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Are College Towns Really Recession Proof?

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ABSTRACT

Labor markets in college towns have been viewed as more resilient to national recessions. This study examines that presumption, using monthly data on county unemployment and employment rates from 1990 through 2019. We find that counties housing college students have lower unemployment rates in response to increases in national unemployment rates than their neighboring non-college counties, consistent with the view that college towns are less exposed to national business cycles. However, college county employment rates also fall more rapidly during national economic downturns, casting doubt on college town labor market resilience. The puzzling result appears to be related to the use of new claims for unemployment benefits in measuring county unemployment rates. Low unemployment rates in college counties are related to a lower probability that unemployed college students would qualify for unemployment benefits due to insufficient job tenure and earnings.

1 | Introduction

Labor markets in college towns have been viewed as more resilient to national recessions. This study tests that presumption, using monthly data on county unemployment and employment rates from 1990 through 2019. We find that counties housing college students have lower unemployment rates in response to increases in national unemployment rates than their neighboring non-college counties, consistent with the view that college towns are less exposed to national business cycles. However, college county employment rates also fall more rapidly during national economic downturns, casting doubt on college town labor market resilience. The puzzling result appears to be related to the use of new claims for unemployment benefits in measuring county unemployment rates. Low unemployment rates in college counties are related to a lower probability that unemployed college students would qualify for unemployment benefits due to insufficient job tenure and earnings.

College towns have long been viewed as having strong, local economies. College towns are frequently listed among the lowest unemployment rates in the country.[1] The press have taken notice of these low unemployment rates and suggested that college towns were atypically resilient in response to adverse shocks from plant closings or the Great Recession. Several recent studies provided corroborating evidence that the unemployment rates in university towns did not rise as rapidly during the 2007–2009 recessions.[2] This study shows that the finding of greater resiliency in college towns' response to recessions does not hold when employment rates are used to measure the strength of the local labor market. The finding of resiliency when using unemployment rates may be related to a bias in how local unemployment rates are measured in counties with high proportions of college students.

There is broad support for the view that college towns foster strong local labor markets. There is consistent evidence that teaching and research activities raise local wages and growth and create knowledge spillovers that foster innovation. Similar findings are found in Europe.[3] The positive influence on local markets is the greatest in small towns, and is concentrated within a 60 miles radius of the university.[4]

Some of the benefits from housing a local university are similar to findings that capital cities grow faster. State capitals benefit from jobs and infrastructure paid for by residents of other cities through taxes, and from the benefits of being a city of political importance.[5] However, other mechanisms by which universities benefit their host cities differ from capital cities. Localities benefit particularly when the local university has strengths in science or technical fields. Benefits flow particularly to local entrepreneurs. College towns attract in-migration of educated workers and often induce graduates to stay. Higher education institutions have also been associated with better local quality of life.[6]

We show that college towns do have lower unemployment rates and higher employment rates on average. However, the resiliency hypothesis suggests that college towns also suffer less job loss during national recessions. We do find that the unemployment rates in counties with larger population shares of college students respond less to national business cycles, consistent with the resiliency hypothesis. However, employment rates in those same college counties also fall more rapidly than their non-college neighbors during national recessions. This seemingly anomalous result appears related to the method used to measure local unemployment rates. County unemployment rates are approximated, in part, by new applications for unemployment benefits. College towns may experience atypically small increases in filings during recessions because students are less likely to qualify for benefits. Our findings suggest that college towns may not be as recession-proof as previously thought.

2 | Background

Two widely followed indicators of the strength of the labor market are the employment rate and the unemployment rate. The two series are not perfectly inversely correlated because they have different population bases. The unemployment rate ($0 \leq UR \leq 1$) is the ratio of unemployed (U) to the labor force (LF), which is equal to the employed plus the unemployed ($E + U$). The employment rate ($0 \leq ER \leq 1$) is the ratio of the employed to the population (POP).[7] The unemployment rate and employment rate are related by

$$ER = (1 - UR) * LFPR \tag{1}$$

where the labor force participation rate is $LFPR = LF/POP$. It would seem that the employment rate and the unemployment rate would have to be negatively correlated. For the two series to be positively correlated, reductions in the unemployment rate would have to be accompanied by a decrease in the labor force participation rate, meaning that individuals would be exiting the labor market rather than accepting jobs when the economy is expanding.[8]

Figure 1 shows the time paths of employment rates and unemployment rates from 1990 to 2023 for prime-age males. As expected, the two series are highly negatively correlated at −0.73. The negative correlation has become stronger since 2000 with greater variation in the business cycle.

While the expected pattern holds overall in the economy, some local markets may deviate from the norm. This is particularly true because local measures of unemployment and employment do not have survey data that are used in deriving the national measures. Instead, local employment and unemployment measures are based on administrative information, nonrepresentative firm surveys, and state-level data that is apportioned to local markets. These approximations may not respond to business cycles in the same way that individual employment and unemployment respond in a survey setting.

Our focus is on local labor markets that include a college or university. While in school, college students typically work part-time jobs in the relatively low-paying retail and service sectors. These jobs may not have sufficient hours or earnings to qualify for unemployment benefits. Because county unemployment rate estimates are based partially on unemployment benefit recipiency, unemployment in college counties may be underestimated. Moreover, the level of underestimation may vary over the business cycle as the importance of layoffs, new entrants, and reentrants varies in expansions versus contractions.

3 | Empirical Strategy

To assess the effect of college presence in the county on the strength of the local labor market, we examine the added effect of having students in the population, holding fixed observed local market factors. Let L_{ist}^{k} be the *kth* labor market indicator for county i in state s and year t. The two indicators we use are the local unemployment rate and the local employment rate for populations aged 16 and over.

We are interested in examining how local labor markets respond to the national business cycle, and whether the response differs by the presence of college students. We measure the business cycle by the national unemployment rate for males aged 45–54, U_t^N. Males in their prime earning years are the most likely to remain in the labor force during recessions, and so fluctuations in their unemployment rates are driven by labor demand shocks and not supply shocks.[9] Historically low (high) national unemployment rates indicate national economic expansions (recessions).

The effect of the national business cycle on local labor markets is presumed to be moderated in college counties. Business cycle shocks are expected to influence private sector jobs, especially those in durable goods, construction, and luxury consumer goods. Enrollment demand responds more slowly to cyclical factors. To the extent that colleges receive tax support, jobs may be even more insulated from business cycle fluctuations. The extent of insulation from cyclical shocks should be greatest in communities with the largest college share of the local economy, C_{ist}.

Consider the specification

$$\begin{aligned} L_{ist}^{k} = \beta_U^k U_t^N + \beta_C^k C_{ist} + \beta_{CU}^k U_t^N \cdot C_{ist} + Z_{ist}' \gamma^k + \mu_s^k + \mu_{is}^k \\ + \varepsilon_{ist}^k;\ k = UR, ER \end{aligned} \tag{2}$$

Z_{ist}' is a vector of other time varying factors that affect the strength of the labor market in county i, μ_s^k represents time

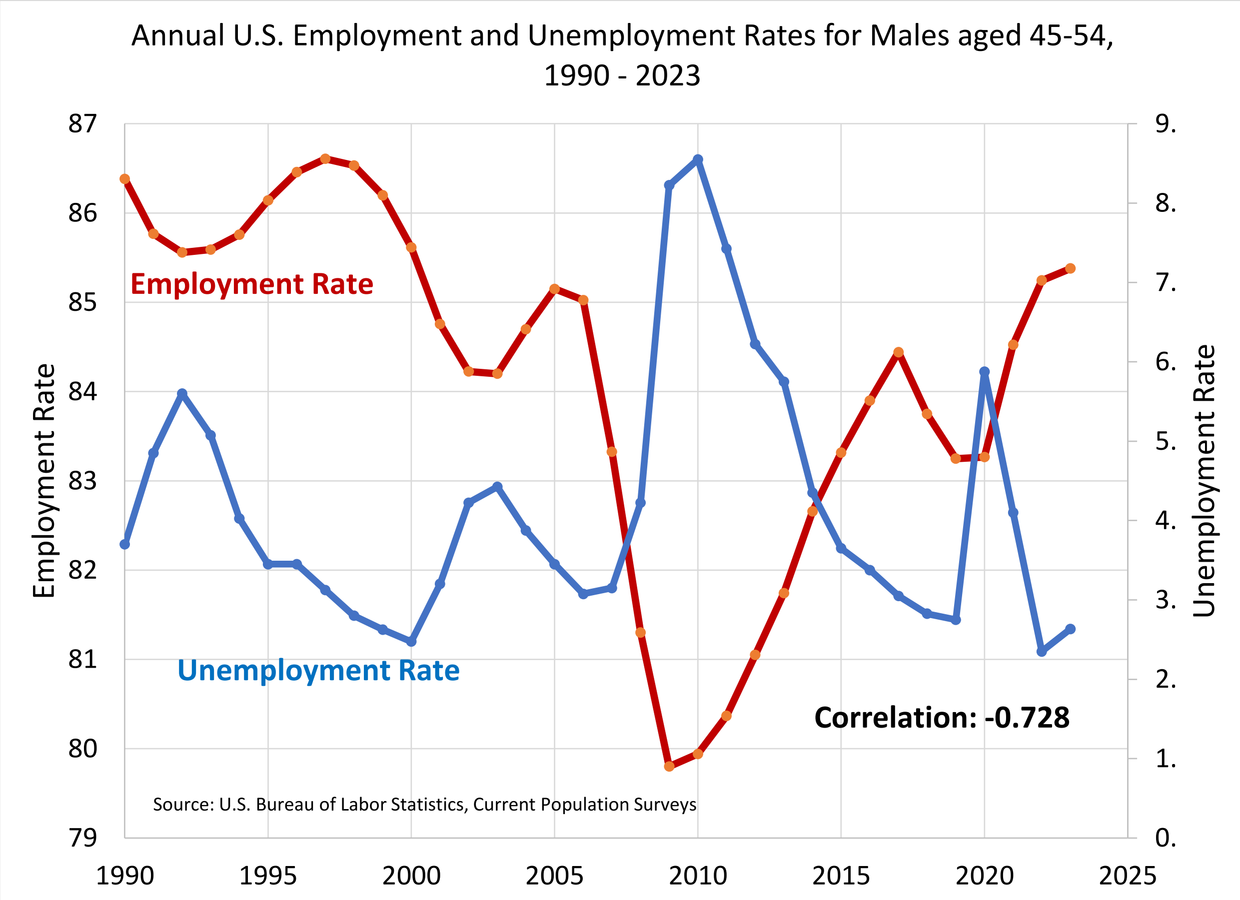

FIGURE 1 | Employment rates and unemployment rates for prime-age males, 1990–2023. Authors' compilation of data on males aged 45–54 obtained from the current population survey, various years.

invariant state-specific market factors, μ_{is}^k represents time invariant county-specific market factors, and ε_{ist}^k represents random local labor market innovations. β_U^k and β_C^k will capture, respectively, the links between national unemployment and the local concentration of college students in the population on the local unemployment rate (UR) or employment rate (ER).[10]

We expect that local labor markets follow the national business cycles, and so $\beta_U^{UR} > 0$ and $\beta_U^{ER} < 0$. The interaction term, β_{CU}, will capture whether college counties moderate the adverse effects of national recessions and amplify expansions. If they do, $\beta_{CU}^{UR} < 0$ and $\beta_{CU}^{UR} > 0$, and so increasing national unemployment will have a smaller positive impact on local unemployment rates and a smaller negative impact on local employment rates as the fraction of students in the population rises.

The local unobserved market factors, μ_{is}^k, are likely to be correlated with the presence or absence of a local college or university. However, inclusion of county fixed effects creates a problem as the control counties will have no local college. Because counties without colleges will lack a college for the entire period, the county fixed effect will remove them from the estimation. Consequently, β_{CU} is identified only by the variation in the share of college students in the population in the sample of counties with colleges or universities.

An alternative mechanism for controlling unobserved local market effects is to assume that these effects are common across adjacent counties. Consider a county j that is adjacent to county i. The county j equivalent to Equation (1) is

$$L_{jst}^k = \beta_U^k U_t^N + \beta_C^k C_{jst} + \beta_{CU}^k U_t^N \cdot C_{jst} + Z_{jst}'\gamma^k + \mu_s^k + \mu_{js}^k + \varepsilon_{jst}^k;\ k = UR, ER \tag{3}$$

Differencing yields

$$L_{ist}^k - L_{jst}^k = \beta_C^k (C_{ist} - C_{jst}) + \beta_{CU}^k U_t^N \cdot (C_{ist} - C_{jst}) + (Z_{ist} - Z_{jst})'\gamma^k + \left(\varepsilon_{ist}^k - \varepsilon_{jst}^k\right);\ k = UR, ER; \tag{4}$$

under the assumption that neighboring counties share the unobserved market factors so that $\mu_{is}^k = \mu_{js}^k$.[11] This allows us to retain the effect of the non-college counties. The estimate of β_{CU}^k should be purged of unobserved market factors and still capture the full range of variation in the local importance of students in the population. For each county i, we define its neighbor j as the average of its surrounding counties.[12] We identified the surrounding counties using the U.S. Census County Adjacency File.[13]

We conduct the estimation using annual observations from 1990 to 2019. The earliest year for which unemployment data was available by county was 1990. We ended the analysis in 2019 as there was an obvious massive change in the data generating process associated with the pandemic and the recovery.

4 | Data

We first need to identify local markets with college students. Since 1990, the National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS) has compiled annual information from every college, university, and technical and vocational institution that participates in any federal student financial aid program. The IPEDS treats branch campuses as separate entities, and so branch campus enrollments are reported by branch site. However, if a school has off-campus classrooms or students, those students would be allocated to the official university or college address. We sum the enrollments for all the post-secondary academic institutions by county, S_{ist}, for every year between 1990–2019, and so the county enrollment is the total number of college students across all the higher education institutions in the county.

To develop an estimate of the size of the local labor market, we make use of the Census Bureau's Population Estimates Program (PEP) that produces annual estimates of the population for counties in the United States from 2000 to 2019. PEP anchors its estimates to the decennial census values for the 2000 and 2010 county population value, then uses other information to interpolate the intercensal values. The 1990 to 1999 PEP did not report the population estimates in the same format, and so we generated values for 1990 to 1999 using linear interpolations between the 1990 and 2000 county census values.[14]

The relevant population for the labor market is aged 16 and over. The 1990 Census reports the population aged 16 and over for county i, $POP16^{C}_{is90}$, along with the total population, POP^{C}_{is90}. We use this ratio, $(POP16^{C}_{is90}/POP^{C}_{is90})$ to adjust the population estimates for 1990–1999. The subsequent PEP values do not report the population aged 16 and over, and so we use the Current Population Survey (CPS) to generate the ratio of 16 and over to the total population by state. Let $POP16^{CPS}_{st}$ be the CPS population aged 16+ in state s and year t with the corresponding total population being POP^{CPS}_{st}.

Our resulting estimates for the county population aged 16 and over is then

$$POP16_{ist} = \left(\frac{POP16^{C}_{is90}}{POP^{C}_{is90}}\right) \times POP_{ist} \text{ for year } 1990-1999$$

$$POP16_{ist} = \left(\frac{POP16^{CPS}_{st}}{POP^{CPS}_{st}}\right) \times POP_{ist} \text{ for year } 2000-2019$$

where POP_{ist} is our estimated annual county population from the interpolated estimates or the PEP.[15] The local college share of the population is $C_{ist} = S_{ist}/POP16_{ist}$.

Annual averages of county unemployment rate and employment statistics were obtained from the Bureau of Labor Statistics, Local Area Unemployment Statistics (LAUS) program. Substate data collection through the LAUS program began in January of 1990. Economic conditions in these reports are evaluated in all census areas to determine the need for government assistance and budget purposes while also providing information on local labor market conditions for the private sector. Individuals counted in the labor force follow the same definition posted by the BLS of being a non-institutionalized civilian over the age of 16. Therefore, we use the county unemployment rate as reported. We generate the local employment rate as the reported county employment in the LAUS divided by our estimate of the county population aged 16 and over.

While the county unemployment and employment rate measures attempt to mimic their state or national counterparts as estimated from the Current Population Survey (CPS), they are based on very different data sources. In particular, the local measures apply a mixture of administrative data, survey information, and extrapolations from state-wide data.

The unemployment estimates use separate measurement strategies for the unemployed who are covered or not covered by unemployment insurance.[16] Covered unemployment includes those who are receiving benefits plus a subset of those who have exhausted benefits and are estimated to be still unemployed, using aggregate data on the distribution of unemployment durations. Uncovered unemployment is estimated by allocating statewide CPS data on new entrants and reentrants. Each county's share of new entrant unemployment is based on its share of the state's 16-19 year-old population, while its share of reentrant unemployment is based on the county's share of the 20+ population.

The employment estimate is based on two sources: the Current Employment Statistics (CES) survey[17] and the Quarterly Census of Employment and Wages (QCEW).[18] The CES collects employment data from a nonrandom sample of cooperating employers. The QCEW is a count of workers covered by the Unemployment Insurance program. Because these data are situated by place of work, various sources of information are used to assign them to residences. Employment not covered by the CES and QCEW are allocated proportionally to each county using state-level information on agricultural workers, non-farm self-employed workers, unpaid family workers, and private household workers.

Is there a reason to suspect that these measures would differ systematically with the business cycle in college counties? The unemployment measure is partially based on covered unemployment. UI recipiency is based on state requirements for wages earned or time worked. Most states require 1 year of prior work and part-time jobs may not accumulate sufficient earnings to qualify. If college students are more likely to work part-time or have a job for under a year, it is plausible that layoffs from such jobs in college counties will be missed, and this problem is likely to be most severe during cyclical downturns. Moreover, college counties will have large shares of 16–19 year-olds, so they get a large share of new entrant unemployment which declines in downturns. Both plausible biases suggest that college counties will have atypically low measured unemployment during recessions. In contrast, there is no clear bias in employment rates associated with college counties.

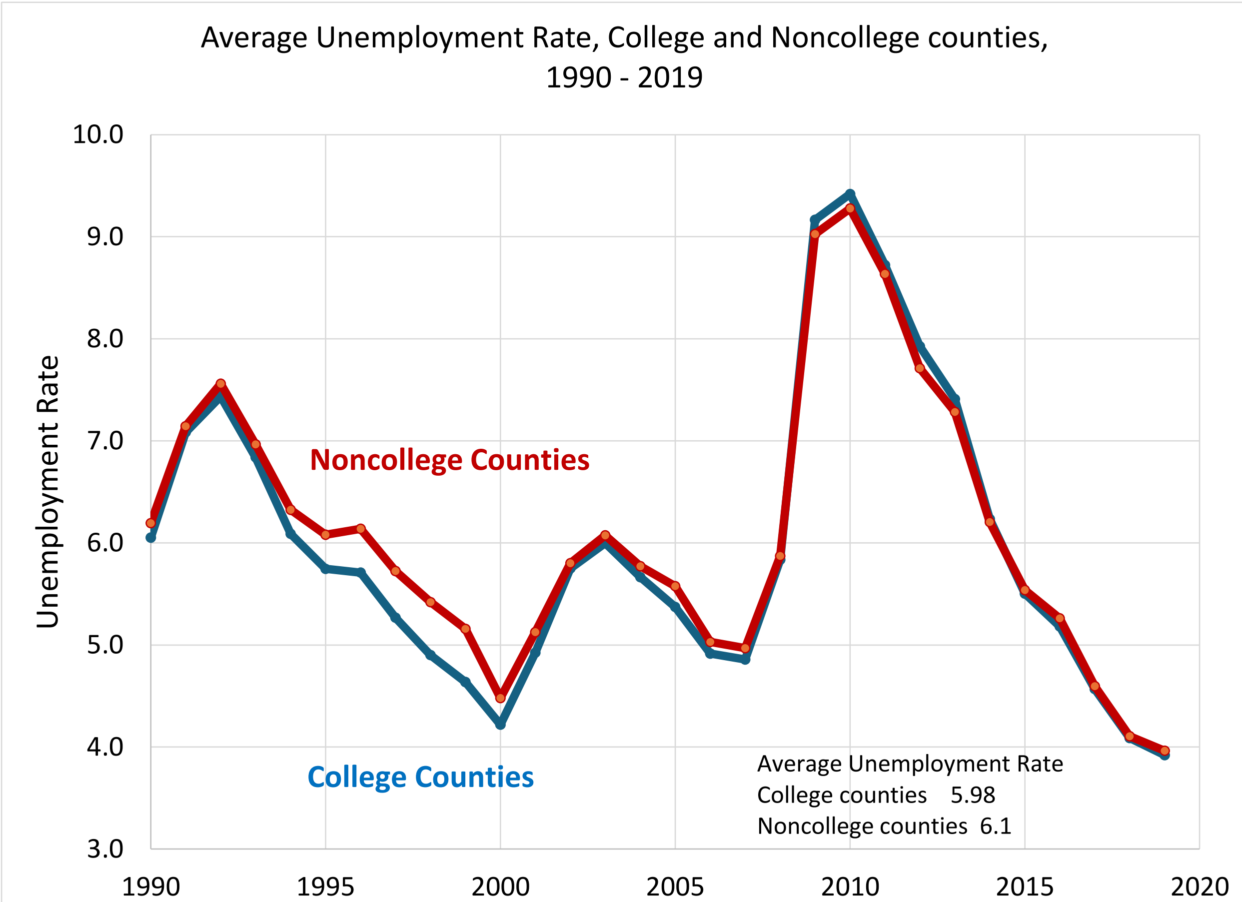

FIGURE 2 | Unemployment rates in counties with and without a college or university, 1990–2019. Authors' aggregation of county-level data from the U.S. Bureau of Labor Force Statistics, local area unemployment statistics, various years.

In Figures 2 and 3, we show the patterns of unemployment and employment rates in counties with and without college students. Figure 2 shows the time path of average unemployment rates. College counties averaged only 0.1% point lower unemployment rates than non-college counties, although the gap was larger before the Great Recession. Since the Great Recession, the difference in unemployment rates between college and non-college counties has disappeared. Over the full sample, unemployment rates in counties with college students averaged 0.06 lower in recessions, a difference that was not statistically significant. During expansions, unemployment rates in college towns averaged 0.14 lower than counties lacking a college, a difference that was significant at the 10th percentile. The employment rates in Figure 3 show a more consistent advantage to counties hosting colleges. The differences averaged 1.08% points during economic expansions and 1.07% points in contractions, both differences being significantly different from zero.

Our analysis holds constant state and county fixed effects, but also tries to control for variation in state policies as our elements of the vector, Z'_{ist}. Many of our counties are located at state borders. While other factors such as industrial mix and sectoral, customer and supplier agglomeration may be commonly experienced between a county and its neighbors, there are sharp discontinuities in government policies at state borders. Among the most salient policies that have been investigated for their influence on firm location and employment decisions at state borders are state tax rates and state minimum wages, and so we add them as controls in our analysis as well.[19]

Our state income tax measure is the highest marginal tax rate as reported by the NBER TAXSIM model.[20] Sales tax rates are the highest state retail sales tax rate ignoring exemptions or rebates as reported annually in *The Book of the States*.[21] The effective property tax rate per $100 of assessed value in the largest city in each state is available from the Government of the District of Columbia.[22] The state minimum wage is available from 1990 to 2019 from the U.S. Department of Labor.[23] Wages are converted to constant 2019 dollars using the Consumer Price Index.

We also incorporated three county-specific measures that are consistently tied to local firm entry. County income per capita in 2019 dollars, a measure of the strength of local consumer demand, was obtained from the U.S. Bureau of Economic Analysis. We also include a measure of natural amenities including favorable county climate, topography, and water features developed by McGranahan (1999). We also include an inverse measure of county economic diversity. Using County Business Patterns data, we derive an annual series of county-level Herfindahl Indexes equal to the sum of squared employment shares in 9 sectors over the 1990–2019 period.[24]

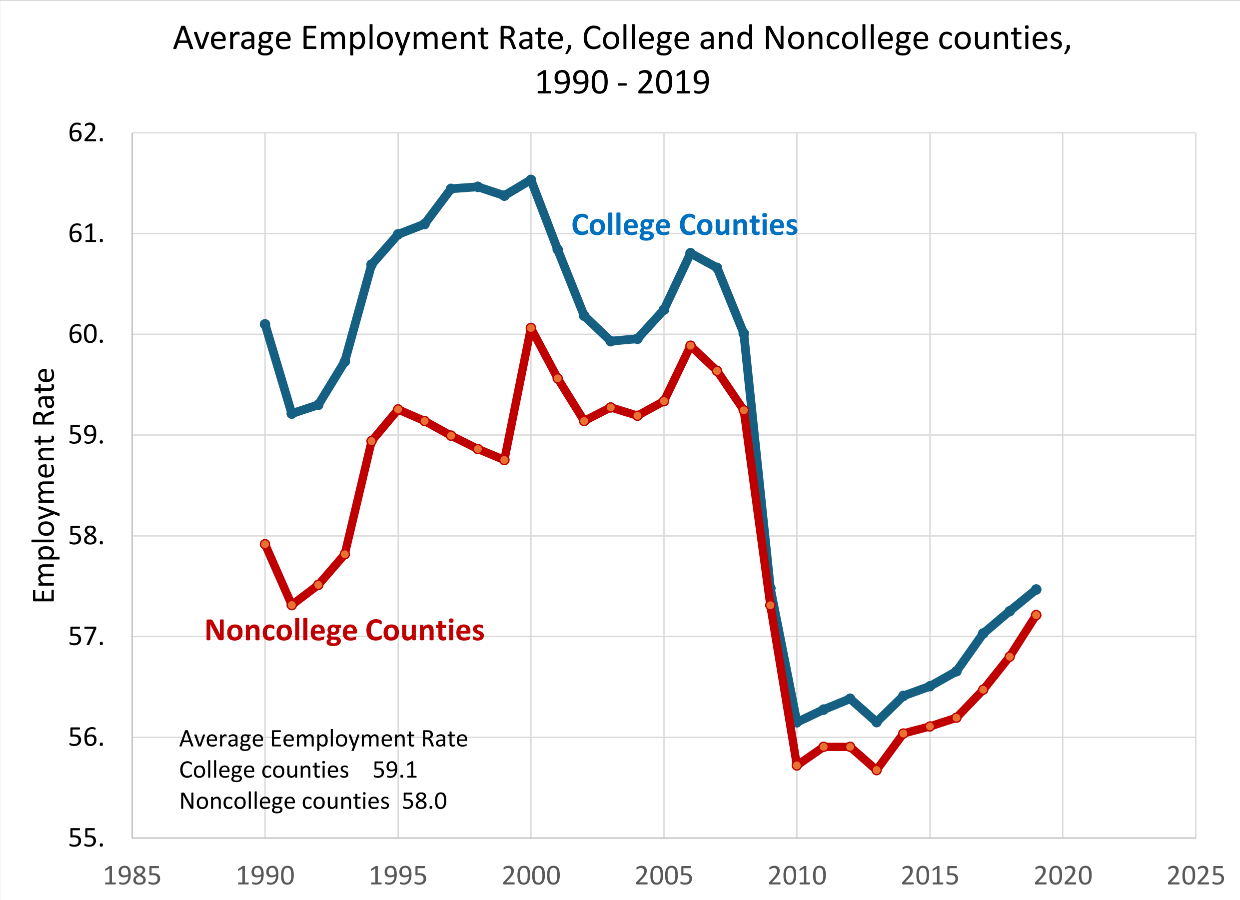

FIGURE 3 | Employment Rates in Counties with and without a college or university, 1990–2019. Authors' aggregation of county-level data from the U.S. Bureau of Labor Force Statistics Current Employment Statistics and the Quarterly Census of Employment and Wages, various years.

5 | Results

In our empirical strategy, we developed a model to test the hypothesis that the presence of a college county, measured by the share of students in the population, moderates the adverse effects of national recessions on local labor market indicators. We have a particular interest in examining whether the expected outcome, that $sgn(\beta_{CU}^{UR}) \neq \text{sgn}(\beta_{CU}^{ER})$, holds for college counties.

Table 1 presents the regression results applying the specification in Equation (1) for both unemployment and employment rates. All estimates correct the standard errors for clustering at the county level. The findings in columns 1 and two incorporate state fixed effects. As expected, the national unemployment rate has a positive effect on local unemployment rate and a negative effect on the local employment rate. The local enrollment share is negatively associated with local unemployment and positively associated with employment, highlighting the broader positive impact of housing a higher education institution in the local labor market shown in Figures 2 and 3. Other factors affecting the strength of the local labor market include sales taxes, income taxes, and minimum wages that raise local unemployment rates and lower employment rates. Local amenities are also associated with higher local unemployment rates and lower employment rates. Higher local per capita incomes correspond with lower unemployment rates and higher employment rates. Property taxes correlate with both lower unemployment and lower employment rates, although the latter effect is not significant.

The key parameters of interest, β_{CU}^{UR} and β_{CU}^{ER}, are the coefficients on the interaction term between the national unemployment rate and the local enrollment share. These coefficients would be expected to have opposite signs, but both are negative. The presence of a college appears to cushion the local unemployment rate against national economic downturns, although the coefficient is not statistically significant. However, it also lowers the employment rate by 0.45% points more than in non-college counties. Hence, the puzzling result that college counties do better on unemployment rates and worse on employment rates than the non-college counties.

The estimated local labor market responses may be biased by unobserved local market factors that are correlated with the presence or absence of a college. For that reason, we repeat the estimation in columns 3 and 4, controlling for county fixed effects. These automatically control for state fixed effects. However, they have the unfortunate feature that they effectively remove all the counties without a college from the analysis as the absence of a college is perfectly correlated with the county fixed effect. As a result, we only identify the college effect by the variation in the college share of the population over time for the counties that have colleges. A consequence of the removal of the

TABLE 1 | Least squares regression estimation of the effect of national business cycles on college and non-college unemployment and employment rates, 1990–2019.

Variables	−1 Local unemployment rate	−2 Local employment rate	−3 Local unemployment rate	−4 Local employment rate
National unemployment rate × enrollment share	−0.0492	−0.452***	−0.190***	−0.235*
	(0.0666)	(0.152)	(0.0576)	(0.127)
National unemployment rate	0.847***	−0.296***	0.860***	−0.378***
	(0.00805)	(0.0151)	(0.00827)	(0.0161)
Enrollment share	−2.076***	9.670***	1.491***	1.058
	(0.345)	(1.180)	(0.438)	(1.799)
Local factors				
Property tax effectiveness rate	−0.0929***	−0.128	−0.0431*	−0.581***
	(0.0261)	(0.0953)	(0.0248)	(0.0832)
Sales tax	0.419***	−2.570***	0.185***	−0.767***
	(0.0326)	(0.109)	(0.0299)	(0.114)
Income tax	0.0820***	0.229***	0.114***	−0.0453
	(0.0151)	(0.0683)	(0.0148)	(0.0630)
Ln per capita income	−4.437***	16.51***	−2.753***	2.420***
	(0.167)	(0.439)	(0.130)	(0.558)
Ln minimum wage	1.186***	−18.83***	0.105	−9.832***
	(0.149)	(0.506)	(0.135)	(0.461)
Amenity index	0.0870***	−0.164**	—	—
	(0.0217)	(0.0723)		
HHI	−0.890***	8.614***	−2.651***	12.69***
	(0.300)	(1.364)	(0.333)	(1.429)
Constant	45.82***	−71.86	29.99***	57.89***
	(1.547)	(4.054)	(1.218)	(5.174)
State fixed effects	√	√	√	√
County fixed effects			√	√
Observations	91,512	91,512	91,512	91,512
R-squared	0.540	0.462	0.777	0.769
No. Of FIPS	47	47	3052	3052

Note: Standard errors corrected for clustering at the county level.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

control counties in the county fixed effect estimation is that enrollment share is now positively related to unemployment rates. Nevertheless, the key result from columns 1 and 2 still holds: college counties have local unemployment rates that are more insulated from national business cycles, even as they have larger decreases in employment rates than their non-college counterparts. Because county fixed effects overcorrect for unobserved local market factors, we apply Equation (4) that allows us to difference each county attribute from the average of its neighbors. If we can assume that neighboring counties share unobserved fixed market strength or weakness, the differenced method will control for these regional fixed effects common to the county and its surrounding counties.[25] This allows us to include the non-college counties from the estimated effects, whereas the county fixed effects in Table 1 effectively removed non-college counties from the analysis. We are also able to include state-by-year fixed effects in this analysis. The results are reported in Table 2. The national unemployment rate is the same in all counties, and so its impact is differenced away. As in columns 1 and two in Table 1, county enrollment share is associated with lower unemployment rates and higher employment rates as expected. The effects are not small. The average college county has a student population share of 10%. Consequently, the coefficients in Table 2 imply that college counties average 0.18 lower unemployment rates and 0.9 higher employment rates than their non-college neighbors.

TABLE 2 | Own relative to neighbor county difference estimation of the effect of national business cycles on college and non-college unemployment and employment rates, 1990–2019.

Variables	−1 Difference in local unemployment rate	−2 Difference in employment rate
Difference in national unemployment rate × enrollment share	−0.0873**	−0.470***
	(0.0414)	(0.135)
Difference in enrollment share	−1.800***	9.884***
	(0.246)	(0.969)
Local factors		
Difference in property tax effectiveness rate	−0.0562	0.914***
	(0.0842)	(0.348)
Difference in sales tax	0.0668	−0.291*
	(0.0554)	(0.175)
Difference in income tax	−0.0879***	0.262***
	(0.0302)	(0.0984)
Difference in Ln per capita income	−3.705***	20.23***
	(0.185)	(0.687)
Difference in Ln minimum wage	2.374**	−9.580***
	(0.922)	(3.253)
Difference in amenity index	0.0237	−0.232***
	(0.0301)	(0.0850)
Difference in HHI	−0.0675	7.396***
	(0.276)	(1.338)
Constant	0.147	−0.159
	(0.206)	(0.351)
State fixed effects	√	√
County regional fixed effects	√	√
State by year fixed effects	√	√
Observations	91,272	91,272
R-squared	0.151	0.256

Note: Standard errors corrected for clustering at the county level.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

For our primary coefficients of interest, the anomalous labor market responses to national business cycles in college counties remain. College counties have consistently lower unemployment rates than their non-college neighbors in response to an increase in the national unemployment rate. At the same time, the college counties also have lower employment rates as national unemployment rises. Both effects are now statistically significant. A unit increase in the national unemployment rate has a 0.09% point smaller effect on college county unemployment rates, but it also lowers the college county employment rate by 0.47% points more than its non-college neighbors.

6 | Robustness

We have presumed homogeneity in the effects of college student population share on employment and unemployment rates during recessions. This is plausible because the measurement error from using increases in unemployment insurance filings to approximate lower unemployment rates should increase with the importance of students in the local labor market. However, as suggested by a referee, it is possible that the odd finding that both unemployment and employment rates fall in recessions in college towns is confined to the less populated counties that would be expected to have unusually large college shares in the population. For example, Travis County (Austin, TX) has a population of 1.4 million and a student population share of 13.5% while Story County (Ames, IA) has a population of 102 thousand and a student share of 42%. To examine that possibility, we replicated the analysis from Table 2 on just the counties with fewer than 50,000 population, the smallest population to qualify as a metropolitan area. Interestingly, there was only a 3% point higher average student share in the nonmetro counties compared to the overall average. Apparently, smaller counties also have smaller colleges.

In Table 3, we report the results of the unemployment and employment rate county difference estimation regressions using only the nonmetro counties. The estimated coefficient on the interaction between college student population share and the national unemployment rate in the small counties is only 5% points greater in magnitude than the effect estimated over all counties. Apparently, the finding that college towns experience atypically large decreases in employment rates during recessions is not due solely to the least populated counties. On the other hand, the effect on the unemployment rate is not significantly different from zero in Table 3 compared to the negative and significant effect when estimated over all counties. That suggests that the finding of atypically low responsiveness of unemployment rates to recessions in college towns holds mainly in the metropolitan areas housing colleges and universities.

7 | Conclusion

This paper casts doubt on the widespread presumption that college towns are more resilient to recessions than non-college towns. While college towns have lower unemployment rates and higher employment rates on average, these advantages have diminished since the Great Recession. Analysis shows that, consistent with the presumption that college towns are resilient to recessions, unemployment rates in college counties rise more slowly than their non-college neighbors in response to increases in the national unemployment rate. However, college county employment rates also fall more quickly as national unemployment rates rise. The anomalous finding appears to be due to the use of new applications for unemployment benefits in estimating local unemployment rates. Because college students are

TABLE 3 | Own relative to neighbor county difference estimation of the effect of national business cycles on college and non-college unemployment and employment rates, 1990–2019, counties with less than 50,000 population.

Variables	−1 Difference in local unemployment rate	−2 Difference in employment rate
Difference in national unemployment rate × enrollment share	0.0173	−0.518***
	(0.0463)	(0.159)
Difference in enrollment share	−1.967***	9.058***
	(0.325)	(1.134)
Local factors		
Difference in property tax effectiveness rate	0.00394	0.884*
	(0.109)	(0.460)
Difference in sales tax	0.0167	−0.268
	(0.0660)	(0.225)
Difference in income tax	−0.133***	0.458***
	(0.0327)	(0.122)
Difference in Ln per capita income	−3.368***	21.86***
	(0.242)	(0.885)
Difference in Ln minimum wage	2.565**	−9.878**
	(1.003)	(4.139)
Difference in amenity index	0.0614*	−0.287***
	(0.0368)	(0.103)
Difference in HHI	−0.434	8.579***
	(0.287)	(1.417)
Constant	0.424*	−0.0696
	(0.255)	(0.419)
State fixed effects	√	√
County regional fixed effects	√	√
State by year fixed effects	√	√
Observations	64,207	64,207
R-squared	0.118	0.246

Note: Standard errors corrected for clustering at the county level.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

less likely to qualify for unemployment benefits, new applications may rise more slowly in counties with larger college student population shares than they do in non-college counties, even as employment falls more rapidly.

Conflicts of Interest

The authors declare no conflicts of interest.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] In the month we are finalizing this paper, 7 of the 10 lowest unemployment rates among metro areas housed large public universities.

[2] Examples of discussions in the popular press include Davis (2016) and Nunn (2018). Econometric evidence is provided by Jump (2024).

[3] Reviews of U.S. evidence include Drucker and Harvey (2007) and Brekke (2021). Evidence from Europe is provided in Agasisti and Alice (2022). Evidence that college towns improve the educational and educational outcomes of children raised in the town is provided in Howard and Weinstein (2022).

[4] Supporting evidence is found in the reviews cited in footnote 3, and in Orlando et al. (2019) and Drucker (2016).

[5] See Dascher (2002) and Bluhm et al. (2021).

[6] Studies that document the benefits of a local college or university to the local labor market include Leten et al. (2014), Audretsch et al. (2012), Winters (Winters 2011a, 2011b), and Winters (2020).

[7] It is convenient for our derivation to define the employment rate and unemployment rate as proportions rather than percentages.

[8] Consider the effect of a positive demand shock to the economy, D. The effect on the employment rate is $\frac{\partial ER}{\partial D} = (1 - UR)\frac{\partial LFPR}{\partial D} - LFPR\frac{\partial UR}{\partial D}$. We can presume that $\frac{\partial UR}{\partial D} < 0$, so that the unemployment rate falls as product demand rises. In addition, $(1 - UR) > 0$ and $LFPR > 0$, so for $\frac{\partial ER}{\partial D} < 0$, it must be the case that $\frac{\partial LFPR}{\partial D} < 0$ and large enough to swamp the effect on unemployment. Because it is more plausible that the labor force would rise as product demand rises, finding that $\frac{\partial ER}{\partial D} < 0$ when $\frac{\partial UR}{\partial D} < 0$ would be very surprising.

[9] The average labor force participation rate for males aged 45–49 is 89.6 with a range of 86.4–93.0 between 1990–2019.

[10] We also used a specification that defined $\varepsilon_{ist}^{k} = \varepsilon_{t}^{k} + \varepsilon_{st}^{k} + \eta_{ist}^{k}$, where the first term is a common year effect across all counties, the second terms is a state-by-year effect common across all counties in the state, and the last term is a random effect. The estimates of β_{CU}^{k} were similar to those using the specification in (1). However, the year fixed effects were perfectly correlated with the national unemployment rate which prevented identifying how local labor markets responded to the national business cycle and the state-by-year fixed effects were perfectly correlated with state tax policy which prevented identifying the sensitivity of local labor markets to state tax policy.

[11] This assumption can be violated when the neighboring counties include counties from other states. In that case, there can be differences between neighboring counties that vary by state and year. We accommodate that potential bias by defining the error term as $\left(\varepsilon_{ist}^{k} - \varepsilon_{jst}^{k}\right) = \left(\varepsilon_{st}^{k} - \varepsilon_{st}^{k}\right) + \left(\eta_{ist}^{k} - \eta_{jst}^{k}\right)$, where the first term can be controlled by a state-by-year fixed effect and the second term is a random error.

[12] This is equivalent to using the spatial lag model (Anselin et al. 2008) where all the neighboring counties are lumped together as an average county rather than including each neighboring county as a separate observation. We obtain virtually the same results for our parameters of interest. However, some of the state-level tax measures which are common between the own county and neighboring counties in the same state are perfectly correlated. Some of the neighboring counties are in a different state, and so the state tax rate differs. Nevertheless, the high correlation causes some of these spatially lagged coefficients to become implausibly large, particularly in the differenced specification used in Table 2. We prefer our simpler specification as a large fraction of the averaged neighboring counties include counties from other states, lowering the degree of correlation in the state tax and expenditure measures and generating more plausible estimates.

[13] https://www.census.gov/programs-surveys/geography/library/reference/county-adjacency-file.html.

[14] To validate our linear interpolation method for 1990 to 1999, we compared similarly generated linear interpolations for 2000 to 2019 to the PEP values. The two series were correlated at 0.9999.

[15] We did not have a reasonable way of estimating the institutional or military populations by county, and so these numbers will be larger than the true relevant population for the labor force.

[16] Details are included in the Bureau of Labor Statistics, *Handbook of Methods* section called Local Area Unemployment Statistics: Estimation https://www.bls.gov/opub/hom/lau/calculation.htm.

[17] https://www.bls.gov/opub/hom/pdf/ces-20110307.pdf.

[18] https://www.bls.gov/opub/hom/cew/.

[19] An example of the effect of minimum wage effects on employment at state borders can be found in Dube et al. (2010). The role of relative tax rates at state borders was analyzed in Chen et al. (2023).

[20] The state income tax rate data are described in Feenberg and Coutts (1993), and are available from https://taxsim.nber.org/state-rates/.

[21] Council of State Governments, Various years.

[22] Government of the District of Columbia, Department of Finance and Revenue, Various years.

[23] Data are available at https://www.dol.gov/agencies/whd/state/minimum-wage/history.

[24] Due to data suppression, data were missing in some years for some counties. The Herfindahl indexes change very slowly, and so we use past values to replace missing values to avoid losing observations. Results were the same when we estimated the model including only the observations with a current Herfindahl index value.

[25] Evidence suggests that commuting patterns span the adjacent county, and potentially, a two-county radius around each county (Khan et al. 2001).

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