational expenses include expenses for janitorial services, building maintenance, groundskeeping, and security, as well as other categories.

[31]Specifically, we restrict to universities at which less than 50 percent of total enrollment was enrolled exclusively in distance education in 2018. When looking at changes in spending over time, we include only these universities (based on the 2018 measure) in each year, and aggregate at the county-year level. We use

We first estimate the following specification, for both the Rust Belt shock, and the acceleration of manufacturing declines in the early 2000s:

$$\frac{\Delta \text{University Spending}_{it}}{\text{Total County Income}_{i,t-1}} = \beta_1 \text{Normal}_i + \beta_2 \text{Mfg Exposure}_i + \beta_3 \text{Normal}_i \times \text{Mfg Exposure}_i + \alpha_{st} + X_i \gamma + \epsilon_{it} \quad (2)$$

Table 6 shows that manufacturing exposure has a negative impact on university spending growth, as a share of base year county income, in asylum counties. Even in asylum counties where the universities are smaller, universities in counties more heavily exposed to manufacturing experienced greater decreases in spending, and these were important for county income.

Manufacturing exposure had less negative effects on university spending growth relative to base year income in normal counties. When analyzing rust-belt exposure, this differential effect (coefficient of .48) explains roughly 13 percent of the differential effect of exposure on income growth in normal counties (3.67 from column 1). When analyzing the effect of 2000 manufacturing exposure, the differential growth in spending explains roughly 16 percent of the overall differential effect on income growth.[32]

Thus, direct spending by the university, including wages and benefits, and operational expenses, but excluding capital outlays such as construction, can account for roughly 15 percent of the differential resilience of normal counties to manufacturing exposure. As we will discuss, this direct university spending arguably also has multiplier effects in the local economy, further explaining the differential resilience. The exclusion of construction and capital spending likely implies that 15 percent is a substantial underestimate of the contribution of university spending.[33]

the same sample of universities when looking at changes in enrollment and changes in staff.

[32]Appendix Figure A9 shows that the differential effect of exposure in normal counties is relatively flat from 1990 through 1997, and then starts to increase timed with when manufacturing employment begins to fall in 1998. There is also an increasing trend from 1980 to 1990, which is consistent with exposure to manufacturing declines in 2000 being correlated with exposure to the shock in the 1980s.

Appendix Figure A10 shows the equivalent event study specification for the Rust Belt Analysis, but because the data starts in 1980, there is no way to look at pretrends.

[33]Delaney and Doyle (2014) show that on average state expenditures on capital outlays in higher education

Table 6: Accounting for County Income and Employment Growth: Role of University Spending and Staff

Rust-Belt Exposure and Growth

Dependent Variable	$\frac{\Delta Income_{s,t}}{Income_{s,t-1}}$	$\frac{\Delta Univ.Spend_{s,t}}{Income_{s,t-1}}$	$\frac{\Delta Empl_{s,t}}{Empl_{s,t-1}}$	$\frac{\Delta Staffs_{s,t}}{Empl_{s,t-1}}$
Manufacturing Share, 1978	-4.012**	-0.441*	-1.046***	-0.0772*
	(1.564)	(0.245)	(0.361)	(0.0453)
Normal*Mfg. Share, 1978	3.670**	0.480*	0.952**	0.0812*
	(1.531)	(0.277)	(0.446)	(0.0486)
Observations	103	103	103	103
R-Squared	0.403	0.265	0.339	0.232
Years	1980-2018	1980-2018	1989-2018	1989-2018

2000 Manufacturing Exposure and Growth

Dependent Variable	$\frac{\Delta Income_{s,t}}{Income_{s,t-1}}$	$\frac{\Delta Univ.Spend_{s,t}}{Income_{s,t-1}}$	$\frac{\Delta Empl_{s,t}}{Empl_{s,t-1}}$	$\frac{\Delta Staffs_{s,t}}{Empl_{s,t-1}}$
Mfg. Share, 2000	-0.993**	-0.168**	-1.065***	-0.0301***
	(0.398)	(0.0667)	(0.347)	(0.0108)
Normal*Mfg. Share, 2000	0.825*	0.130*	0.847**	0.0324**
	(0.481)	(0.0684)	(0.409)	(0.0145)
Observations	320	320	320	320
R-Squared	0.410	0.216	0.405	0.229
Years	2000-2018	2000-2018	2001-2018	2001-2018

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. All regressions include state fixed effects. Robust standard errors are presented in Panel A, and standard errors clustered at the state level in Panel B. Regressions in Panel A include controls for Ln(Population, 1950) and Ln(Population, 1978), while regressions in Panel B include controls for Ln(Population, 1950) and Ln(Population, 1980). See text for details.

We implement a similar exercise for identifying the role of university staff and enrollment growth in the overall employment effects. We show results for university staff growth in rust-belt counties from 1989-2018 as the IPEDS staff survey started as a biennial survey in 1987, but was missing for many universities in the first year. In all counties, we show university staff growth from 2001-2018. Increasing manufacturing exposure has a negative

were roughly 30 percent of total state appropriations for higher education in 2004.

effect on staff growth in asylum counties (column 4), and this is differentially smaller in normal counties. However, this differential effect can account for only about 8.5 percent of the employment growth differential when looking at rust-belt exposure, and 4 percent when looking at 2000 manufacturing exposure.

Direct employment by the university plays a smaller role in employment growth, than university spending plays in income growth. This is consistent with universities playing a direct role in the local economy in ways beyond directly employing staff. Magnitudes suggest changes in enrollment account for a larger share of the differential employment effect than changes in staff (Appendix Table A15).[34] However, the effects are not precisely estimated.

The evidence here suggests that manufacturing exposure has smaller adverse impact in normal counties in large part because it has smaller adverse impacts on university spending. This is consistent with the universities in normal counties being large state universities, with more robust student demand as well as potentially more stable budgets due to state allocations. There is some evidence that enrollment is more resilient in normal counties (Appendix Table A15), but the evidence is not very strong, and is also consistent with an important role for state allocations.

4.2 Sectoral Evidence

In this section, we test the extent to which differential employment effects are explained by the tradable or nontradable sectors. One possible explanation for our results is that the manufacturing in normal counties is different than in asylum counties, and was not affected as much by these shocks. This would suggest differential employment effects in manufacturing. Another explanation is that university spending creates a local multiplier, implying effects

[34] However, the years over which we calculate the enrollment effects are aligned with the spending effects, not the staff effects.

in nontradable sectors. We estimate the following specification:

$$\frac{\Delta \text{ Sectoral Employment}_{it}}{\text{Total Employment}_{i,t-1}} = \beta_1 \text{Normal}_i + \beta_2 \text{Mfg Exposure}_i + \beta_3 \text{Normal}_i \times \text{Mfg Exposure}_i + \alpha_{st} + X_i \gamma + \epsilon_{it} \quad (3)$$

If we had a full breakdown of employment by sector, we could add up all the βs from the different sectors and they would sum to the total employment result. Because of the change from SIC to NAICS classifications in 2000, we split our analysis of the rust-belt shock into growth from 1978-2000 and growth from 2001-2018.

Column 1 of Table 7 shows that increasing 1978 manufacturing share by 10 percentage points has a differentially positive effect on percent employment growth in normal counties from 1978-2000 of nearly 11 percentage points, relative to asylum counties. Differential effects on employment growth in services account for nearly 30 percent of this effect, retail accounts for approximately 17 percent, and federal government for roughly 6 percent. Effects for the remaining industries are smaller and/or less precise. Importantly, we cannot rule out that the effect of exposure on manufacturing growth was the same in normal and asylum counties. This implies resilience is not driven by differential exposure to the broad shock, or by differential resilience of the manufacturing sector to the same shock.[35]

Panel B shows the analogous results analyzing exposure to the 2000 manufacturing declines.[36] We find significant and substantial effects in retail, services, government, and con-

[35] Appendix Table A19 shows the results from 2001 to 2018 for rust belt counties.

[36] There is considerably more missing sectoral employment data when using the NAICS classifications post-2000. To maximize our sample size, we analyze percent growth in average employment from 2001-2004 to 2015-2018. This allows us to include counties which are missing employment for a given sector in 2001 but not in 2002, for example. Counties missing data in a lower employment year will have a higher multi-year average than had employment been nonmissing in that year. We adjust the multi-year averages based on the particular years that make up the average in each county, using national industry employment. For example, we compute the average national employment in retail from 2001-2004, and then the average from 2002-2004. We compare the 2002-2004 average to the 2001-2004 average to get a multiplier. We adjust county-level average retail employment for which the county only has retail data in 2002-2004 rather than in all four years. If national employment in 2002-2004 is 1.005 times average retail employment in 2001-2004, then for counties with retail data in only 2002-2004, we divide by 1.005. This averaging allows us to include 10 to 20 percent more counties.

Even with multi-year averages, some counties are still missing employment data for some sectors. To avoid comparing results based on different samples, we limit the regressions to a fixed sample of 249 counties. These counties have employment for sectors that are nonmissing for nearly all counties (at least 99 percent

Table 7: Differential Employment Growth in Normal Counties, by Sector

A: Rust Belt, 1978-2000										
$Y = \frac{\Delta \mathrm{Empl}_{s,t,t-1}}{\mathrm{Empl}_{t-1}}$	All	Constr.	Mfg.	Transp.	Whole-sale	Retail	FIRE	Serv.	Fed. Gov.	State & Local
Mfg. Share, 1978	-1.249***	-0.050	-0.342***	-0.010	0.001	-0.168*	-0.134***	-0.373**	-0.040	-0.069
	(0.359)	(0.034)	(0.111)	(0.045)	(0.028)	(0.092)	(0.044)	(0.152)	(0.027)	(0.103)
Normal*Mfg., 1978	1.091**	0.075	0.140	0.023	0.030	0.190*	0.048	0.321*	0.062**	-0.065
	(0.500)	(0.047)	(0.135)	(0.051)	(0.036)	(0.110)	(0.057)	(0.177)	(0.027)	(0.132)
Observations	103	102	103	98	101	103	103	103	103	103
R-Squared	0.646	0.431	0.547	0.424	0.572	0.463	0.412	0.526	0.164	0.426

B. All Counties, 2001-2018										
$Y = \frac{\Delta \mathrm{Empl}_{s,t,t-1}}{\mathrm{Empl}_{t-1}}$	All	Constr.	Mfg.	Retail	Finan. & Insur.	Real Estate	Prof. Serv.	Admin Serv.	Fed.	State & Local
Mfg. Share, 2000	-1.126***	-0.034	-0.172***	-0.069	-0.090	-0.047*	-0.089**	-0.065**	-0.020**	-0.081**
	(0.378)	(0.028)	(0.052)	(0.043)	(0.057)	(0.026)	(0.037)	(0.025)	(0.008)	(0.037)
Normal*Mfg., 2000	1.075**	0.061*	0.025	0.096**	0.078	0.022	0.071	0.099***	0.034**	0.125***
	(0.408)	(0.031)	(0.052)	(0.047)	(0.065)	(0.025)	(0.044)	(0.035)	(0.013)	(0.044)
Observations	249	249	249	249	249	249	249	249	249	249
R-Squared	0.432	0.431	0.444	0.400	0.238	0.413	0.339	0.407	0.281	0.311
State Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. Robust standard errors in parentheses in panel A. Standard errors clustered at the state level in parentheses in panel B. All regressions include state fixed effects. Panels A includes controls for Ln(Population, 1950) and Ln(Population, 1978). Panel B includes controls for Ln(Population, 1950) and Ln(Population, 1980). Panel B includes only counties with non-missing industry employment for these listed industries. Dependent variable is the change in sectoral employment from t-1 to t relative to total employment in t-1. See text for details.

struction. We find no differential effect on manufacturing growth. We also see important effects in industries which had more missing data, and so were not included in these main results (see Appendix Tables A7 and A8). In particular, we see evidence suggesting effects on health employment.

In sum, greater exposure to manufacturing is associated with smaller long-run employment growth, but this effect is significantly less negative for counties that had normal schools. The differential effect is explained by employment growth across many non-tradable sectors,

after the multi-year averaging), as well as employment in professional, scientific, and technical services, and administrative and support services (which are covered for 90 percent of rust-belt counties after the averaging).

We include these services sectors because they seem especially relevant. The connection between higher education and professional, scientific, and technical services, is intuitive and has been explored in other work (e.g. Andrews, 2020). Administrative and support services includes firms that provide services to other firms, for example cleaning, groundskeeping, and security. Given the growth in contracting out these types of occupations (see Weil 2014), differential growth of universities may be captured by state and local employment as well as administrative and support services. For completeness, we show results for all sectors, not restricting to a fixed sample of counties, in Appendix Tables A7 and A8.

with the largest effects in services and retail. Importantly, we do not see strong evidence that the differential effect in normal counties is explained by less negative effects on manufacturing employment. The results are consistent with counties benefiting from a large and stable source of demand: the university and its students.

4.3 Multipliers

The previous sections established the role of university growth as a resilience mechanism. Quantitatively, university spending is directly responsible for 15 percent of the resilience. As we alluded, this spending may also have indirect effects that further explain the resilience.

The fact that the positively-affected industries are non-tradable and span the economy suggest that spending could be responsible for a large fraction of the resilience through a multiplier effect. However, quantifying these indirect effects requires knowledge of the local spending multiplier, beyond the scope of this paper. Other papers, from a variety of settings, have a range of estimates from 1.25 to 5 or more.[37] Taking a multiplier from Moretti (2010) in the middle of this range (3.5) suggests that university spending is responsible for half of the resilience (15 percent times 3.5 is 53 percent). At the high end, it could be explaining a large majority of the resilience.We leave it up to the reader's judgement to decide how large the indirect contribution may be.

This analysis does not include the multiplier that would likely come from additional student spending, meaning that it is probably an underestimate of the spillover effects that come from spending on local goods and services. In Appendix Table A15, the same regression but for enrollment estimates a coefficient that is significantly larger than the effect on staff in terms of magnitude, but which is statistically insignificant.

We are also likely underestimating the total effect because the data does not include university spending on construction projects. Recall in Table 7 that construction employment

[37] Moretti (2010) presents a multiplier from skilled tradable jobs to local goods and services (3.5), Weinstein (2018) from financial services (6), Moretti and Wilson (2014) from biotech (13.5), Marchand (2012) from energy jobs (2), Black, McKinnish and Sanders (2005) from coal (1.25), and Zou (2018) from military contractions (2.2).

did contribute to the estimated resilience. Taking the share of construction spending from Delaney and Doyle (2014), if construction spending were everywhere proportional to other spending, we would want to increase our estimates by about 40 percent.

5 Conclusion

In this paper, we investigate whether regional universities make the local economy more resilient to economic shocks. We do so using a novel identification strategy, comparing counties that were assigned normal schools to counties that were assigned insane asylums by state governments in the 19th and early 20th centuries. Criteria for selecting these counties was quite similar, and we show these counties are observationally very similar before they are chosen.

Overall, we have found that regional universities do increase local resilience. First, we show that the long-run negative effects of manufacturing exposure are significantly smaller for counties that were assigned normal schools. We find similar effects for mining exposure during the 1980s decline. We also show that counties that had normal schools recover more quickly during and after recessions. Our analysis suggests an important mechanism is that public, regional university spending is resilient to these shocks, and this improves local economic resilience.

We think these results are especially policy relevant as regional universities are currently experiencing financial challenges. While there are many costs and benefits of funding regional universities, we show that one benefit of these universities is that they improve local economic resilience.

References

Aghion, P., L. Boustan, C. Hoxby, and J. Vandenbussche. 2009. "The Causal Impact of Education on Economic Growth." *Working Paper.*

Alder, Simeon, David Lagakos, and Lee Ohanian. 2019. "Labor Market Conflict and the Decline of the Rust Belt." *Working Paper.*

Alton Evening Telegraph. 1915. "In a Hurry for Insane Hospital." March 10, 1915.

American Council on Education. 1952. *American universities and colleges sixth edition 1952.* Washington, D.C.:American Council on Education.

Andes, Scott, Mitch Horowitz, Ryan Helwig, and Bruce Katz. 2017. *Capturing the next economy: Pittsburgh's rise as a global innovation city.* Anne T. and Robert M. Bass Initiative on Innovation and Placemaking at Brookings.

Andrews, Michael. 2020. "How do Institutions of Higher Education Affect Local Invention? Evidence from the Establishment of U.S. Colleges." *Working Paper.*

Autor, David, David Dorn, and Gordon H Hanson. 2013. "The China syndrome: Local labor market effects of import competition in the United States." *American Economic Review*, 103(6): 2121–68.

Bartik, Timothy J. 2018. "What Works to Help Manufacturing-Intensive Local Economies?"

Black, Dan, Terra McKinnish, and Seth Sanders. 2005. "The Economic Impact of the Coal Boom and Bust." *The Economic Journal*, 115(April).

Cantoni, Davide, and Noam Yuchtman. 2014. "Medieval Universities, Legal Institutions, and the Commercial Revolution." *Quarterly Journal of Economics.*

Council of State Governments. 1950. *The Mental Health Programs of the Forty-Eight States: A Report to the Governor's Conference.* Chicago, IL: Council of State Governments.

Delaney, Jennifer A., and William R. Doyle. 2014. "State Spending on Higher Education Capital Outlays." *Research in Higher Education*, 55.

Deming, David J., and Christopher R. Walters. 2017. "The Impact of Price Caps and Spending Cuts on U.S. Postsecondary Attainment." *Working Paper.*

Dixon Evening Telegraph. 1951. "The Dixon State Hospital."

Feng, Andy, and Anna Valero. 2020. "Skill-Biased Management: Evidence from Manufacturing Firms." *Economic Journal*, 130(May).

Feyrer, James, Bruce Sacerdote, and Ariel Dora Stern. 2007. "Did the Rust Belt Become Shiny? A Study of Cities and Counties that Lost Steel and Auto Jobs in the 1980s." *Brookings-Wharton Papers on Urban Affairs.*

Foster, E.M., H.G. Badger, M.J.S. Carr, B.K. Choate, M. Farr, R.M. Smith, F.J. Kelly, W.J. Greenleaf, and Office of Education (ED) United States Department of the Interior. 1937. *Biennial Survey of Education in the United States, 1932-1934. Bulletin, 1935, No. 2. Chapter IV: Statistics of Higher Education, 1933-34.* ERIC Clearinghouse.

Furbush, E. M., Pollock H. M. (Horatio Milo), A. Veronica Hagan, W. C. (William Chamberlin) Hunt, and United States Bureau of the Census. 1926. *Patients in hospitals for mental disease, 1923.* Washington, D.C.: Government Printing Office. *HathiTrust Digital Library,* https://catalog.hathitrust.org/Record/002085507.

Glaeser, Edward L., and Albert Saiz. 2004. "The Rise of the Skilled City." *Brookings-Wharton Papers on Urban Affairs.*

Grob, Gerald. 2008. *Mental Institutions in America: Social Policy to 1875.* Routledge.

Hartt, Maxwell, Austin Zwick, and Nick Revington. 2019. "Resilient shrinking cities." *The Routledge Handbook of Urban Resilience.*

Hausmann, Naomi. 2020. "University Innovation and Local Economic Growth." *Working Paper.*

Henderson, Tim. 2018. "The Mystery of Pittsburgh: How Some Shrinking Cities are Thriving in the New Economy." *Pew.*

Hoopes, Lauren. 2015. "On the Periphery: A Survey of Nineteenth-Century Asylums in the United States." *All Theses*, 2123.

Humphreys, Harry Christopher. 1923. *The Factors Operating in the Location of State Normal Schools.* Teachers College, Columbia University.

Indiana Business Research Center. 2020. "SatsAmerica." `http://www.statsamerica.org/CityCountyFinder/`.

Jordà, Òscar. 2005. "Estimation and inference of impulse responses by local projections." *American economic review*, 95(1): 161–182.

Kantor, Shawn, and Alexander Whalley. 2014. "Knowledge Spillovers from Research Universities: Evidence from Endowment Value Shocks." *Review of Economics and Statistics*, 96(1).

Kantor, Shawn, and Alexander Whalley. 2019. "Research Proximity and Productivity: Long-Term Evidence from Agriculture." *Journal of Political Economy*, 127(2).

Kirkbride, Thomas Story. 1854. *On the construction, organization and general arrangements of hospitals for the insane. Sabin Americana, 1500-1926.*, Philadelphia:Lindsay Blakiston.

Labaree, David F. 2008. "An Uneasy Relationship: The History of Teacher Education in the University." In *Handbook of Research on Teacher Education: Enduring Issues in Changing Contexts (3rd ed.).* , ed. Marilyn Cochran-Smith, Sharon Feiman Nemser and John McIntyre. Washington, DC:Association of Teacher Educators.

Lin, Jeffrey. 2012. "Regional Resilience." *Federal Reserve Bank of Philadelphia Working Papers*, 13-1.

Marchand, Joseph. 2012. "Local Labor Market Impacts of Energy Boom-Bust-Boom in Western Canada." *Journal of Urban Economics*, 71(1).

Martin, Ron. 2012. "Regional economic resilience, hysteresis and recessionary shocks." *Journal of economic geography*, 12(1): 1–32.

Maxim, Robert, and Mark Muro. 2020. *Brookings Metropolitan Policy Program.*

Moretti, Enrico. 2004. "Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data." *Journal of Econometrics*, 121.

Moretti, Enrico. 2010. "Local multipliers." *American Economic Review Paper & Proceedings*, 100(2): 373–77.

Moretti, Enrico, and Daniel J Wilson. 2014. "State incentives for innovation, star scientists and jobs: Evidence from biotech." *Journal of Urban Economics*, 79: 20–38.

Ogren, Christine. 2005. *The American state normal school: An instrument of great good.* Springer.

Ottawa Free Trader. 1869. "Northern Insane Asylum."

Pierce, Justin R, and Peter K Schott. 2016. "The surprisingly swift decline of US manufacturing employment." *American Economic Review*, 106(7): 1632–62.

Quinton, Sophie. 2020. "COVID-19 Could Be End of Line For Some Regional Colleges."

Ruggles, Steven, Sarah Flood, Sophia Foster, Ronald Goeken, Jose Pacas, Megan Schouweiler, and Matthew Sobek. 2021. "IPUMS USA: Version 11.0 [dataset]." https://doi.org/10.18128/D010.V11.0.

Seltzer, Rick. 2020. "Pa. State System Moves Forward with Modified Merger Plan." *Inside Higher Ed.*

The Cairo Evening Bulletin. 1869. "The Southern Illinois Insane Asylum." June 22, 1869.

The Economist. 2020. "From rustbelt to brainbelt." *The Economist.* Special report: The Midwest.

United States Department of Education. National Center for Education Statistics. 1998. *Higher Education General Information Survey (HEGIS), 1970: Fall Enrollment.*

United States Department of Education. National Center for Education Statistics. 1999. *Higher Education General Information Survey (HEGIS), 1975: Fall Enrollment.*

U.S. Department of Education, National Center for Education Statistics. 2020. "Integrated Postsecondary Education System (IPEDS)." `https://nces.ed.gov/ipeds/`.

Valero, Anna, and John Van Reenen. 2019. "The Economic Impact of Universities: Evidence from Across the Globe." *Economics of Education Review*, 68.

Warren County Democrat. 1895. "Rock Island Got It." IX(12).

Weinstein, Russell. 2018. "Dynamic responses to labor demand shocks: Evidence from the financial industry in Delaware." *Journal of Urban Economics*, 106: 27–45.

Wolman, Harold, Howard Wial, Travis Clair, and Edward Hill. 2017. "Coping with Adversity, Regional Economic Resilience Public Policy ACSP paper 2017."

Yanni, Carla. 2007. *The Architecture of Madness: Insane Asylums in the United States.* University of Minnesota Press.

Zou, Ben. 2018. "The Local Economic Impacts of Military Personnel." *Journal of Labor Economics*, 36(3).

A Data Appendix

This appendix provides a description of our data sources and the construction of key variables used in our paper.

A.1 College-year roster

Our analysis includes data on university characteristics at the county level. We construct these data by first constructing an institution-by-year roster using IPEDS data, comprised of two-year and four-year Title IV institutions. We then construct and match institution-by-year variables to the roster, including total degrees granted, student enrollments, financial variables, employees, and staff in the fall semester.

Step 1: Define characteristics

For each institution, we defined its control (public or private), type (two-year or four-year) and Title IV accreditation. These characteristics are obtained from the annual "Institutional Characteristics" survey provided by the Integrated Postsecondary Education Data System (IPEDS, U.S. Department of Education, National Center for Education Statistics (2020)) .

Public institutions: An institution is considered public if its *"control"* is "Public only" or "Combination of public and private."

Two-year and four-year institutions: In 1980, an institution is considered two-year if its *"type"* is "Two year," "2-year branch campus of a multi-campus university" or "2-year branch campus of other 4-year multi-campus inst", and an institution is four-year if its *"type"* is "University (must offer at least two first professional programs)," or "Other four year." If an institution is neither two-year nor four-year, then it is categorized as a less than two-year institution. Similarly, from 1984 to 2017, we define an institution as a two-year institution if its *"iclevel"* is "At least 2 but less than 4 years below the Baccalaureate" or "Below the Baccalaureate." We define an institution as four-year if its *"iclevel"* is "4 or more years (Baccalaureate or higher degree)" or "Baccalaureate or higher degree." Institutions with *"iclevel"* equal to "Below Associates Degree" are categorized as less than two-year institutions.

Title IV institutions: From 1986 to 1997, we classify a college as a Title IV institution if it is eligible for any of "Financial Aid," "Veteran Administration Educational Benefits," "Pell Grants," "Supplementary Education Opportunity Grants," "Stafford Loans," "College Work Study Program," "National Direct Student Loan," "Higher Education Assistance Loan," or "Other Federal Student Financial Aid Programs." From 1998 to 2015, we use the variable *"opeflag"* to identify Title IV institutions, if they are coded as "Participates in Title IV federal financial aid programs." We did not include in this classification institutions coded as "Branch campus of a main campus that participates in Title IV" nor "Deferment only - limited participation." We fill missing Title IV information in 1980, 1984, and 1985 with Title IV information in 1986.

Step 2: Fill missing values

Given each institution is often present multiple times across the years, we filled missing values using values of the same institution in the next year. We began with filling missing county, institution name, state, and city using the values in the next year. Then, we filled missing FICE code, public school indicator and zip code using values of the same institution in other years. Particularly, when filling county names and zip code, we further required the other observation to be listed as being located in the same city. This ensures we do not impute the wrong locations for institutions that moved.

Next, we imputed missing county FIPS using the FIPS of the same institution in other years. First, we identified institutions that have the same non-missing FIPS for all observations. For these institutions, we imputed the missing FIPS using the FIPS in neighboring years. For those institutions that had inconsistent FIPS across years, we imputed using other observations for the same institution, as long as the city and state were the same.

Some institutions in our sample were listed as "system," which is a single administrative body that controls two or more institutions.[38] We identified an institution as an observa-

[38] The definition of "institution system" can be found on IPEDS Data Collection System (U.S. Department of Education, National Center for Education Statistics, 2020*b*).

tion for the administrative system if its name contained "System" or similar words. Before proceeding to the next step, we dropped (1) institutions that were not eligible for Title IV programs; (2) institutions that were below two-year or types were "non-response" or "administrative unit;" and (3) institutions that reported as a system.

Step 3: Fill missing FIPS codes

First, we identified observations that were still missing FIPS.

Second, we used zip code to cross walk to FIPS. Note that not all observations in our sample had ZIP codes. Moreover the ZIP code to county FIPS crosswalk is not necessarily one-to-one. We only crosswalk ZIP to FIPS for observations with a one-to-one ZIP to FIPS matching.

Third, there were still 1991 observations missing a FIPS code out of 166,513 observations, and we filled them in by hand following the procedures below:

1. If an observation contained county name, we identified its FIPS using County FIPS Codes from USDA website (United States Department of Agriculture, 2020).

2. If an observation did not have a county name but had a city name, we first identify county name using its city name on STATSAMERICA (Indiana Business Research Center, 2020), then we identified the FIPS code.

Finally, we pooled together observations that were not originally missing FIPS, those for which we used ZIP to match to FIPS codes, and those for which we filled in FIPS by hand. At this stage, all the observations in our sample matched with a county FIPS code.

A.2 Degrees

The institution-by-year degree data were obtained from the IPEDS "Completions" survey U.S. Department of Education, National Center for Education Statistics (2020). We used the variable "awlevel" from the raw table to identify the degree level. Depending on the year, we defined associate's degrees, bachelor's degrees and post-bachelor's degrees in the following way:

- *Associate's degree*: "Associate degree creditable toward bachelor's degree" (1980), "Associate degree not creditable toward bachelor's degree" (1980), "Associates degrees" (1984 to 2017).
- *Bachelor's degree*: "Bachelor's degree."
- *Post-Bachelor's degree*: "Masters degrees," "Intermediate degrees," "Doctors degrees," "First-professional degrees," "Post-masters certificate," "Doctors degree (old degree classification)," "First-professional degree (old degree classification)," "First-professional certificate (old degree classification)," "Doctors degree - research/scholarship," "Doctors degree - professional practice," and "Doctors degree - other (new degree classification)."

For each institution in a given year, we extracted the total degrees granted to male and female students for each degree level and summed together to get the total degrees granted (the total degrees from 2008 to 2017 were reported in the survey, and so we used this variable instead). We merged the degree data to the institution roster and kept the matched institutions.

To verify the validity of the data construction, we compared the total degrees awarded at universities in our roster with the 2019 NCES Digest of Education Statistics.[39] Figure A1a and Figure A1b show that total degrees awarded at the universities in our roster based on our construction is very similar to that reported by the NCES Digest of Education Statistics.

[39] We compare with the 2019 NCES Digest of Education Statistics.(U.S. Department of Education, National Center for Education Statistics, 2019*b*) For post-BA degrees, we restrict to years before 2011, as after this time doctoral degrees include many degrees that were previously classified as first-professional degrees.

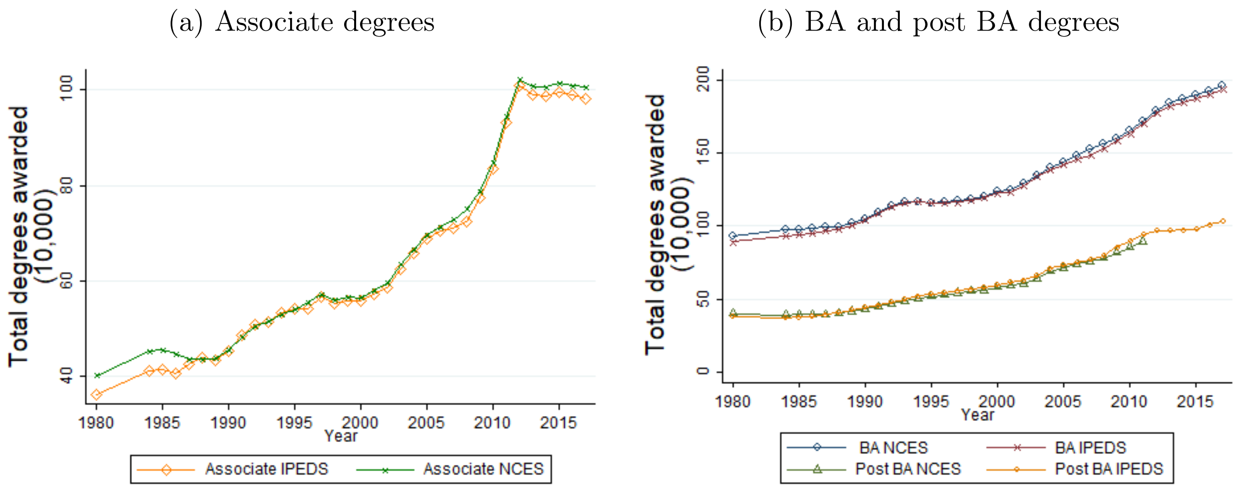


Figure A1: Comparing Sample Degrees and the NCES Reported Total

Notes: Figure A1a compares total associate's degrees by year in our university roster and total numbers reported by the NCES Digest of Education Statistics. Figure A1b compares total bachelor's and post bachelor's degrees by year in our university roster and total numbers reported by the 2019 NCES Digest of Education Statistics.

A.3 Enrollment

We obtained institution-by-year enrollment from IPEDS "Fall Enrollment" survey U.S. Department of Education, National Center for Education Statistics (2020). For each observation, we defined full-time and part-time enrollment separately using variable "line" in the raw data. Then, we calculated total full-time and total part-time enrollment by summing up male and female enrollment of each enrollment type. The total enrollment is the sum of total full-time and part-time enrollment. To generate the sample enrollment data, we merge institution-by-year enrollment to our roster and kept matched institutions.

A.4 University Employment

We measure growth in university employment from 1989 to 2018 for Rust Belt counties, and from 2001 to 2018 for all counties. We obtain university employment data from the IPEDS

Fall Staff survey U.S. Department of Education, National Center for Education Statistics (2020). The IPEDS Fall Staff survey starts in 1987, but more than half of the 1987 survey was imputed, and so we use staff in 1989 as the survey was administered every two years at that time. We use staff in 2001 when analyzing growth for all counties. We calculate total fall staff as the sum of total full-time and part-time staff.

Aggregating staff at all universities in our roster by year yields similar results to NCES publications of total employees at degree-granting universities in 2001 and 2018. In 2001, our total is 3,044,873 and the NCES total is 3,083,353. In 2018, our total is 3,883,766 and the NCES total is 3,923,374 (U.S. Department of Education, National Center for Education Statistics, 2019*a*).

We aggregate total staff at all universities in our roster at the county level, and use this measure in our analysis.

A.5 University finance

We obtain data on university expenditures from the IPEDS "Finance" survey, which starts in 1980. We calculate growth in county-level university expenditures from 1980 to 2018 for rust-belt counties, and from 2000 to 2018 for all counties. There is some change over time in the expenditure variables. In 1980 we use current funds expenditures (B19). In 2000 public universities, private-for-profit universities, and private-not-for-profit universities report differently. We use total current funds expenditures and transfers (B223) for public institutions, total expenses for private-for-profit and private-not-for-profit institutions (F3E07 and F2E121 respectively). In 2018, we use total expenses and deductions current year total for public institutions reporting using GASB (F1C191). We use total expenses for public institutions reporting using FASB and for private-not-for-profit institutions (F2E131), and for private-for-profit institutions (F3E071).

Data Appendix References

Indiana Business Research Center. 2020. "SatsAmerica." http://www.statsamerica.org/CityCountyFinder/.

United States Department of Agriculture. 2020. "County FIPS Codes." https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/home/?cid=nrcs143_013697.

U.S. Department of Education, National Center for Education Statistics. 2019*a*. "Digest of Education Statistics (Table 314.20)." https://nces.ed.gov/programs/digest/d19/tables/dt19_314.20.asp, Accessed 03/31/21.

U.S. Department of Education, National Center for Education Statistics. 2019*b*. "Digest of Education Statistics (Table 318.10)." https://nces.ed.gov/programs/digest/d19/tables/dt19_318.10.asp, Accessed 03/31/21.

U.S. Department of Education, National Center for Education Statistics. 2020*a*. "Integrated Postsecondary Education System (IPEDS)." https://nces.ed.gov/ipeds/.

U.S. Department of Education, National Center for Education Statistics. 2020*b*. "Integrated Postsecondary Education System (IPEDS) Data Collection System." https://surveys.nces.ed.gov/ipeds/public/glossary.

Table A1: **Resilience to the 1981 Mining Employment Decline**

	(1) Employment	(2) Employment	(3) Employment	(4) Population	(5) Earnings	(6) Transfers
Mining Share, 1981	-1.656**	-3.675**	-3.290***	-2.651***	-1.551***	1.610***
	(0.629)	(1.478)	(0.901)	(0.550)	(0.194)	(0.366)
Normal * Mining Share, 1981	0.444	2.374	2.185**	1.427**	0.236	-1.048***
	(0.775)	(1.563)	(1.006)	(0.583)	(0.204)	(0.388)
Observations	326	321	321	321	321	321
State Fixed Effects	N	Y	Y	Y	Y	Y
Control for 1950-1980 Pop. Growth	N	N	Y	Y	Y	Y

Notes: Dependent variables are measured in log growth, 1981-2018. Standard errors clustered at the state level in parentheses. Mining share is a fraction of total employment in the county, as measured in the BEA data. Columns that include controls for 1950-1980 population growth include log 1950 and log 1980 population as additional control variables. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

B Resilience to Mining Declines

In addition to the manufacturing decline, there was a large decline in mining employment during the 1980s, led primarily by a decrease in the oil and coal industries. In this section, we analyze whether regional universities provided local economic resilience to the counties with large mining employment shares in 1981, the year in which mining employment peaked. During the 1980s, mining employment fell by nearly 50 percent from its 1981 peak. By 2003, at its trough, it was around 40 percent of its 1981 peak.

Our strategy to determine if regional universities cause resilience to mining declines is similar to the strategy we used in the main text for manufacturing declines. The only difference is that instead of using the 1978 manufacturing share, we look at the 1981 mining share, and we use a base year of 1981.

Table A1 shows our results. When controlling for state fixed effects and 1950 and 1980 log population, as we do in our manufacturing analysis, an increase in 1981 mining share leads to a large decline in employment over the subsequent 37 years. The point estimate indicates that for asylum counties, having an additional one percent of 1981 employment in mining leads to a 3.3 percent decline in jobs. However, this adverse impact of exposure is nearly two thirds smaller in counties that were assigned normal schools. Without the population controls, the coefficients are similar, but the standard errors are larger and the

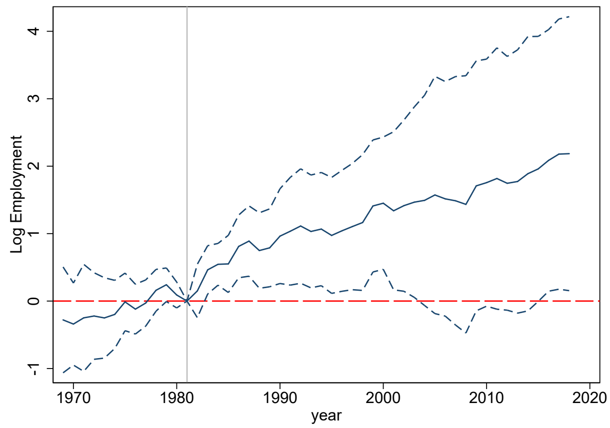


Figure A2: **Differential Effect of 1981 Mining Exposure on Normal Counties Relative to Asylum Counties.** Effects are relative to 1981, and include county and state-year fixed effects, and interactions between year fixed effects and log 1950 population and separately log 1980 population. This plot shows coefficients on the interaction between the year indicator, whether the county had a normal school, and 1981 share employed in mining. Dotted lines are 95 percent confidence intervals, with standard errors clustered at the state level.

effect is not statistically significant.

Consistent with our results on employment, we find a similar effect for population, with mining share causing a significant decline in population, and this adverse impact is smaller in normal school counties. Unlike the results from our manufacturing analysis, there is no significant resilience effect on earnings. The effect on transfers is consistent with our manufacturing results.

Figure A2 shows event-study results. We plot the differential effect of 1981 mining exposure in normal counties, relative to 1981. The differential effect in normal counties arises immediately after 1981, which is when mining employment was declining most rapidly, but the effect gets gradually larger throughout the entire timeframe. There does not seem to be a differential effect before 1981.

B.1 Mechanisms

To study the mechanisms, we estimate the same regressions as we do for the manufacturing analysis, but using 1981 as a base year and the 1981 mining share as our economic shock.

Table A2: **Resilience to the 1981 Mining Employment Decline, Effect of University Spending**

	(1) Emp Growth	(2) Staff Contrib.	(3) Income Growth	(4) Spending Contrib.
Mining Share, 1981	-3.501***	-0.0299	-9.400***	-0.0958
	(0.600)	(0.0428)	(3.444)	(0.193)
Normal * Mining Share, 1981	1.925**	-0.0117	4.755	-0.0470
	(0.778)	(0.0455)	(3.052)	(0.225)
Observations	321	321	321	321
State Fixed Effects	Y	Y	Y	Y
Control for 1950-1980 Pop. Growth	Y	Y	Y	Y
Years	1980-2018	1989-2018	1980-2018	1980-2018

Notes: Regressions include state fixed effects. Standard errors clustered at the state level. Regressions include controls for Ln(Population, 1950) and Ln(Population, 1980). $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

The university spending results are noisy. Recall that the university employment data does not begin until 1989. Because the resilience to mining was particularly strong in the 1980s, our test may not be capturing the most critical years. We also do not find a large effect on university spending, but our standard errors are large, and we cannot rule out a similar-sized effect as we found for manufacturing, percentage-wise. If we focus on the period to 2003—when mining employment hit its trough—and we control for the manufacturing share interacted with normal counties (i.e. jointly estimating the resilience to manufacturing and to oil), then the point-estimate is the same order of magnitude as it was for manufacturing (not shown). However, it is still insignificant.

When we look at the industry composition of resilience, we see similar results as we do in our manufacturing analysis. Here, we focus on the 1981-2000 changes in employment in a variety of industries, and we look at the growth in employment in that industry as a percent of total 1981 employment, so that it is a decomposition.[40] Of the effects significant at the 5 percent level, we see that services explains the largest share of the resilience, followed by state and local government, and then construction. Significant amounts of resilience are coming from construction, services, and state and local government. The point estimate on

[40]For mining employment, a significant number of counties are missing in 2000 that were not missing in 1981. For this exercise, our sample is the group of counties for which the growth rate of interest is available.

retail is also positive. The resilience is not coming from preventing the decline in mining, but rather comes through other sectors, especially services. This would be consistent with the university having spillovers to local non-tradable sectors.

Table A3: **Resilience to the 1981 Mining Employment Decline, Employment by Sector**

	(1) Emp Growth	(2) Mining	(3) Constr.	(4) Manuf.	(5) Retail	(6) FIRE	(7) Services	(8) Federal	(9) State & Local
Mining Share, 1981	-3.501***	-0.598***	-0.316***	-0.212	-0.394***	-0.158*	-1.031***	-0.00867	-0.401***
	(0.600)	(0.143)	(0.0462)	(0.131)	(0.109)	(0.0890)	(0.179)	(0.0159)	(0.0939)
Normal * Mining Share, 1981	1.925**	-0.0102	0.156**	0.0960	0.221*	0.0779	0.818***	-0.0142	0.294**
	(0.778)	(0.130)	(0.0738)	(0.146)	(0.126)	(0.0896)	(0.280)	(0.0231)	(0.145)
Observations	321	185	314	320	320	313	318	321	321
State Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control for 1950-1980 Pop. Growth	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Regressions include state fixed effects. Standard errors clustered at the state level. Regressions include controls for Ln(Population, 1950) and Ln(Population, 1980). $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

C Cyclicality of the Local Economy

In this appendix, we turn to another measure of resilience, resilience to the business cycle. We investigate whether economic growth during recessions is different in normal relative to asylum counties. Our approach is to compare the movement of economic variables around the years in which NBER-defined recessions begin: 1980, 1990, 2001, and 2007.[41] We estimate the local projection

$$y_{i,t+r} - y_{it} = \beta_r \text{Recession}_t \times \text{Normal School}_i + \alpha_{st} + \epsilon_{i,t} \quad (4)$$

where y is the outcome of interest and r ranges from -3 to 4, Recession_t is 1 in a year the NBER defines as a business cycle peak, and Normal School_i is an indicator variable for the county having a normal school. We include state-year fixed effects, α_{st}. We use the sample of normal and asylum counties as previously defined. The coefficients β_r traces out the

[41] We consider the 1981 recession to be an extension of the 1980 recession. In principle, the BEA data would allow us to include the 1969 and 1973 recessions, but we prefer to start when normal schools' conversions to universities have largely finished and they are established within their counties.

difference between normal counties and asylum counties in the years around a recession.[42]

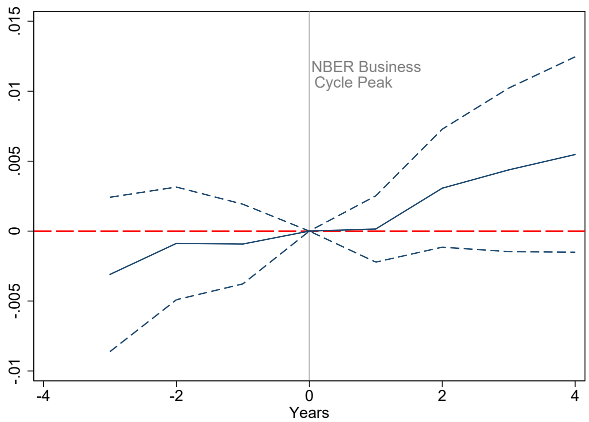
Note that the baseline regression does not include a term for Normal School$_i$ or a county fixed effect. The rationale for this is to compare the growth rate of normal counties to asylum counties in years around recessions, without also comparing them to growth rates in other years. We plot several years before and after the recession, so that whether the effect is cyclical should be easy to see in a figure. Therefore, the specification gives a description of how normal counties grow compared to asylum counties in the years around a recession.

We cluster standard errors by state-year, which is effectively as state-recession, since only the growth rates from recession years are used to calculate the β_r. This accounts for correlations in outcomes across counties within states, but assumes that different recessions are effectively independent observations.[43] While there are in theory efficiency gains from estimating the β_r coefficients jointly, Jordà (2005) shows that such gains are very small, so we estimate each β_r in its own regression.

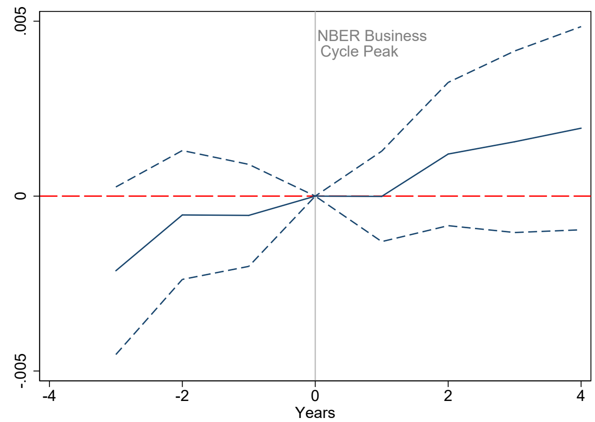
The results of this regression are shown in Figure A3, for various outcomes y. For log employment, employment-to-population ratio, and log per capita personal income, normal counties grow faster between the first and second year after a business cycle peak. This effect is significant at the 10 percent level. We do not see evidence that normal and asylum counties are experiencing differential growth leading up the recession, although there are increases in the coefficient between $t-3$ and $t-2$ for log employment and the employment to population ratio. The magnitude of the effect is about half a percent for employment and income after three or four years. For comparison, employment growth in our sample is about 1.2 percent per year. For log unemployment insurance, normal counties have significantly less growth in

[42]This specification is a local projection (Jordà, 2005). An alternative would be to estimate an event-study distributed-lag model, which would lead to the exact same regression coefficients in some cases. For example, we could limit our dataset to only include the 3 years around an business cycle peak, and estimate a regression with six coefficients for β_{-3} to β_3 (without a β_0), and with a county fixed effect. The main downside is that we cannot extend it beyond 3 years because the the 2000 recession and the 2007 recession would start to overlap.

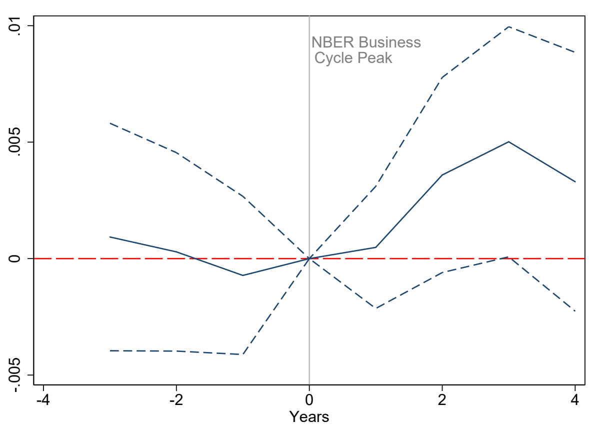
[43]A more conservative approach would be to cluster by state due to concerns that even across the recessions, there is a correlation in growth rates. In that case, the results in Figure A3 are not significant, even at the 10 percent level.



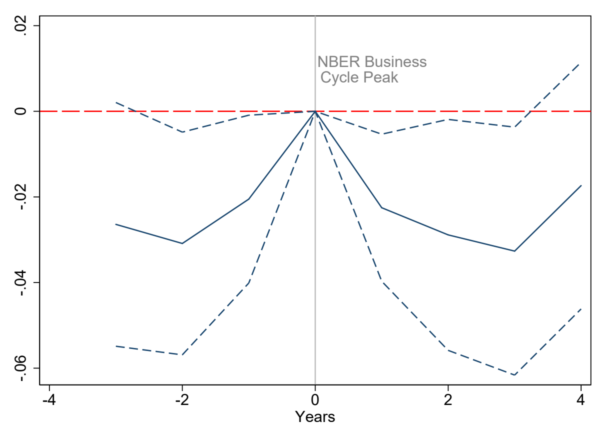
(a) Log Employment



(b) Employment to Population Ratio



(c) Log Personal Income



(d) Log Unemployment Insurance

Figure A3: **Local projections before and after recession years.** Plots show coefficient estimates from equation (4), and indicate the differential in normal counties in the log-change in the indicated variable since the business cycle peak. Regressions include state-year fixed effects. Dashed lines are 95 percent confidence intervals. Standard errors are clustered at the state-year level (effectively state-recession level because only the growth rates from recession years are used to calculate the coefficients). Economic variables come from the BEA.

the years after a recession. Interestingly, they have more growth relative to asylum counties in the years prior to a recession, also indicative of the fact that normal counties seem to be less cyclical overall.

It is interesting to note that for most of these variables, the biggest differential growth occurs in the second year after the business cycle peak. For many of the recessions, that is a time where the economy—measured by GDP—has started to recover, although the number of jobs nationally is still shrinking or stagnant.

The cyclicality is also apparent in comparing the outcomes year-by-year, from the regression

$$y_{it} = \beta_t \text{Normal}_i + \alpha_{st} + \epsilon_{it}$$

We show the plot of β_t in Appendix Figure A4, and there is clear cyclicality in the within-state difference of normal and asylum counties.

For robustness, we also estimate the same regression as 4, but include county fixed effects, which allows for differences in average growth rate of y across counties.

$$y_{i,t+r} - y_{it} = \beta_r \text{Recession}_t \times \text{Normal School}_i + \alpha_{st} + \alpha_i + \epsilon_{i,t} \tag{5}$$

In this specification, β_r measures the difference in the average within-county change in growth during recessions, in normal relative to asylum counties. This focuses on the differences between normal and asylum counties that arise during recessions, as we measure these differences relative to the average growth rate of the county.[44] These results are shown in Appendix Figure A5, and are largely indistinguishable from Figure A3.

[44]An alternative way to think about this specification is that we are still comparing the effect of normal schools and asylums on the growth rate of the county around a recession, but now we are looking at the (r-year) growth rate after the recession in excess of the average (r-year) growth rate in that county.

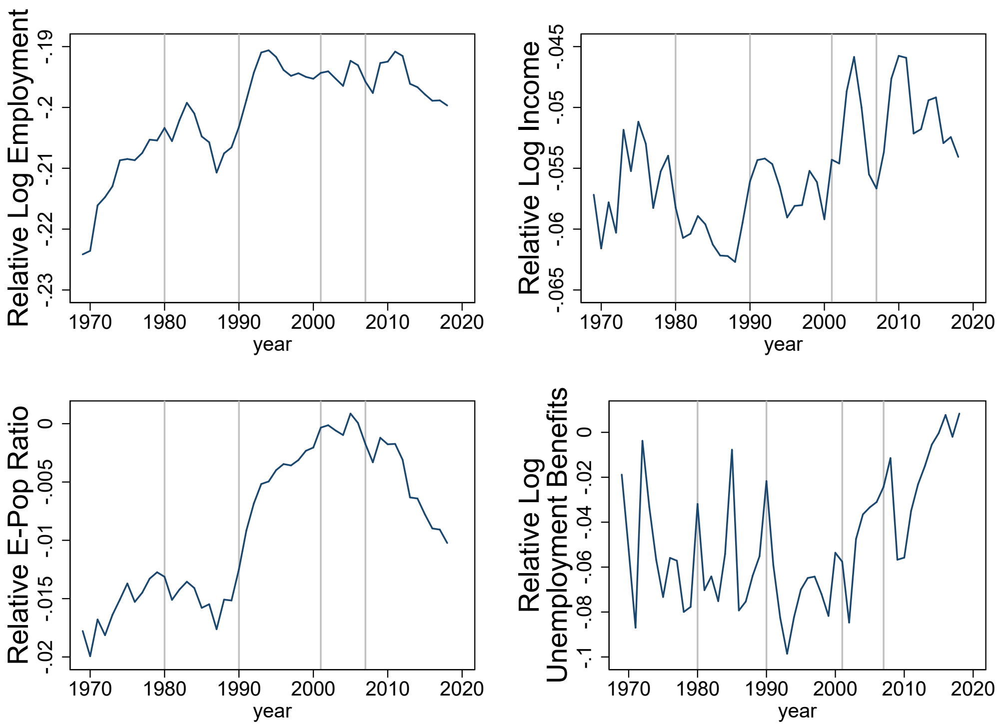
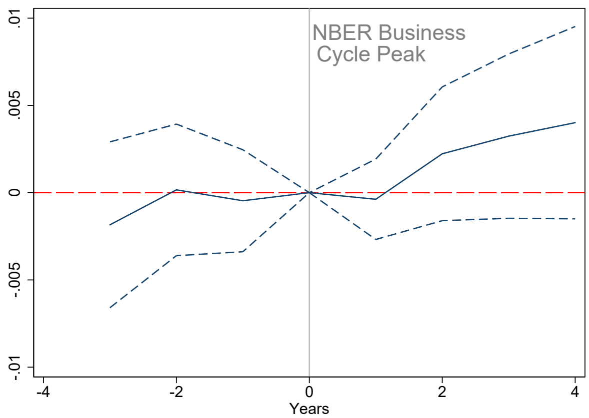
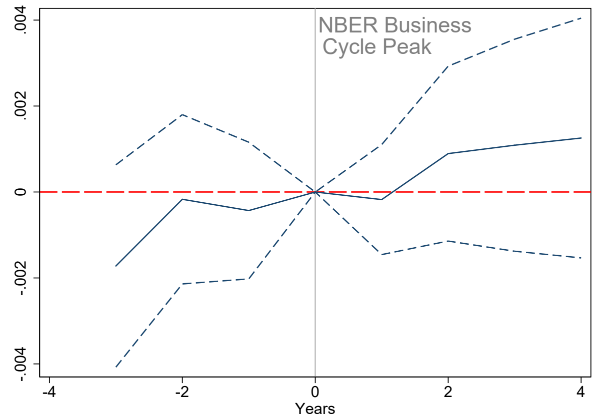


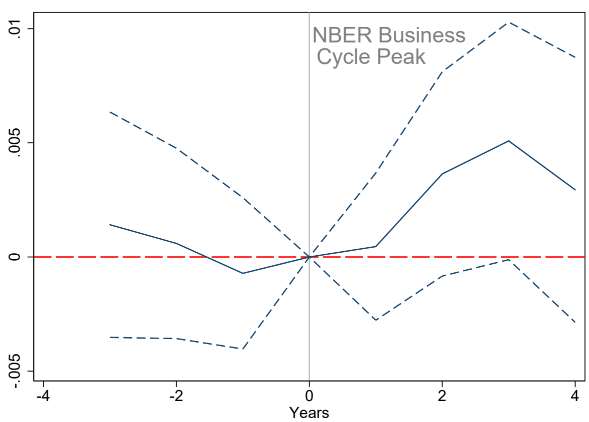
Figure A4: **Relative economic outcomes by year, normal versus asylum.** Each point represents the coefficient estimate on Normal county from a regression of the economic outcome on an indicator for a normal county, with state fixed effects. Gray lines indicate an NBER business cycle peak.



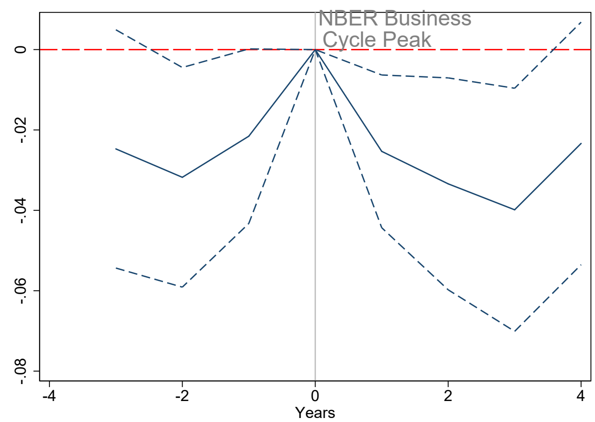
(a) Log Employment



(b) Employment to Population Ratio



(c) Log Personal Income



(d) Log Unemployment Insurance

Figure A5: **Local projections before and after recession years, with county fixed effects.** Plots show coefficient estimates from equation (5), and indicate the differential in normal counties of the change in the indicated variable since the business cycle peak, relative to the average growth rate of the county. Regressions include state-year and county fixed effects. Dashed lines are 95 percent confidence intervals. Standard errors are clustered at the state-year level. Economic variables come from the BEA.

C.1 Enrollment Increases During Recessions

Is the resilience mechanism for business cycles the same as it was for the manufacturing decline? Looking at the cyclicality of university finance is difficult as the data are missing for many counties in some key years, such as 2002 and 2009. Instead, we look at enrollment as a percentage of the population. We estimate a specification similar to equation (4), but use the number of students enrolled as a fraction of the population as the left-hand side variable.[45]

Figure A6 shows a clear increase in enrollment as a percent of population during the first few years after a business cycle peak. This suggests that universities are expanding relative to their population during the recession, and based on our previous analysis the direct and indirect effects of that growth presumably help the resilience of the local economy.

The setting and available data make it harder to estimate what percentage of resilience the spending channel might explain, but the qualitative evidence suggest that it is likely at work.

D Resilience through Upskilling

An alternative explanation for why universities make their economies more resilient is that universities result in a more educated workforce, and this makes the economy more resilient. As we discussed, Glaeser and Saiz (2004) show a relationship between bachelor's degree share and resilience to negative shocks, while Feyrer, Sacerdote and Stern (2007) do not find this relationship among rust-belt counties.

We suspect this is not a dominant mechanism given our results on university spending, which imply spending by the university could explain much of the resilience. To test this further we analyze changes in the share of the population with a bachelor's degree, as well

[45] The business cycle peaks used for the regression are 1980, 1990, 2001, and 2007, as in the main regression. The regressions prior to the peak do not include the 1980 recession because the student data starts in that year.

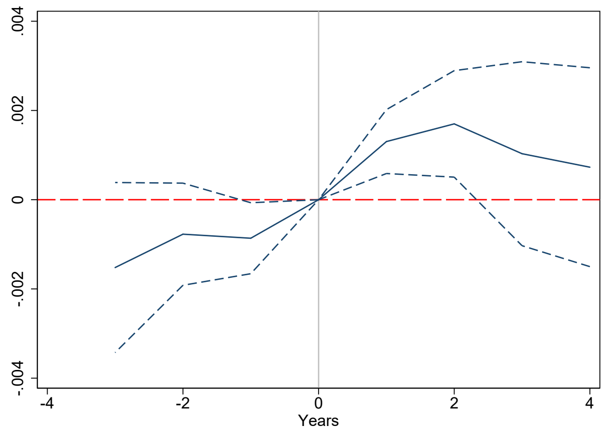


Figure A6: **Local projections of enrollment per capita, before and after recession years.** Each point indicates the differential change in normal counties in enrollment per capita since the business cycle peak on whether a county has a normal county. Regressions include state-year fixed effects. Dashed lines are 95 percent confidence intervals. Standard errors are clustered at the state-year level (effectively state-recession level because only the growth rates from recession years are used to calculate the coefficients).

as changes in the age composition.

Given the declines at exposed asylum county universities, the differential normal county university growth may have led to differential growth of highly educated workers, if graduates stay in the county. Alternatively, differential university growth in exposed normal counties may have led to retention of more educated workers in the area, either university staff or employees of companies that serve the university, or were attracted to locate near the university.

In Table A4, we do not find a significant effect that the population with a Bachelor's degree increased differentially in response to the manufacturing decline in normal versus asylum counties. However, we cannot rule out some resilience through this channel due to large standard errors. In response to the Rust Belt decline in particular, the point-estimate would suggest some additional degrees compared to asylum counties.

Recall from the main text that there is little evidence that students remain in the county after graduation. Figure 3 demonstrates the age profiles look quite similar outside the 18-22 range.

Table A4: Change in Population Share with a Bachelor's Degree

	Δ Share of Population with a BA	
	1980-2016	2000-2016
Manufacturing Share, t	-0.214***	-0.093**
	(0.070)	(0.036)
Normal County*Mfg. Share, t	0.129	-0.001
	(0.080)	(0.049)
N	103	320
R-Squared	0.596	0.351

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. All regressions include state fixed effects. *Manufacturing, t* in column 1 refers to the manufacturing share in 1978, and in column 2 to manufacturing share in 2000. Robust standard errors are presented in column 1, and standard errors clustered at the state level in column 2. Column 1 includes controls for Ln(Population, 1950) and Ln(Population, 1978), while column 2 includes controls for Ln(Population, 1950) and Ln(Population, 1980). See text for details.

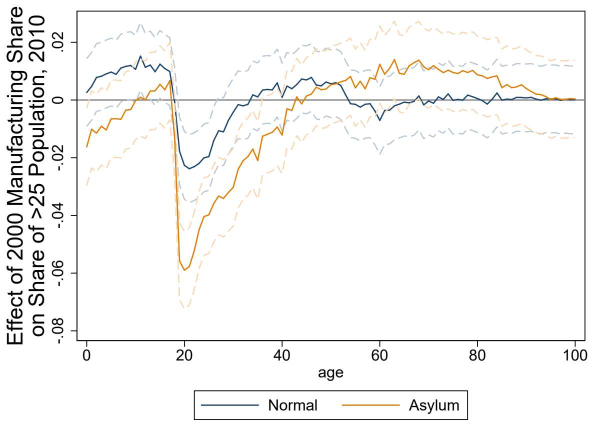
We extend this analysis by looking at the effects of the manufacturing decline on age composition. In Figure A7, we look at the effect of manufacturing on the change in population for each age in normal versus asylum counties. Each point is the β_a of the regression:

$$\frac{\text{Population of age } a_{i,2010}}{\text{Over 25 Population}_{i,2010}} = \beta_a \text{Manufacturing Share}_i + \alpha_{as} + \epsilon_{ia}$$

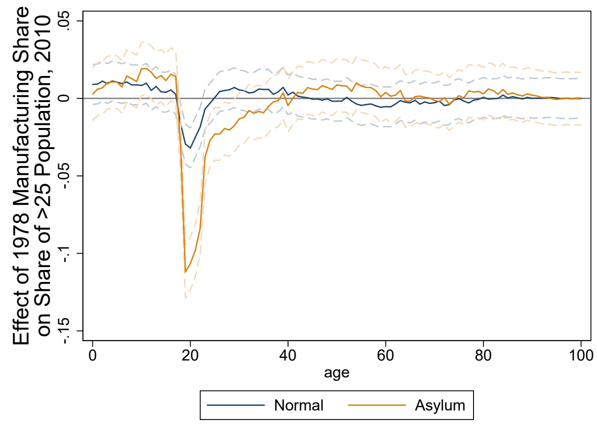
where α_{as} is an age-state fixed effect. We run this separately on normal counties and asylum counties. We also run it separately on the Rust Belt, using 1978 manufacturing share, and the whole country, using 2000 manufacturing share.

In asylum counties, having a higher share of manufacturing leads to young people leaving the county. The drop-off is dramatic around the age 18, and is presumably driven by poor local labor market opportunities. The pattern is similar in normal counties but it is a significantly smaller decrease than in asylum counties, meaning that normal counties are not losing their young people to the same degree, or the losses are somewhat reduced by the inflow of college students. Focusing on the Rust Belt gives a similar picture.

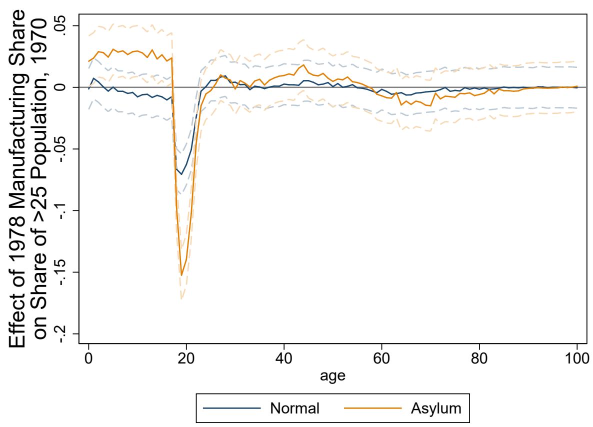
For comparison, we also show the same figure but for 1970 in the Rust Belt, preceding the Rust Belt manufacturing declines. In this figure, while higher manufacturing predicts



(a) Whole U.S., 2010



(b) Rust Belt, 2010



(c) Rust Belt, 1970

Figure A7: **The Effect of Manufacturing on Age Composition, Normal Relative to Asylum Counties.** Each point represents the coefficient of a regression of the age share on the manufacturing share of the county (in the year 2000 for the whole U.S., in 1978 for the Rust Belt). Regression run separately on normal counties and asylum counties. Dashed lines are 95 percent confidence intervals, based on standard errors clustered at the state level. Age share is defined as the population of a specific age divided by the total population over 25 years old. Population by age data is from NHGIS.

lower age shares around age 20, that is not true for even the mid-20s. This suggests that even if some people leave for college in high-manufacturing areas, they do not stay away after graduation. This provides further support for the effects in 2010 being driven by manufacturing declines, rather than some persistent difference between normal and asylum counties.[46]

While it is tempting to attribute the difference in age profiles to the idea that normal schools encourage young people to go to college instead of leaving the county, we are unable to distinguish that story from a story in which the normal school makes the economy more resilient for another reason, and the improved economy induces young people to stay. So overall, the effect on the age profile is consistent with a story of upskilling but not necessarily conclusive evidence of such a channel.

[46]For the whole U.S., the figure in Panel (a) looks similar when we use 1990 or 2000. For the rust belt, the "Normal" line looks fairly similar in all decades between 1970 and 2010. For the "Asylum" line, the effects on the ages after college gradually increase each decade between 1970 and 2010.

E Robustness Appendix

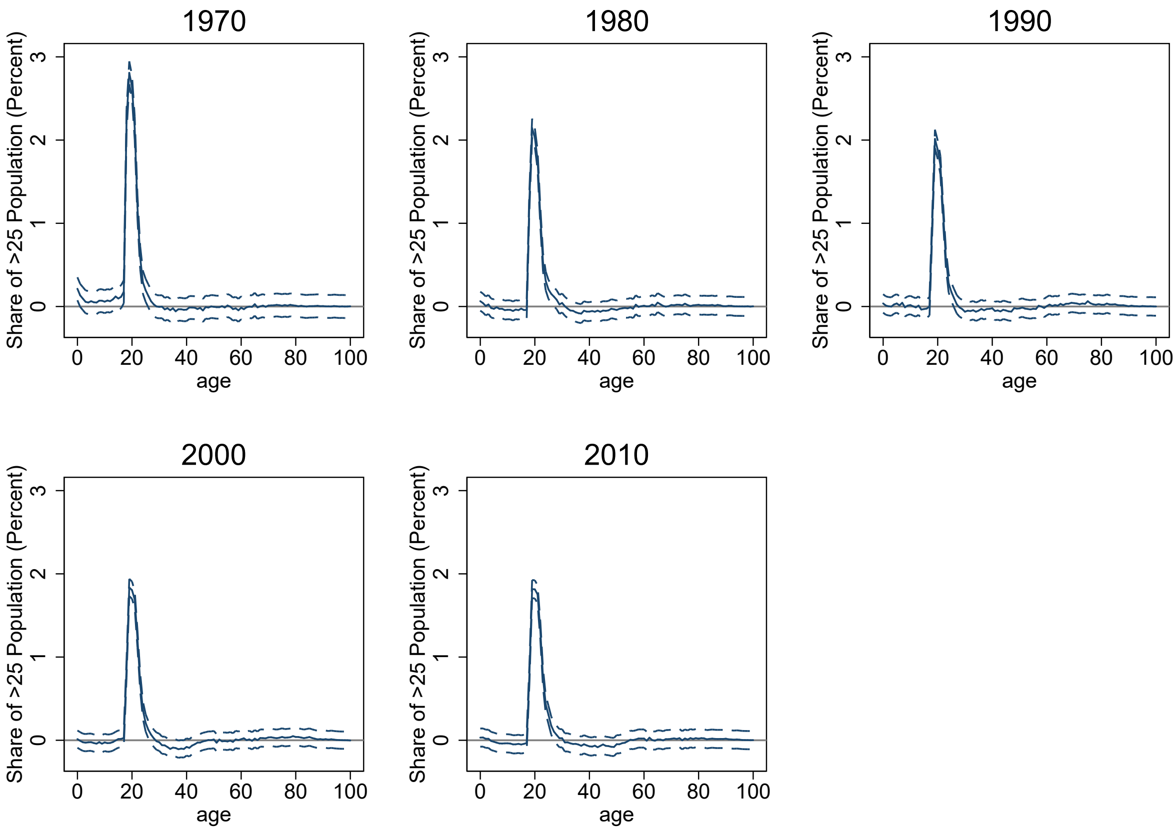


Figure A8: **Age Profile in Different Years.** Each point in the plots is the coefficient on Normal county, from a regression of age share on normal county, including state fixed effects. Dashed lines are 95 percent confidence intervals, based on standard errors clustered at the state level. Age share is defined as the population of a specific age divided by the total population over 25 years old. Population by age data is from NHGIS.

Table A5: **Effect on Industry Employment (Percent of Total Employment) in 1980**

	(1)	(2)	(3)
	Variable Means		Difference in Means
			With State FE
	Normal	Asylum	(1) - (2)
Agriculture	0.9210	0.7760	0.0278
	(1.337)	(0.846)	(0.14)
Mining	1.3100	0.9550	0.2973
	(3.424)	(2.722)	(0.392)
Construction	4.7730	4.8970	-0.2018
	(1.371)	(2.251)	(0.241)
Manufacturing	16.4490	17.6660	-1.4947*
	(8.693)	(8.261)	(0.824)
Transportation and Public Utilities	4.3300	4.3660	0.0523
	(2.036)	(1.555)	(0.191)
Wholesale Trade	4.0100	3.9990	0.0121
	(1.723)	(1.763)	(0.211)
Retail Trade	16.3120	15.4890	1.1275***
	(2.581)	(2.818)	(0.313)
Finance, Insurance, and Real Estate	6.0120	6.2700	-0.1564
	(2.226)	(2.152)	(0.285)
Services	19.9380	20.0050	0.1544
	(4.37)	(5.179)	(0.663)
Government	19.7980	19.8840	-0.3873
	(8.12)	(8.684)	(1.078)
Observations	200	126	326

Notes: This table shows mean and standard deviation of industry share in 1980 using BEA data. Column (3) displays coefficients from regressing each variable on the normal county indicator with state fixed effects. The size of each variable varies. For agriculture, we have 195 normal and 124 asylum counties. For mining we have 193 normal and 124 asylum counties. For construction, manufacturing, FIRE, and government we have 200 normal and 126 asylum counties. For Transportation and services we have 198 normal and 126 asylum counties. For wholesale and retail trade we have 199 normal and 126 asylum counties. The robust standard errors are clustered at state level and reported in parentheses for OLS.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table A6: **Effect on Industry Employment (Percent of Total Employment) in 2001**

	(1)	(2)	(3)
	Variable Means		Difference in Means With State FE
	Normal	Asylum	(1) - (2)
Forestry	0.7950	0.6010	0.0114
	(1.182)	(1.255)	(0.214)
Mining	0.8210	0.7930	-0.1343
	(1.692)	(1.966)	(0.283)
Utilities	0.4180	0.3970	0.0008
	(0.521)	(0.36)	(0.071)
Construction	5.7750	5.8730	-0.2329
	(1.631)	(1.879)	(0.228)
Manufacturing	10.1440	11.3080	-0.7670
	(5.125)	(5.772)	(0.813)
Wholesale Trade	3.0090	3.3090	-0.3943**
	(1.291)	(1.407)	(0.19)
Retail Trade	11.9710	11.3900	0.5812**
	(1.912)	(1.968)	(0.24)
Transportation and Warehousing	3.1050	3.0700	0.0664
	(1.959)	(1.53)	(0.244)
Information	1.6860	1.7080	-0.0091
	(0.915)	(1.035)	(0.145)
Finance and Insurance	3.6520	4.0420	-0.3998*
	(1.874)	(2.046)	(0.237)
Real Estate	2.6750	2.6510	-0.0250
	(0.968)	(0.918)	(0.118)
Professional Services	4.4620	4.6410	-0.1905
	(2.392)	(2.514)	(0.315)
Management	0.7980	0.7630	0.1108
	(0.858)	(0.75)	(0.155)
Administrative	4.6690	4.7000	-0.0666
	(1.809)	(1.855)	(0.262)
Educational Services	1.6500	1.6950	-0.0917
	(1.527)	(1.534)	(0.167)
Health Care	10.1430	10.3800	-0.1836
	(2.871)	(3.408)	(0.428)
Arts and Entertainment	1.6990	1.5600	0.1029
	(1.093)	(0.657)	(0.09)
Accommodation and Food Services	7.1270	6.1320	0.9833***
	(2.252)	(1.743)	(0.213)
Other Services	5.5290	5.3900	0.1476
	(0.869)	(0.847)	(0.103)
Government	17.7680	16.9830	0.8502
	(6.945)	(7.261)	(0.968)

Notes: This table shows mean and standard deviation of industry share in 2001 using BEA data. Column (3) displays coefficients from regressing each variable on the normal county indicator with state fixed effects. The size of each variable varies. For forestry, we have 106 normal and 70 asylum counties. For mining, we have 129 normal and 79 asylum counties. For utility we have 129 normal and 82 asylum counties. For construction and real estate, we have 200 normal and 126 asylum counties. For manufacturing, we have 199 normal and 124 asylum counties. For wholesale we have 184 normal and 114 asylum counties. For retail and government, we have 200 normal and 126 asylum counties. For transportation, we have 148 normal and 93 asylum counties. For information, we have 194 normal and 122 asylum counties. For finance and other services, we have 197 normal and 124 asylum counties. For professional services we have 169 normal and 111 asylum counties. For management, we have 152 normal and 92 asylum counties. For administrative, we have 172 normal and 106 asylum counties. For educational services, we have 170 normal and 104 asylum counties. For health care, we have 171 normal and 104 asylum counties. For arts and entertainment, we have 195 normal and 121 asylum counties. For accommodation and food services, we have 197 normal and 121 asylum counties. The robust standard errors are clustered at state level and reported in brackets.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

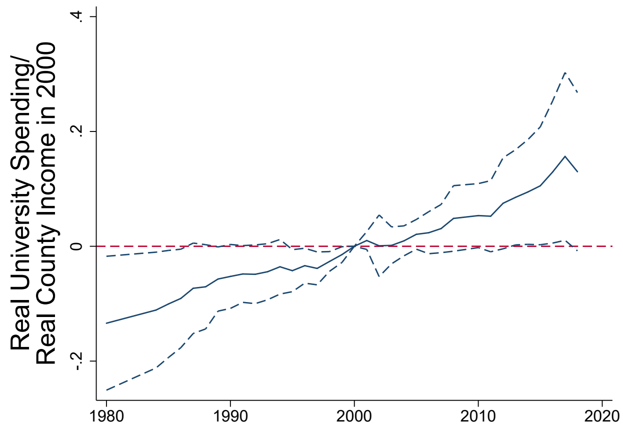


Figure A9: **Differential Effect of 2000 Manufacturing Exposure on Normal Counties Relative to Asylum Counties.** Effects are relative to 2000, and include county and state-year fixed effects. This plot shows coefficients on the interaction between the year indicator, whether the county had a normal school, and 2000 share employed in manufacturing. Dotted lines are 95% confidence intervals, with standard errors clustered at the state level. Spending data are not available in 1981-1983, or in 2009. Controls include interactions between year fixed effects and ln(population, 1950) and between year fixed effects and ln(population, 1980).

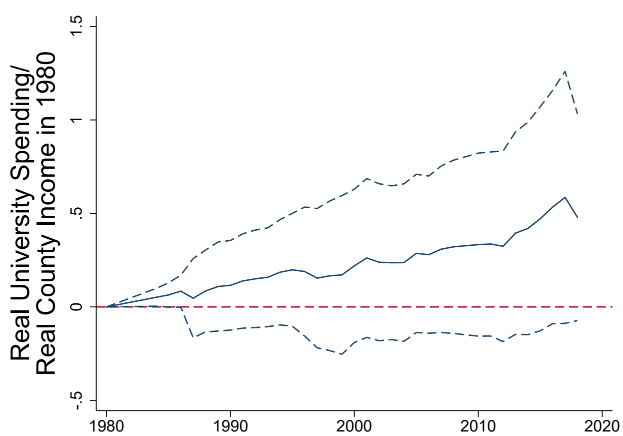
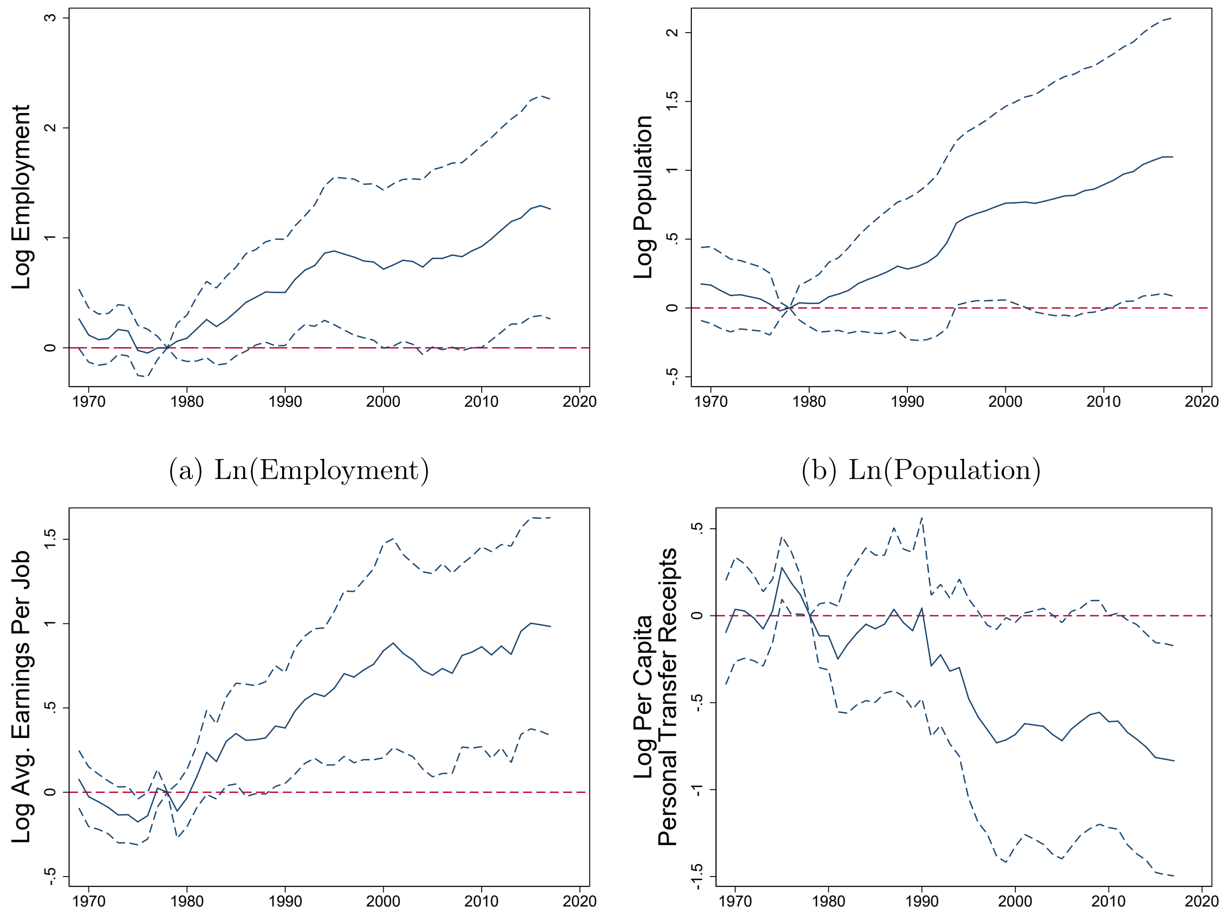


Figure A10: **Differential Effect of 1978 Manufacturing Exposure on Normal Counties Relative to Asylum Counties.** Effects are relative to 1980, and include county and state-year fixed effects. This plot shows coefficients on the interaction between the year indicator, whether the county had a normal school, and 1978 share employed in manufacturing. Dotted lines are 95% confidence intervals, with standard errors clustered at the county level. Spending data are not available in 1981-1983, or in 2009. Controls include interactions between year fixed effects and ln(population, 1950) and between year fixed effects and ln(population, 1978).



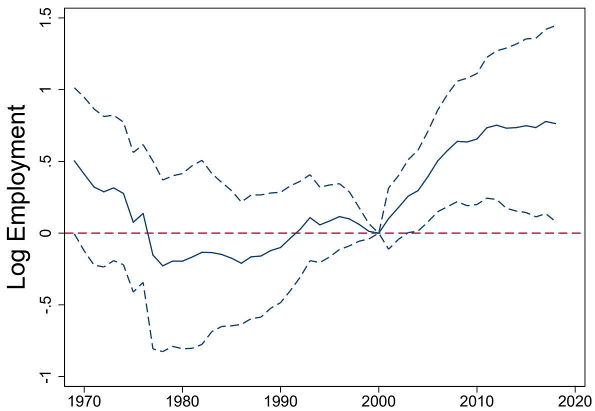
(a) Ln(Employment)

(b) Ln(Population)

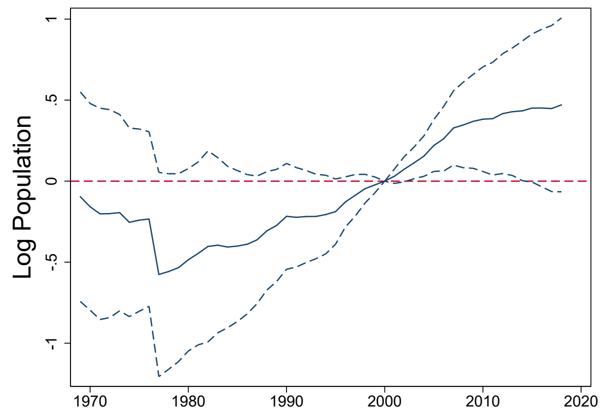
(c) Ln(Avg. Earnings Per Job)

(d) Ln(Per Capita Personal Transfer Receipts)

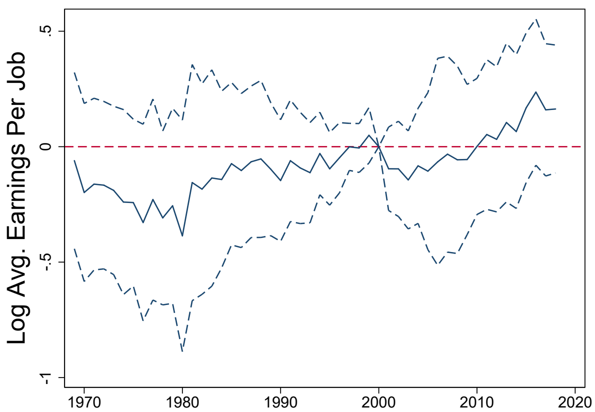
Figure A11: **Differential Effect of 1978 Manufacturing Exposure on Normal Counties Relative to Asylum Counties in Rust-Belt States.** Effects are relative to 1978, and include county and state-year fixed effects, and interactions between year fixed effects and ln(population, 1950), and separately ln(population, 1978). This plot shows coefficients on the interaction between the year indicator, whether the county had a normal school, and 1978 share employed in manufacturing. Dotted lines are 95% confidence intervals, with standard errors clustered at the county level.



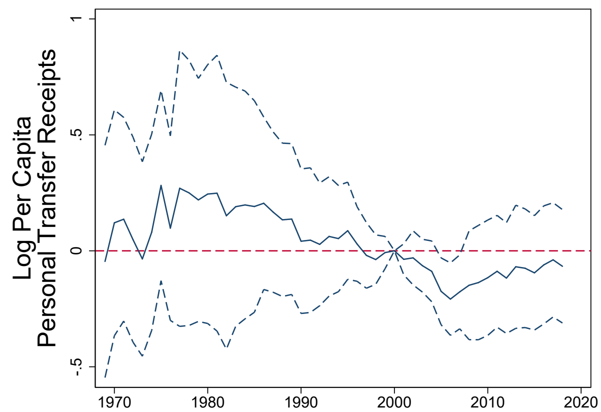
(a) Ln(Employment)



(b) Ln(Population)



(c) Ln(Avg. Earnings Per Job)



(d) Ln(Per Capita Personal Transfer Receipts)

Figure A12: **Differential Effect of 2000 Manufacturing Exposure on Normal Counties Relative to Asylum Counties in Rust-Belt States.** Effects are relative to 2000, and include county and state-year fixed effects, and interactions between year fixed effects and ln(population, 1950), and separately ln(population, 1980). This plot shows coefficients on the interaction between the year indicator, whether the county had a normal school, and 1980 share employed in manufacturing. Dotted lines are 95% confidence intervals, with standard errors clustered at the county level.

Table A7: **Differential Employment Growth in Rust-Belt Normal Counties, by Sector.**

Y = (Average 2001-2004)-(Average 2015-2018) Employment Growth	All	Forestry	Mining	Utilities	Constr.	Mfg	Wholesale	Retail	Transport.	Info	Finance and Insurance
Manufacturing Share, 1978	-0.552**	-0.000	0.026	-0.007	-0.028*	-0.049	0.003	-0.020	0.002	-0.040**	-0.048
	(0.224)	(0.004)	(0.042)	(0.006)	(0.015)	(0.051)	(0.017)	(0.022)	(0.032)	(0.019)	(0.032)
Normal*Mfg. Share, 1978	0.532**	0.000	0.043	0.008	0.045*	-0.060	0.032	0.025	-0.007	0.045**	0.020
	(0.239)	(0.005)	(0.055)	(0.007)	(0.024)	(0.062)	(0.022)	(0.025)	(0.037)	(0.020)	(0.033)
Observations	103	57	66	70	102	103	92	103	84	100	102
R-Squared	0.328	0.249	0.582	0.093	0.307	0.264	0.182	0.280	0.244	0.163	0.118

Y = (Average 2001-2004)-(Average 2015-2018) Employment Growth	Real Estate	Prof./Tech. Services	Mgmt. Companies	Admin Services	Ed Services	Health	Arts	Accom./ Food	Other Services	Federal	State and Local
Manufacturing Share, 1978	-0.046***	-0.080***	-0.016	-0.076***	-0.022*	-0.066	-0.031***	-0.002	-0.027***	-0.007	-0.052
	(0.013)	(0.021)	(0.022)	(0.025)	(0.013)	(0.042)	(0.009)	(0.034)	(0.009)	(0.008)	(0.062)
Normal County*Manufacturing	0.037**	0.071***	0.026	0.080***	0.030*	0.063	0.017	0.010	0.034***	0.010	0.061
	(0.016)	(0.023)	(0.022)	(0.029)	(0.015)	(0.052)	(0.011)	(0.035)	(0.013)	(0.010)	(0.065)
Observations	102	93	82	93	89	89	100	101	101	103	103
R-Squared	0.305	0.372	0.238	0.245	0.135	0.333	0.394	0.237	0.462	0.157	0.350

All regressions include state fixed effects, and controls for Ln(Population, 1950) and Ln(Population, 1978). Robust standard errors in parentheses.

Table A8: **Differential Employment Growth in Normal Counties, by Sector.**

Y = (2001-2004)-(2015-2018) Employment Growth	All	Forestry	Mining	Utilities	Constr.	Mfg	Wholesale	Retail	Transport.	Info.	Finance and Insurance
Manufacturing Share, 2000	-1.065***	0.0119	0.00397	-0.00150	-0.0256	-0.176***	-0.0199	-0.0231	0.000642	0.000986	-0.0549
	(0.347)	(0.00765)	(0.0546)	(0.00385)	(0.0188)	(0.0331)	(0.0150)	(0.0331)	(0.0321)	(0.0122)	(0.0348)
Normal*Mfg. Share, 2000	0.847**	-0.0180*	0.0112	0.00289	0.0486**	0.00179	0.0492**	0.0303	0.0193	0.00562	0.0421
	(0.409)	(0.0101)	(0.0872)	(0.00515)	(0.0235)	(0.0492)	(0.0207)	(0.0418)	(0.0390)	(0.0134)	(0.0446)
Observations	320	160	194	211	317	319	289	320	246	311	318
R-Squared	0.405	0.339	0.460	0.229	0.435	0.407	0.244	0.361	0.275	0.189	0.213

Y = (2001-2004)-(2015-2018) Employment Growth	Real Estate	Prof./Tech. Services	Mgmt. Companies	Admin Services	Ed Services	Health	Arts	Accom./ Food	Other Services	Federal	State and Local
Manufacturing Share, 2000	-0.0331*	-0.0930***	-0.00708	-0.0437*	-0.0321***	-0.116***	-0.0274***	-0.0300	-0.0305*	-0.0423**	-0.0592
	(0.0172)	(0.0306)	(0.0168)	(0.0248)	(0.0116)	(0.0241)	(0.0101)	(0.0256)	(0.0157)	(0.0199)	(0.0437)
Normal*Mfg. Share, 2000	0.000486	0.0763**	0.00438	0.0791**	0.0417***	0.0964***	0.0138	0.000845	0.0276	0.0593***	0.0642
	(0.0171)	(0.0366)	(0.0180)	(0.0365)	(0.0154)	(0.0338)	(0.0129)	(0.0327)	(0.0181)	(0.0208)	(0.0496)
Observations	317	285	241	281	266	267	308	310	313	320	320
R-Squared	0.369	0.335	0.259	0.409	0.276	0.480	0.318	0.396	0.425	0.203	0.304

All regressions include state fixed effects, and controls for Ln(Population, 1950) and Ln(Population, 1980). Standard errors are clustered at the state level.

Table A9: **1978 Manufacturing Exposure and Differential 1978-2018 Changes in Normal Counties**

Y = % Growth	Employment	Population	Earnings per Job	Per Capita Transfers
Manufacturing Share, 1978	-1.704*	-0.967	-2.924***	4.237**
	(0.905)	(0.617)	(0.686)	(1.815)
Normal*Mfg. Share, 1978	1.800*	1.536**	1.511**	-3.199
	(0.995)	(0.681)	(0.722)	(2.587)
Observations	321	321	321	321
R-Squared	0.493	0.486	0.347	0.542
State FE	Y	Y	Y	Y
Control for 1950-1978 Pop. Growth	Y	Y	Y	Y

Notes: Robust standard errors in parentheses. Dependent variable is $(Y_t/Y_{t-1})-1$. Columns that control for 1950-1978 population growth include controls for Ln(Population, 1950) and Ln(Population, 1978).
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table A10: **Employment Growth Specifications with Additional Controls**

Y = Employment Growth	% Growth 1978-2018/100	% Growth 2000-2018/100
Manufacturing Exposure	-1.839***	-1.416**
	(0.689)	(0.561)
Normal*Mfg. Exposure	1.877**	1.075**
	(0.808)	(0.524)
Observations	103	320
R-Squared	0.633	0.476
Mfg. Exposure Year	1978	2000
State Fixed Effects	Y	Y
Controls for Pre-Period Population Growth	Y	Y
Other Controls	Y	Y

Notes: Robust standard errors in parentheses in column 1, and clustered at the state level in column 2. Dependent variable is $(Y_t/Y_{t-1}) - 1$. Column 1 includes controls for Ln(Population, 1950) and Ln(Population, 1978), and column 2 for Ln(Population, 1950) and Ln(Population, 1980). Other controls include share of the population with a bachelor's degree in 1980, log of average earnings in 1969 and in 1978, log of average per capita transfers in 1969 and 1978, log of per capita income in 1969 and 1978, log of nearby population in 1980 based on a gravity model, log water coverage, and an indicator for whether the county is within 150 miles of the state capital.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table A11: **1978 Manufacturing Exposure and Differential Growth in Transfers in Normal Counties**

Y = % Growth	Per Capita Transfers		
	Income Maintenance	Unempl. Insurance	Retirement
Manufacturing Share, 1978	14.148***	2.206**	8.263***
	(5.079)	(1.012)	(2.712)
Normal*Mfg. Share, 1978	-9.059	-1.286	-7.500*
	(6.113)	(1.172)	(3.827)
Observations	103	103	103
R-Squared	0.655	0.412	0.427
State Fixed Effects	Y	Y	Y
Controls for 1950-1978 Population Growth	Y	Y	Y

Notes: Robust standard errors in parentheses. Dependent variable is $(Y_t/Y_{t-1})-1$. Columns that control for 1950-1978 population growth include controls for Ln(Population, 1950) and Ln(Population, 1978).
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table A12: **2000 Manufacturing Exposure and Differential Growth in Transfers in Normal Counties**

Y = % Growth	Per Capita Transfers		
	Income Maintenance	Unempl. Insurance	Retirement
Manufacturing Share, 2000	1.803***	-0.631	0.461*
	(0.479)	(0.456)	(0.268)
Normal*Mfg. Share, 2000	-0.102	-0.367	-0.197
	(0.743)	(1.062)	(0.333)
Observations	320	320	320
R-Squared	0.684	0.589	0.557
State Fixed Effects	Y	Y	Y
Controls for 1950-1980 Population Growth	Y	Y	Y

Notes: Standard errors clustered at the state level in parentheses. Dependent variable is $(Y_t/Y_{t-1}) - 1$. Columns that control for 1950-1980 population growth include controls for Ln(Population, 1950) and Ln(Population, 1980).
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table A13: **The Rust-belt Shock and Differential Changes from 1978-2018 in Normal Counties, Using Above-Median Manufacturing as Exposure**

Y = % Growth	Employment	Population	Earnings per Job	Per Capita Transfers
Normal County	-0.148	-0.091	-0.476**	0.393
	(0.097)	(0.094)	(0.207)	(0.426)
Above Median Manufacturing Share, 1978	-0.219**	-0.079	-0.668***	0.432
	(0.084)	(0.076)	(0.207)	(0.388)
Normal*Above Median Mfg. Share, 1978	0.157	0.072	0.581**	-0.132
	(0.120)	(0.104)	(0.237)	(0.489)
Observations	103	103	103	103
R-Squared	0.511	0.407	0.296	0.474
State FE	Y	Y	Y	Y
Control for 1950-1978 Pop. Growth	Y	Y	Y	Y

Notes: Robust standard errors in parentheses. Above Median Manufacturing Share, 1978 is an indicator for whether the county's share employed in manufacturing was above the median for normal and asylum rust-belt counties in 1978. Dependent variable is $(Y_t/Y_{t-1}) - 1$. Columns that control for 1950-1978 population growth include controls for Ln(Population, 1950) and Ln(Population, 1978).
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table A14: **2000 Manufacturing Exposure and Differential Changes from 2000-2018 in Normal Counties, Using Above-Median Manufacturing as Exposure**

Y = % Growth	Employment	Population	Earnings per Job	Per Capita Transfers
Normal County	-0.0653	-0.0266	-0.0180	-0.0453
	(0.0675)	(0.0382)	(0.0268)	(0.0290)
Above Median Manufacturing Share, 2000	-0.125*	-0.0577	-0.0766***	0.0378
	(0.0629)	(0.0397)	(0.0256)	(0.0319)
Normal*Above Median Mfg. Share, 2000	0.105	0.0592	0.0397	0.00239
	(0.0739)	(0.0482)	(0.0352)	(0.0364)
Observations	320	320	320	320
R-Squared	0.373	0.472	0.465	0.560
State FE	Y	Y	Y	Y
Control for 1950-1978 Pop. Growth	Y	Y	Y	Y

Notes: Robust standard errors in parentheses. Above Median Manufacturing Share, 2000 is an indicator for whether the county's share employed in manufacturing was above the median for normal and asylum counties in 2000. Dependent variable is $(Y_t/Y_{t-1})-1$. Columns that control for 1950-1978 population growth include controls for Ln(Population, 1950) and Ln(Population, 1978).
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table A15: Accounting for County Income and Employment Growth: Role of University Spending, Staff, and Enrollment

Rust-Belt Exposure and Growth

Dependent Variable	$\frac{\Delta Income_{s,t}}{Income_{s,t-1}}$	$\frac{\Delta Univ.Spend_{s,t}}{Income_{s,t-1}}$	$\frac{\Delta Empl_{s,t}}{Empl_{s,t-1}}$	$\frac{\Delta Enroll_{s,t}}{Empl_{s,t-1}}$	$\frac{\Delta Empl_{s,t}}{Empl_{s,t-1}}$	$\frac{\Delta Staff_{s,t}}{Empl_{s,t-1}}$
Manufacturing Share, 1978	-4.012**	-0.441*	-2.023***	-0.184	-1.046***	-0.0772*
	(1.564)	(0.245)	(0.541)	(0.251)	(0.361)	(0.0453)
Normal*Mfg. Share, 1978	3.670**	0.480*	1.776**	0.223	0.952**	0.0812*
	(1.531)	(0.277)	(0.687)	(0.442)	(0.446)	(0.0486)
Observations	103	103	103	103	103	103
R-Squared	0.403	0.265	0.494	0.189	0.339	0.232
Years	1980-2018	1980-2018	1980-2018	1980-2018	1989-2018	1989-2018

2000 Manufacturing Exposure and Growth

Dependent Variable	$\frac{\Delta Income_{s,t}}{Income_{s,t-1}}$	$\frac{\Delta Univ.Spend_{s,t}}{Income_{s,t-1}}$	$\frac{\Delta Empl_{s,t}}{Empl_{s,t-1}}$	$\frac{\Delta Enroll_{s,t}}{Empl_{s,t-1}}$	$\frac{\Delta Empl_{s,t}}{Empl_{s,t-1}}$	$\frac{\Delta Staff_{s,t}}{Empl_{s,t-1}}$
Mfg. Share, 2000	-0.993**	-0.168**	-1.192***	-0.00932	-1.065***	-0.0301***
	(0.398)	(0.0667)	(0.426)	(0.0698)	(0.347)	(0.0108)
Normal*Mfg. Share, 2000	0.825*	0.130*	0.994**	0.0966	0.847**	0.0324**
	(0.481)	(0.0684)	(0.486)	(0.0758)	(0.409)	(0.0145)
Observations	320	320	320	320	320	320
R-Squared	0.410	0.216	0.378	0.337	0.405	0.229
Years	2000-2018	2000-2018	2000-2018	2000-2018	2001-2018	2001-2018

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. All regressions include state fixed effects. Robust standard errors are presented in Panel A, and standard errors clustered at the state level in Panel B. Regressions in Panel A include controls for Ln(Population, 1950) and Ln(Population, 1978), while regressions in Panel B include controls for Ln(Population, 1950) and Ln(Population, 1980). See text for details.

Table A16: Manufacturing Exposure and Differential Growth in Normal Counties, Accounting for Other Mechanisms

Rust-Belt Exposure and Growth

Dependent Variable	Employment	Employment	Employment	Employment
Manufacturing Share, 1978	-2.374***	-1.997*	-3.532	-0.882
	(0.552)	(1.121)	(5.163)	(5.306)
Normal*Mfg. Share, 1978	1.967***	1.745**	1.724**	1.791**
	(0.726)	(0.785)	(0.737)	(0.837)
BA Share 1980*Mfg. Share, 1978		-0.435	0.868	3.335
		(5.778)	(7.542)	(7.570)
Log Nearby Population 1980*Mfg. Share, 1978			0.083	-0.104
			(0.435)	(0.423)
State Fixed Effects	Y	Y	Y	Y
Controls for 1950-1978 Population Growth	Y	Y	Y	Y
Additional Controls	N	N	N	Y
Observations	103	103	103	103
R-Squared	0.543	0.548	0.571	0.634

2000 Manufacturing Exposure and Growth

Dependent Variable	Employment	Employment	Employment	Employment
Manufacturing Share, 2000	-1.192***	-2.091***	-0.170	0.0396
	(0.426)	(0.754)	(3.540)	(3.192)
Normal*Mfg. Share, 2000	0.994**	0.744	0.671	0.897
	(0.486)	(0.570)	(0.558)	(0.630)
BA Share 1980*Mfg. Share, 2000		6.823	6.998	5.385
		(5.471)	(5.289)	(5.816)
Log Nearby Population 1980*Mfg. Share, 2000			-0.159	-0.164
			(0.257)	(0.243)
Observations	320	320	320	320
R-Squared	0.378	0.384	0.395	0.479
State Fixed Effects	Y	Y	Y	Y
Controls for 1950-1980 Population Growth	Y	Y	Y	Y
Additional Controls	N	N	N	Y
Observations	320	320	320	320
R-Squared	0.378	0.388	0.396	0.468

Notes: *** p-value $\leq .01$, ** p-value $\leq .05$, * p-value $\leq .1$. All regressions include state fixed effects. Robust standard errors are presented in Panel A, and standard errors clustered at the state level in Panel B. Other controls include share of the population with a bachelor's degree in 1980, log of average earnings in 1969 and in 1978, log of average per capita transfers in 1969 and 1978, log of per capita income in 1969 and 1978, log of nearby population in 1980 based on a gravity model, log water coverage, and an indicator for whether the county is within 150 miles of the state capital. See text for details.

Table A17: Manufacturing Exposure and Differential Growth in Normal Counties and Research University Counties

Dependent Variable	Employment	Employment	Employment	Employment
Manufacturing Share	-1.521*	-1.398	-1.124**	-1.185**
	(0.789)	(0.924)	(0.474)	(0.447)
Normal*Mfg. Share	1.807**	1.578	0.820*	0.775*
	(0.897)	(1.008)	(0.464)	(0.450)
Research Univ.*Mfg. Share		0.639		0.948
		(1.360)		(0.638)
Observations	103	110	325	362
R-Squared	0.584	0.575	0.308	0.295
States	Rust Belt	Rust Belt	All	All
Exposure Year	1978	1978	2000	2000
Census Division Fixed Effects	Y	Y	Y	Y
Controls for Pre-Period Population Growth	Y	Y	Y	Y
Additional Controls	Y	Y	Y	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. All regressions include census division fixed effects. Research university counties are those with a public R1 or R2 university in the county, based on 1987 Carnegie Classifications, established between 1830 and 1930. Manufacturing share is measured in 1978 for columns 1 and 2, and in 2000 for columns 3 and 4. The sample includes only rust belt states in columns 1 and 2, but all states in columns 3 and 4. Robust standard errors are presented in columns 1 and 2, and standard errors clustered at the state level in columns 3 and 4. Controls for pre-period population growth include log population in 1950 and 1978 in columns 1 and 2, and in 1950 and 1980 in columns 3 and 4. Other controls include share of the population with a bachelor's degree in 1980, log of average earnings in 1969 and in 1978, log of average per capita transfers in 1969 and 1978, log of per capita income in 1969 and 1978, log of nearby population in 1980 based on a gravity model, log water coverage, and an indicator for whether the county is within 150 miles of the state capital. See text for details.

Table A18: Manufacturing Exposure and Differential Growth in Normal Counties, Matching

Rust-Belt Exposure and Growth

Dependent Variable	Employment	Employment
Mfg. Exposure	-1.219**	-2.416***
	(0.590)	(0.552)
Mfg. Exposure*Normal	0.673	1.770**
	(0.711)	(0.692)
Observations	110	110
R-Squared	0.611	0.552
State Fixed Effects	Y	Y
Controls for 1950-1978 Population Growth	Y	Y
Matching Variables	Ln(Pop 1920)	Ln(Pop 1920)
		1920 Urban Pop. Share
		1920 Mfg. Empl. per Pop.

2000 Manufacturing Exposure and Growth

Dependent Variable	Employment	Employment
Mfg. Exposure	-0.683***	-0.474**
	(0.207)	(0.187)
Mfg. Exposure*Normal	0.390	0.242
	(0.333)	(0.271)
N	394	392
R-Squared	0.382	0.415
State Fixed Effects	Y	Y
Controls for 1950-1980 Population Growth	Y	Y
Matching Variables	Ln(Pop 1920)	Ln(Pop 1920)
		1920 Urban Pop. Share
		1920 Mfg. Empl. per Pop.

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. All regressions include state fixed effects. The sample in column 1 includes normal counties, as well as nearest-neighbor matches based on Ln(1920 population), with exact matching on state. In column 2, we estimate a linear probability model in which the dependent variable is an indicator for being a normal county, and the predictors are state fixed effects, Ln(1920 population), 1920 urban population share, and 1920 manufacturing employment over population. We calculate the predicted probability of being a normal county based on the 1920 characteristics, and identify the nearest-neighbor match for each normal county, with exact matching on state. In both columns we implement matching without replacement, and cluster standard errors at the level of the matched set. See text for details.

Table A19: Differential Employment Growth in Normal Counties, by Sector

A: Rust Belt, 1978-2000										
$Y = \frac{\Delta Empl_{s,t,t-1}}{Empl_{t-1}}$	All	Constr.	Mfg.	Transp.	Whole-sale	Retail	FIRE	Serv.	Fed. Gov.	State & Local
Mfg. Share, 1978	-1.249***	-0.050	-0.342***	-0.010	0.001	-0.168*	-0.134***	-0.373**	-0.040	-0.069
	(0.359)	(0.034)	(0.111)	(0.045)	(0.028)	(0.092)	(0.044)	(0.152)	(0.027)	(0.103)
Normal*Mfg., 1978	1.091**	0.075	0.140	0.023	0.030	0.190*	0.048	0.321*	0.062**	-0.065
	(0.500)	(0.047)	(0.135)	(0.051)	(0.036)	(0.110)	(0.057)	(0.177)	(0.027)	(0.132)
Observations	103	102	103	98	101	103	103	103	103	103
R-Squared	0.646	0.431	0.547	0.424	0.572	0.463	0.412	0.526	0.164	0.426
B. Rust Belt, 2001-2018										
$Y = \frac{\Delta Empl_{s,t,t-1}}{Empl_{t-1}}$	All	Constr.	Mfg.	Retail	Finan. & Insur.	Real Estate	Prof. Serv.	Admin Serv.	Fed. Gov.	State & Local
Mfg. Share, 1978	-0.762***	-0.019	-0.096*	-0.043	-0.087*	-0.037**	-0.074***	-0.085***	-0.005	-0.005
	(0.231)	(0.020)	(0.056)	(0.026)	(0.045)	(0.017)	(0.024)	(0.026)	(0.005)	(0.037)
Normal*Mfg., 1978	0.673**	0.036	-0.020	0.051*	0.046	0.027	0.064**	0.093***	0.009	0.012
	(0.267)	(0.029)	(0.069)	(0.030)	(0.041)	(0.020)	(0.025)	(0.028)	(0.006)	(0.044)
Observations	85	85	85	85	85	85	85	85	85	85
R-Squared	0.351	0.251	0.329	0.364	0.177	0.296	0.414	0.278	0.117	0.416
C. All Counties, 2001-2018										
$Y = \frac{\Delta Empl_{s,t,t-1}}{Empl_{t-1}}$	All	Constr.	Mfg.	Retail	Finan. & Insur.	Real Estate	Prof. Serv.	Admin Serv.	Fed.	State & Local
Mfg. Share, 2000	-1.126***	-0.034	-0.172***	-0.069	-0.090	-0.047*	-0.089**	-0.065**	-0.020**	-0.081**
	(0.378)	(0.028)	(0.052)	(0.043)	(0.057)	(0.026)	(0.037)	(0.025)	(0.008)	(0.037)
Normal*Mfg., 2000	1.075**	0.061*	0.025	0.096**	0.078	0.022	0.071	0.099***	0.034**	0.125***
	(0.408)	(0.031)	(0.052)	(0.047)	(0.065)	(0.025)	(0.044)	(0.035)	(0.013)	(0.044)
Observations	249	249	249	249	249	249	249	249	249	249
R-Squared	0.432	0.431	0.444	0.400	0.238	0.413	0.339	0.407	0.281	0.311
State Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Robust standard errors in parentheses in panels A and B. Standard errors clustered at the state level in parentheses in panel C. All regressions include state fixed effects. Panels A and B include controls for Ln(Population, 1950) and Ln(Population, 1978). Panel C includes controls for Ln(Population, 1950) and Ln(Population, 1980). Panels B and C include only counties with non-missing industry employment for these listed industries. Dependent variable is the change in sectoral employment from t-1 to t relative to total employment in t-1. See text for details.