The Effect of Postsecondary Educational Institutions on Local Economies: A Bird's-Eye View[1]

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Abstract: Postsecondary institutions affect the economy of the area around them, but the question is how. In the early 2000s, the United States experienced a rapid increase in both the number of students attending college and the number of branch campuses serving these students. We examine branch campus openings that took place in two states, Tennessee and Texas, that are representative of the underlying patterns in the nation as a whole. We provide estimates of the impacts of these branches campuses on local economic conditions. Because the impacts of these branch campuses could be more localized than county- or state-level data might reveal, we use satellite images to construct otherwise unavailable measures of economic development around these small branch-campus regions. We find a clear positive association. In Tennessee, this effect seems to be driven largely by two-year campuses, while the effect is higher for four-year campuses in Texas. As the location of new branch campuses is likely endogenous to local economic conditions, simple estimates may not reflect a causal effect. For Texas, we are able to use an instrumental variable to estimate causal effects. Our instrument takes advantage of local taxing regulations that likely influence the decision to open a branch campus in certain locations but not the local economic conditions. Using this exogenous variation, we find an even larger positive effect. Given that many states use higher education as a strategy to induce economic growth, particularly in rural areas, this paper contributes some of the first empirical estimates of the impact of campus openings on regional economic activity and offers perspectives on using this approach as an economic development tool.

JEL Codes: I23, I25, I26, J24, R11

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I. Introduction

Education has both private and public returns. While education can improve individual student's economic and non-economic outcomes (e.g., Bianchi & Giorcelli, 2020; Böckerman & Haapanen, 2013; Oreopoulos & Petronijevic, 2013; Walker & Zhu, 2018), education can also generate significant impacts on its local community (e.g., Andrews, 2023; Cowan & Zinovyeva, 2013; Moretti, 2004; Pfister et al., 2021). Education, particularly institutions of higher education[2]—the focus of our paper—can produce social returns in many ways. Externalities from a more educated workforce, for example, may improve economic conditions in the neighboring communities (e.g., Bianchi, 2020; Kamhöfer et al., 2019; Moretti, 2004). In addition, research oriented universities may affect local economic growth by facilitating patents, transferring knowledge, and training a skilled worked force (e.g., Anselin et al., 1997; Pfister et al., 2021; Toivanen & Väänänen, 2016). This impact on the local community or the social return to education is exactly the focus of this paper.

However, measuring the impact of educational institutions on local communities (or the neighboring regions) is difficult. It requires on the one hand variation in the availability or opening of educational institutions and on the other hand reliable economic data that can accurately capture the catchment area of a particular institution. This is especially difficult in the United States, where most four-year colleges have existed for decades and even centuries, well before systematic data on local economic conditions were accessible. The research on effects of opening postsecondary educational institutions to date has largely come from the European context and has focused on patent and innovation activity as outcomes (e.g., Bianchi & Giorcelli, 2020; Leten et al., 2014; Pfister et al., 2021; Rammer et al., 2020; Toivanen & Väänänen, 2016).

[2] We use "higher education" and "post-secondary education" interchangeably throughoutt the paper.

Our work expands on this literature by measuring the impact of opening colleges on local communities. We focus our attention on the large expansion of postsecondary education that took place since the 1970s in the United States. We particularly focus on the states of Tennessee and Texas. We focus on these states for two reasons. First and foremost, these states are representative of different types of postsecondary education growth that took place in that time period more generally across the United States. From 1984 through 2020 (the observation period of our empirical analyses), fall enrollment at public postsecondary institutions has increased by 42.3% in Tennessee and by 110.5% in Texas.[3] The surge in enrollment occurred across the states and overwhelmed the respective higher education systems. Second, these two states represent two ends of a spectrum of densely populated states with short travel times and high community connectivity on the one hand and sparsely populated states with long travel times and community connectivity. Thus, providing a comprehensive view of the varying impacts of new educational institutions in diverse demographic and geographic contexts across US States. Third, for these two states we were able to gather historical data on new colleges, data that are unfortunately not readily available in administrative data bases.

To accommodate the enrollment surge, Texas and Tennessee, like many other states, did not create additional main campuses but, rather, expanded capacity at existing institutions and established new branch campuses at new locations. Branch campuses are geographically separate from the main campus and offer two-year or four-year programs that can be completed fully at the branch campus location.[4] Between 1984 and 2020, the number of public branch campuses

[3] According to enrollment data from the National Center for Education Statistics' Digests of Education Statistics.
[4] We exclude "special purpose" branch campus locations such as high schools (which offer a limited selection of dual enrollment courses that may or may not lead to a degree) and prisons (which offer a limited selection of courses and/or programs to currently incarcerated individuals). In Tennessee, what we refer to as branch campuses in this paper are called "branch campuses" when they are affiliated with a Tennessee College of Applied Technology (i.e., technical college) and "off-campus centers" when they are affiliated with a community college or university. The

increased from 82 to 137 (67.1%) in Texas and from 35 to 104 (197.1%) in Tennessee, representing a substantial growth.

This expansion of postsecondary education institutions via branch campuses is the focus of our research. Specifically, we measure the impact of the establishment of branch campuses on economic growth in their local communities and surrounding regions. The establishment of these new branch campuses injected newly trained workers into communities and geographic areas where heretofore local postsecondary options did not exist. These branch campuses are teaching institutions aimed at expanding college access to a wider and larger audience. They create a pool of trained students and graduates who could provide attractive workers to new or existing firms in the respective region.[5] The aim of our paper is to study the causal effect this may generate in the local economies.

However, identifying causal effects of branch campuses is difficult because their location may be endogenous to the local economic conditions. For example, states may see a branch campus as a strategy to revitalize a struggling local economy. Creating a more educated supply of local labor may attract industry to communities experiencing economic declines. Alternatively, states and institutions may choose to open branch campuses in communities already experiencing economic growth and therefore have urgent workforce demands. Both of these potential endogeneity problems in the site selection process make it difficult to assess whether a branch

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precise definitions are included in the Tennessee Higher Education Commission's Academic Policies for Off-Campus Instructions A 1.4A (https://www.tn.gov/content/dam/tn/thec/bureau/aa/academic-programs/program-approv/aca-pol/CC_Univ_Off_Campus_Policy_Website.pdf) and A 1.4B (https://www.tn.gov/content/dam/tn/thec/bureau/aa/academic-programs/program-approv/aca-pol/TCAT_Off_Campus_Policy_Website.pdf). In Texas, we include locations that offer "off campus face-to-face" instruction according to the Texas Higher Education Coordinating Board's Distance Education Program Inventory (https://apps.highered.texas.gov/program-inventory/?view=DESearchForm).

[5] While previous literature on tertiary education expansions in Europe has analyzed the resulting regional innovation activities and other economic outcomes (e.g., Pfister et al., 2021; Schlegel et al., 2022; Toivanen & Väänänen, 2016), the findings of this literature are not generalizable to college branch campuses in the U.S., which focus on teaching rather than innovation, research, and scientific discovery.

campus opening leads to economic growth in the local area or vice versa. Our empirical strategy tries to account for such endogeneity.

A second problem with measuring the impact of branch campuses is identifying the “local” community that likely could be affected and to gather the corresponding economic indicators for that “local” area. Texas has geographically large counties, and the true catchment area of a branch campus might represent only a fraction of the economic volume measured in the typically available administrative data on county-wide economic indicators. While county-level data are the lowest geographic unit for which annual administrative data on economic activity are available,[6] it may not capture the true catchment area of a branch campus. We attempt to identify the true catchment area more precisely by focusing on the much smaller census tracts and their proximity to new campuses. However, while administrative data are available for each census tract, they are only available once a decade, which is not sufficiently frequent to study the effect of newly established branch campuses. Additionally, even if we focused on the county-level data, the smallest area covered by administrative data, they are only available as early as the mid-1990s making it difficult to account for the earliest construction of branch campuses nearly a decade earlier. To solve these problems, we developed a disaggregated metric based on daytime satellite imagery and use it to study the effects of branch campus openings in this paper. This metric allows us to create annual economic data at the census tract level.

While recent work in economics and geography has frequently utilized nightlight satellite imagery data as a means for measuring economic conditions (e.g., Ebener et al., 2005; Faber & Gaubert, 2019; Lee, 2018; Sutton & Costanza, 2002) we apply our novel approach that uses daytime satellite imagery and a land-cover classification to proxy economic activity at a much

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[6] County-level administrative GDP data are available from 2001.

more disaggregated level such as census tracts (Lehnert et al., 2023). In comparison to other common satellite-based economic proxies (e.g., night light intensity), our proxy offers higher precision in predicting economic activity at smaller geographic areas, allowing us to study the effects of branch campus openings at the level of disaggregation where the effects are most plausible based on typical empirical commuting patterns (between 10 to 40 miles around a campus). Moreover, this novel approach offers an extended, annual time series back until 1984, allowing us to consider more historic branch campus openings in our analyses. The level of disaggregation of daytime satellite imagery allows us for the first time to isolate the economic activity in close proximity to branch campuses (treated areas) in comparison to other (non-treated) areas for the period of heavy expansion of branch campuses.

Empirically, we use multiple strategies. First, we make use of the longitudinal structure of our data by estimating fixed effects (FE) models to determine how the establishment of a branch campus impacts the local economic conditions. We apply a traditional difference-in-differences (DD) approach that captures time-invariant unobservable characteristics of census tracts for both Tennessee and Texas respectively. Second, we extend our DD model to estimate heterogeneity robust panel differences-in-differences models (Callaway & Sant'Anna, 2021). This approach more fully considers both the dynamic nature of the impacts as well as the varied start date of the treatment. Both traditional and the heterogeneity robust panel DD results suggest a positive association that increases in magnitude as we consider the potential impacts over a wider radius. In Tennessee, the positive impacts on growth seem to be driven by branch campuses of two-year institutions, while the effects are attributable to branch campuses of both two- and four-year institutions in Texas.

While the DD approaches allow us to understand some differences in trends across different locations, the assumptions necessary to establish causality in such models may be difficult to justify. To better establish causality, we additionally use an instrumental variable (IV) approach that solves the problem of endogenous branch campus location decisions in Texas by exploiting regional differences in the incentives to create new branch campuses. The IV results, which we regard as a more credibly causal estimate, similarly find positive and significant impacts of branch campus openings.

The paper proceeds as follows: Section II summarizes relevant literature; Section III describes our data and methods; Section IV presents our main results, including both the DD and IV specifications; Section V discusses the results and concludes.

II. Background and Setting

Higher education can create both private and public returns. In terms of private returns, college-educated people enjoy higher earnings, more stable employment, greater job and life satisfaction, better health, and are more civically engaged than students who did not attend college (e.g., Doyle & Skinner, 2017; Ma et al., 2020; Oreopoulos & Petronijevic, 2013; Oreopoulos & Salvanes, 2011). Public returns, the focus of our paper, also accrue to communities as more individuals complete postsecondary education (e.g., Andrews, 2020; Moretti, 2004). These positive externalities or social returns include such factors as higher wages for all, regardless of education level (Moretti, 2004); increased innovation activity and patenting (e.g., Bianchi & Giorcelli, 2020; Leten et al., 2014; Pfister et al., 2021; Rammer et al., 2020; Toivanen & Väänänen, 2016); increased local economic productivity, particularly in the manufacturing sector (Liu, 2015); and knowledge spillovers (Belenzon & Schankerman, 2013; Kantor & Whalley, 2014; Neumark & Simpson, 2014

Given the social returns to postsecondary education, many states in the U.S. have invested in improving educational attainment to stimulate economic development. The logic behind these investments is that producing more college graduates will not only supply trained workers to existing firms in the state but will also attract new firms and industries. The presence of a university often increases local population density, resulting in agglomeration economies (Liu, 2015), and shifts the composition of the local labor market toward more employment in human-capital-intensive industries (Russell et al., 2021).

Moreover, while most public four-year campuses in the United States have existed for decades or even centuries, their locations do not fully match migratory patterns for the last 30 years. The spatial variation of campuses leads to "education deserts," locations with no postsecondary institutions within a reasonable commuting distance (Hillman, 2016; Hillman & Weichman, 2016). Given the fact that having a university in the local area has a demonstrable and long-lasting impact on educational attainment (Russell et al., 2021) and that the majority of college students in the U.S. attend a school within 50 miles of home (Eagan et al., 2014; Wozniak, 2018), these education deserts may exacerbate inequality. Education deserts tend to be in communities with substantial Hispanic populations (e.g., Texas) and low educational attainment (e.g., Tennessee), whereas communities with large white or Asian populations tend to have more options for postsecondary education nearby (Hillman, 2016).

As states grappled with how to take advantage of the social returns of education and how to eliminate (or at least reduce the size of) these desert spaces, states could either expand the number of full universities or establish branch campuses (Neumark & Simpson, 2015. The rapid increase in branch campuses has been the predominant way in which states have spatially expanded higher education. Many of these branch campuses opened in remote or rural areas that previously did not have a postsecondary institution nearby, while other branch campuses opened in urban and suburban areas that were previously underserved by existing institutions.

We focus on Texas and Tennessee because their expansion of branch campuses was similar to national trends. They both substantially expanded branch campuses in the early 2000s. The branch campuses helped to eliminate higher education “deserts” and accommodated a substantial increase in college enrollment. At two-year branch campuses, the programs with large numbers of students were, for example, “health professions & related programs”, “computer & information science and support programs”, “liberal arts types of general programs” or “education programs”. These programs provide training that enables students to either directly enter the local labor market or to transfer to four-year colleges. By offering such programs, the new branch campuses provide an affordable entry point into higher education for economically disadvantaged students who are more likely to attend college if a campus is closer to their home. At four-year branch campuses, the programs with large numbers of students were again, for example, “education, health professions & related programs”, “computer & information science and support programs”, as well as “business & management oriented programs” and “public administration & social services programs”. These programs prepare graduates for jobs that are typically available in any region and thus again offer either a direct entrance to a university education or an educational career option for students transferring from two-year branch campuses.

For example, graduates with an Associate degree in education from a two-year program may directly enter the labor market by working as a teaching assistant, a classroom aide, or an early childhood educator. Alternatively, they could move on to a four-year program to earn a Bachelor degree and catch up with those who immediately began studies in a four-year program. With a four-year degree in education, graduates could become a school teacher after an additional certification, an educational administrator, or a curriculum developer. In computer and information sciences, graduates with a two-year associate degree may directly enter the labor market and work as a computer support specialist or IT technician, or they may move on to a four-year program. Graduates from a four-year program may, for example, work as a software engineer. In the health professions, graduates with a two-year Associate degree may directly enter the labor market by working as a nursing assistant, or move on to a four-year program to earn a Bachelor degree. Graduates from four-year programs could work as a registered nurse, a healthcare administrator, or a therapist.

Consequently, both types of branch campuses (two-year and four-year) help improve the human capital basis of the local economy because more students are attracted to higher education if a branch campus is closer to their home. Therefore, the establishment of a new branch campus should help foster local economic growth around the new campus.

III. Data and Methods

We construct two novel datasets to be able to study economic effects of campus openings on a very local regional level. The first dataset focuses on branch campus openings (our main independent variable). Dates on openings and specific geographic location are not readily available in single administrative databases. We assembled these data for Tennessee and Texas. In Tennessee, we were able to obtain administrative data on branch campus openings from both Tennessee's community and technical college system and from Tennessee's Board of Regents. In Texas, we were able to obtain a list of currently operating branch campuses from the Texas Higher Education Coordinating Board and conducted an extensive web search and phone survey to collect the opening dates of each campus.[7] We define a branch campus's opening date as the date that campus began offering classes and enrolling students.

Our second dataset focuses on regional economic activity as our outcome variable. Data on economic activity are not available on small enough local levels and particularly not for historical timelines. As such, we measure local economic activity by a proxy based on daytime satellite imagery, which we construct by applying a novel methodology developed by Lehnert et al. (2023). Details are described in the following section. Given that counties are smaller in Tennessee than in Texas, our choice of states also provides some contrast in the saliency of our more localized measure of economic activity as compared to county-level economic variables.

Construction of Proxy for Local Economic Activity and Definition of Catchment Areas

We construct a proxy for local economic activity by applying a novel methodology developed by Lehnert et al. (2023) that allows us to create annual economic data for regional levels as small as the census tract level for the U.S. The proxy offers two major advantages over other extant metrics. First, the proxy has a high validity for very small regional units (e.g., units as small as one square kilometer for the states in our sample). Therefore, we can disaggregate our outcome to regional units below those available in administrative statistics (which have counties as the lowest regional units). Moreover, Lehnert et al.'s (2023) proxy achieves higher precision in predicting economic activity at disaggregated levels than other common proxies such as night light satellite imagery data. This high validity at disaggregated levels allows us to identify local developments, which we expect to occur within a limited radius of a few dozen miles around a branch campus and are, thus, unobservable at the county level, the most disaggregated metric

[7] We leveraged institution websites as well as local news articles to find branch campus opening dates.

publicly available. Second, Lehnert et al.'s (2023) proxy offers a consecutive and consistent annual time series starting in 1984, extending administrative statistics (which start in 2001) and night light intensity data (which start in 1992).[8] This extended time series allows us to investigate the regional economic activities around all branch campuses that opened after 1984. With many branch campuses having opened in the 1980s, this increased variation greatly expands our sample and facilitates estimation.

To construct the proxy for regional economic activity at the census tract level, we proceed in two steps. As a first step, we train an OLS model on the land-cover classification based on daytime satellite imagery for the entire continental U.S. to obtain estimation coefficients for predicting economic activity at the census tract level. In doing so, we use county-level GDP data which are available from the Bureau of Economic Analysis for the years 2001 through 2020.[9] In addition, we calculate each county's area belonging to one of six land cover categories—built-up areas, grass, forest, cropland, areas without vegetation or buildings, and water—measured as the number of satellite data pixels per category. We take the natural logarithms of both the GDP and land cover measures. Since we intend to use the county-level coefficients from the predicted model to predict census-tract level GDP, we standardize all variables before the estimation. We then estimate Equation 1 as follows:

[8] We follow the suggestion in Lehnert et al. (2023) not to use observations where more than 10 percent of a region's area is covered by clouds (i.e., each time that the satellite passed over that particular region, making it impossible to observe ground cover in those years) and observations where the number of built-up pixels deviate too strongly from the median of built-up pixels among all observations of a region. In Texas, we additionally exclude nine census tracts at the border to Mexico from our analyses, because a visual inspection of the land-cover classification revealed a time-constant pattern of misclassification. From 1984 through 2020, we thus do not use the land-cover classification for 2.87 percent of the potential census-tract observations in Tennessee and 3.21 percent of the potential census-tract observations in Texas. Again following Lehnert et al. (2023), we can impute most of these observations as we use the three-year moving average of the GDP prediction as dependent variable in our analyses. After this imputation, we can use 99.51 percent of the potential census-tract observations in Tennessee and 98.81 percent of the potential census-tract observations in Texas.

[9] Available at https://apps.bea.gov/regional/downloadzip.cfm (accessed June 20, 2022).

$$(1) \qquad Y_{jt} = \lambda + \kappa LC_{jt} + \nu_{s[j]} + \tau_t + \mu_{jt}$$

Where Y is standardized log GDP for county j in year t, LC is a vector including the six standardized log pixel counts per land-cover category for county j in year t, ν_s is a set of state dummies, τ_t is a set of year dummies, and μ is the error term.[10] The standardization is necessary to use the obtained coefficients for predicting GDP at a different regional level, in our case the census tracts. The OLS model explains as much as 59 percent (adjusted R^2) of the county-level variation in GDP across the entire U.S. Additional validation analyses across states further show that the proxy's validity is even higher for small regional levels (e.g., 91% of the variation in GDP in Tennessee, a state with small average county size) , thus emphasizing its validity as a proxy for census tract-level economic activity.

As a second step, we use the OLS estimation coefficients of the variables in LC to obtain a census tract-level prediction of standardized log GDP. Ideally, we would estimate the same model as in Equation 1 except that we would like to estimate it at the census tract level. However, as we cannot observe GDP at the census-tract level, we assume that the land cover metrics have the same relationship at the census tract level as at the county level, and given our standardization in Equation 1, we can use the pixel counts per land cover category to then predict GDP.

This procedure thus provides us with a prediction of standardized log GDP as an annual measure for census tract-level economic activity starting in 1984. We use these data to estimate the effect of opening a branch campus on the regional economic activity in a rather precise catchment area around the new campus. To define the radius of impact, we make a consideration

[10] In addition to this set of explanatory variables, we follow Lehnert et al.'s (2023) suggestion and include a measure for cloud cover in the satellite data, which affects only very few observations, to further improve the prediction.

based on commuting distance. In 2021, the mean commuting time was 25.2 minutes in Tennessee and 25.9 minutes in Texas, and approximately 93% of people in Tennessee and Texas had a commute of less than an hour (American Community Survey, 2021). Therefore, we decide to use a 25-mile radius to correspond with these commuting times. However, we also perform robustness checks using a 10-mile radius as a very localized lower bound and a 40-mile radius as a geographically more widespread upper bound of an approximate commuting zone around the new branch campus.

Methods

We apply three different econometric methods to estimate the impact of branch campus openings on local economies. First, we use a difference-in-differences (DD) empirical strategy to estimate the effects for the different radii (10, 25, and 40 miles). Our basic specification is:

$$(2) \qquad \widehat{Y_{it}} = \alpha + \beta BranchCampusOpen_{it-4} + \gamma_i + \delta_t + \varepsilon_{it}$$

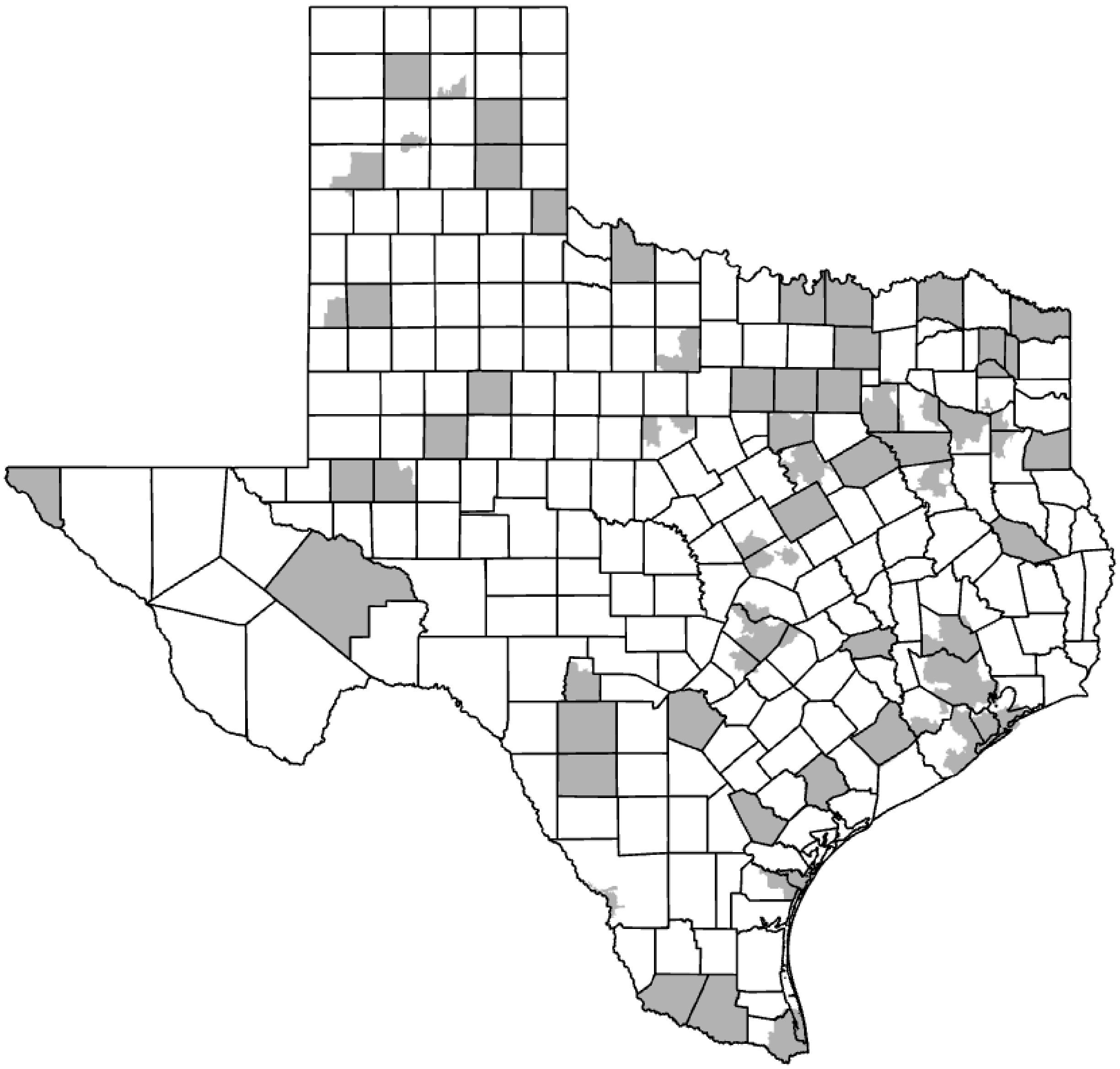
$\widehat{Y_{it}}$ is our proxy for GDP in tract i in year t obtained through the previously described procedure. $BranchCampusOpen_{it-4}$ is a binary indicator equal to 1 for the tracts within the specified radius in the year a branch campus opens and each subsequent year (i.e., the indicator remains equal to 1 in all years after the campus opens). We lag this variable by four years to account for the fact that it takes several years for a branch campus to graduate a cohort of students who could potentially contribute to local economic activity if they work near the campus from which they graduate. γ_i represents tract-level fixed effects, and δ_t represents year-level fixed effects. By including tract-level fixed effects, we ensure that our identification relies on new school openings throughout the period we analyze. We estimate our model with robust standard errors (ε_{it}).[11]

Second, we apply Callaway and Sant'Anna's (2021) heterogeneity-robust DD estimator. While the above DD model deals with time-invariant regional characteristics that potentially influence branch campus location decisions, it does not consider (a) that the impact of a branch campus might not be inherently constant over time and (b) that differences and treatment timing might bias the results by attaching different weights to each campus opening (see de Chaisemartin & D'Haultfœuille, 2022, for a survey of the corresponding literature); Callaway & Sant'Anna's (2021) heterogeneity-robust DD estimator addresses both these issues.

Third, as neither conventional nor heterogeneity-robust DD may fully solve endogeneity problems, we also estimate the impact of branch campuses using an instrumental variables strategy. However, this is only possible for Texas due to its unique institutional setting. We develop a new instrument based on the existence or non-existence of institutionalized incentives to create additional branch campuses that are exogenous to the colleges. Although branch campuses may often target campus locations based on economic characteristics of the nearby community, there is an important exception that provides the basis for an alternative identification strategy in Texas.

[11] As we are estimating a Fixed Effects regression, the robust standard errors are identical clustering standard errors at the census tract level.

Figure 1: Map of Texas Community College Taxing Districts



Notes: Black lines denote county borders. Shaded areas denote taxing districts.

To understand this exception, we review the two ways in which Texas community colleges have been formed. The first way relies on the state. The Texas Higher Education Coordinating Board can unilaterally create a community college. Community colleges created in this way rely on state appropriations for financing and have no local taxing authority. The second way to create a community college relies on a set of school districts joining forces. Multiple districts can join to form a community college district. The school districts have taxing authority, and they can grant some of that taxing authority to the community college district that they formed. These community college districts (and their boundaries) were largely formed over 50 years ago. About 30 percent of counties in Texas have a community college district with taxing authority, and the location of these districts is shown in Figure 1, where the shaded areas denote taxing districts.[12]

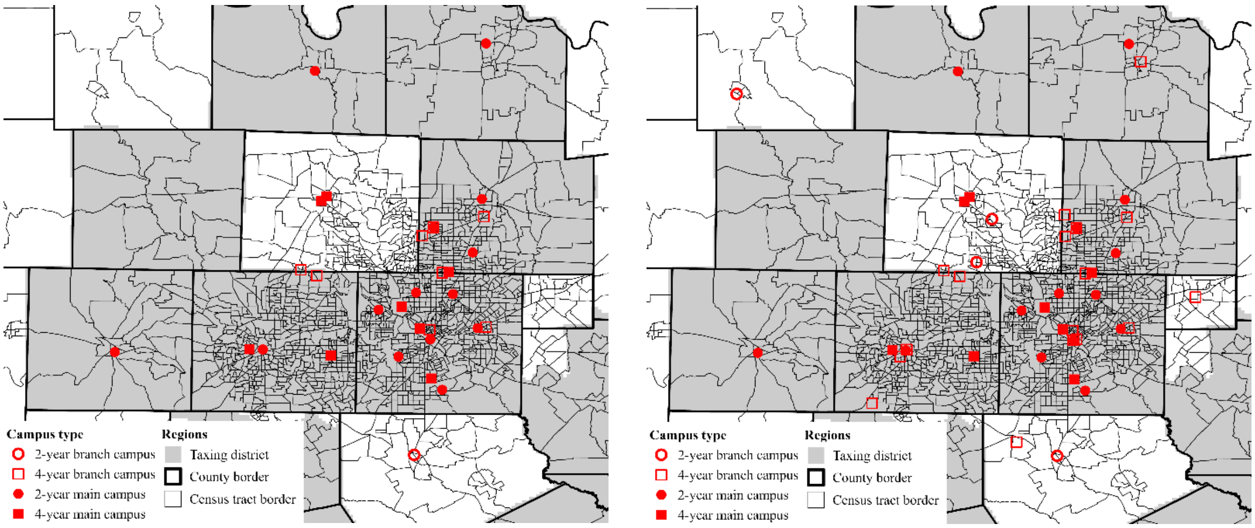
Community colleges with taxing authority charge in-district and out-of-district (higher) tuition rates, and these community colleges have incentives to establish branch campuses near the borders of their taxing district to "capture" out-of-district enrollments that strengthen their revenue or to "protect" potential enrollment loss to other community college districts. If the additional out-of-district tuition price exceeds the marginal cost of educating a student, then the district may have a stronger incentive to establish a branch campus.

Over the period we study, we do not have changes in the taxing authority of any community college districts; however, as new branch campuses are created both inside and outside of community college districts, it changes the incentives for subsequent creation of branch campuses. As such, we create instruments based on the interaction between a taxing district (time invariant) and the proximity of the census tract to existing branch campuses (time variant). More specifically, our set of instrumental variables comprises the log average distance between a census tract (centroid) and the five closest branch campuses (lagged by nine years)[13] and the interaction of this log distance with a dummy for whether the county in which a tract is located has a community

[12] As geographic data delineating the exact taxing district borders are not available anywhere, we manually reproduce the taxing district borders in ArcGIS using a PDF map provided by the Texas Association of Community Colleges as a basis (available from https://tacc.org/sites/default/files/documents/2018-10/17r0057_taxing_districts.pdf, last retrieved December 10, 2022).
[13] The nine year lag in the instrument corresponds to a five year lag respective to the campus opening, because we lag the campus opening by another four years as explained in Equation (1).

college district with taxing authority. We choose to use the average distance to the five closest campuses instead of only the distance to the closest campus to account for the regional density of college provision. Our results do not change when we use the closest campus alone. In the specifications in which we differentiate between 2- and 4-year branch campuses, we also distinguish between the distance to 2- and 4-year campuses in the set of instrumental variables. Thus, we capture incentives for branch campus creation that results from both the regional necessity of college provision (if other branch campuses are located only far away) and the possibility to generate taxing revenue (if a college has taxing authority in a region). The identifying assumption underlying this IV approach is that these incentives influence the location decisions for branch campuses independent of economic development. Our first stage results (Appendix Table A5) comport with our predictions. As original campuses are located in urban areas, the greater the distance from the original campuses, the less likely that a branch campus forms; however, for taxing districts, this is different. The taxing district has a greater incentive to form branch campuses and hence the penalty for distance is greatly reduced.

Figure 2: Branch Campus Locations in the Greater Dallas Area



A. 1984 **B.** 2020

Figure 2 show examples of branch campus locations in the greater Dallas area in 1984 and subsequently in 2020. The first interesting trend is that the initial campus tends to be near the geographic center of the county in 1984. This is also closer to the population center as demonstrated by the concentration of census tracts. All branch campus creation has to be farther away (hence a negative relationship between distance to the nearest cluster of campuses and the likelihood that a branch campus is formed); however, taxing districts do not have as strong of a relationship in these distances as branch campuses are locating closer to population centers to capture greater market share. The new location of campuses near to the borders of the taxing district also corresponds to greater likelihood of establishing branch campuses with a hope of enticing students from neighboring areas to come to a taxing district campus.

IV. Results

Table 1 presents our DD estimates of the effect of branch campus openings on economic activity in Tennessee (columns 1 and 2) and Texas (columns 3 and 4) with our 25-mile radius of impact. Columns 1 and 3 present estimates that use one binary independent variable identifying the opening of any branch campus. Columns 2 through 4 present estimates that include separate indicators for branch campuses affiliated with a two-year institution and branch campuses affiliated with a four-year institution. The indicator for the branch campus always corresponds to whether in a given year a branch campus existed within 25 miles.

Table 1: DD Estimates of Branch Campus Effect on Economic Activity within 25-Mile Radius of Impact in Tennessee and Texas

	Tennessee		Texas	
	(1)	(2)	(3)	(4)
Any Branch Campus	0.039***		0.165***	
	(0.008)		(0.008)	
Two-Year Branch Campus		0.049***		0.065***
		(0.008)		(0.010)
Four-Year Branch Campus		-0.003		0.142***
		(0.011)		(0.009)
Observations	62,630	62,630	251,680	251,680
Number of tracts	1,701	1,701	6,875	6,875
Within-R^2	0.207	0.208	0.192	0.189

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. The treatment variables are lagged four years so that we estimate the economic impact of a branch campus four years after its opening date. All models include constant, census tract FE, and year FE. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

We see a consistently positive and statistically significant estimate using our radius of 25 miles, suggesting that local economies with a branch campus opening see larger increases in GDP than local economies without a branch campus opening. The estimates for Tennessee are much smaller in magnitude than the estimates for Texas. This may suggest that Tennessee takes a “rural revitalization” approach to branch campus site selection by intentionally choosing to locate branch campuses in areas that were experiencing economic decline. In this case, the economic growth associated with a branch campus opening may be positive but modest in magnitude. Another explanation for this finding might be that branch campuses in Tennessee accommodate on average fewer students than those in Texas.

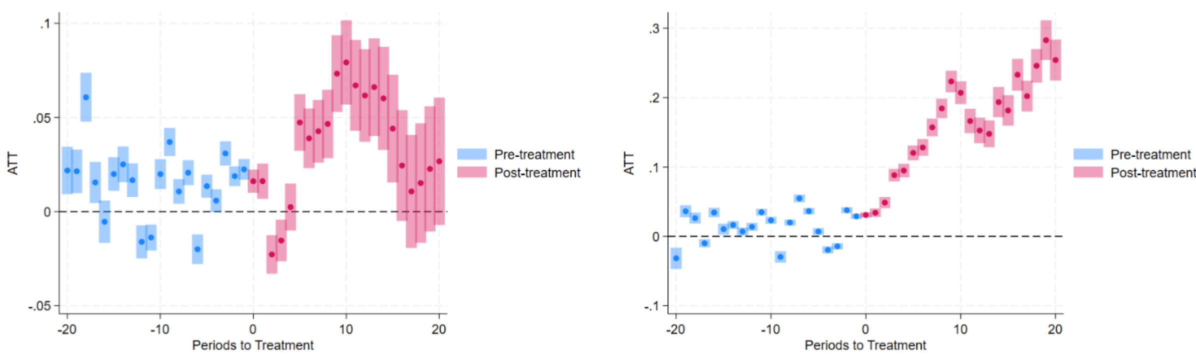
The generally larger coefficients in Texas may indicate that the branch campus openings are responsive to population growth in Texas. It could be the case that population growth spurs the state or institution to open a branch campus, and increasing access to higher education enhances an already-growing economy. Finally, in Tennessee, the overall estimate in Column 1 seems to be driven by the positive and significant estimates for two-year branch campuses in Column 2.

The magnitude of the estimates are modest across most specifications. We are predicting standardized growth across regions, and the impacts are in standard deviation units within the respective census tract over time. So, for example, the estimated effect of 0.165 in Column 3 for Texas corresponds to an increase in economic activity of 0.165 standard deviations in its local economic activity on average once a campus opens. For Tennessee, this effect amounts to 0.039 standard deviations.

Translating this effect into a more interpretable metric is possible with some assumptions. When we outlined our prediction models for economic growth, we standardized the dependent and independent variables across the U.S. distribution. To move our estimated impact in Column 2 to be a GDP number, we have to find a way to decompose the county-level GDP into the census-tract GDP. To do this, we try two assumptions. One is that economic activity is uniformly distributed across all census tracts. This is likely infeasible but provides one potential lower bound for the estimates. Second, we make the more feasible assumption that economic activity is distributed according to built-up area. In each case, we can then mathematically reverse our standardization.

Under these assumptions, we produce a lower bound and what we consider a realistic estimate of the growth in GDP associated with a branch campus opening. For Texas, the coefficient in Column 2 translates into a 5.93 percent growth in GDP under the lower-bound assumption and a 14.63 percent growth in GDP under the more realistic assumption. For Tennessee, the coefficient in Column 1 represents a lower-bound growth in GDP by 1.37 percent and a more realistic growth by 3.28 percent.

Figure 3: Callaway and Sant'Anna DD Estimates of Effects within 25-Mile Radius of Impact in Tennessee and Texas



A. Tennessee **B.** Texas

Figure 3 presents the event-study plots using Callaway and Sant'Anna's (2021) heterogeneity-robust DD estimator. Following Roth's (2023) guidance for DD designs with staggered treatment timing, we implement this estimator (Callaway & Sant'Anna, 2021; Sant'Anna & Zhao, 2020) using the csdid package in Stata. The results from 20 years prior to treatment to 20 years after treatment yield important insights. First, the estimates are flat and near zero in the years leading up to treatment, thus indicating parallel pre-treatment trends on both treatment and control groups. Second, they confirm the results from the conventional DD estimates, with positive and significant point estimates across all radii in Texas and for the 25- and 40-mile radii in Tennessee. Third, Tennessee and Texas differ in the timing of the treatment effects. While the point estimates are increasing and staying significant in all post-treatment periods in Texas, the treatment effect takes about five years to set in in Tennessee and, in the 25-mile specification, vanishes after 15 years. More importantly, the estimated impacts in Table 1 hide important heterogeneity where impacts tend to increase over time after the establishment of a branch campus. In sum, the findings from the heterogeneity-robust DD estimates align with our intuition that it takes a couple of years for the impact of a branch campus to be realized.

Table 2: IV Estimates of Branch Campus Effect on Economic Activity within 25-Mile Radius of Impact in Texas

	(1)	(2)
Any Branch Campus	0.196***	
	(0.039)	
Two-Year Branch Campus		0.108***
		(0.024)
Four-Year Branch Campus		0.197***
		(0.019)
First first-stage F-value of instruments	458.99***	2,183.95***
Second first-stage F-value of instruments		3,268.45***
Observations	251,680	251,680
Number of tracts	6,875	6,875
Within-R^2	0.192	0.186

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. The treatment variables are lagged four years so that we estimate the economic impact of a branch campus four years after its opening date. All models include constant, census tract FE, and year FE. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 2 presents our IV estimates of the effect of branch campus openings on economic activity in Texas. Similar to Table 1, Column 1 presents the result from a specification that includes one binary independent variable for branch campus openings, and Column 2 presents the results from a specification that includes separate indicators for two-year and four-year branch campuses. In both specifications, the estimates are positive and significant. The IV estimates are generally larger in magnitude than the DD estimates.

V. Robustness Checks

To evaluate whether our results are robust to alternative specification of the branch campuses' radius of impact, we repeat our estimations with radii of 10 and 40 miles. We present the results of these estimations in Appendix Tables A1 and A2 (conventional DD estimates for), Figures A1 and A2 (Callaway and Sant'Anna DD estimates), and Tables A3 and A4 (IV estimates).

From these alternative specifications, we conclude that our results hold for the larger radius of 40 miles and partly also for the smaller radius of 10 miles. For both Tennessee and Texas, we find the same patterns of the effects when applying the 40-mile radius as in our preferred 25-mile specifications in Section IV. For Texas, the results for the 10-mile radius also align with those for the 25-mile radius across the different estimators we use, with the exception of the coefficient on two-year branch campus openings turning insignificant in the conventional DD estimates. For Tennessee, however, the overall effect of a branch campus opening turns insignificant when applying the 10-mile radius and the coefficient for four-year branch campuses even turns negative and significant at the five-percent level. We argue that in Tennessee, which is far more densely populated than Texas, 10 miles seem to be too small a radius of impact to pick up the branch campus effect, and the results may have a downward bias due to census tracts located outside this radius of impact (and thus assigned to the control group in this specification) profiting from the branch campus opening as well.

VI. Discussion and Conclusion

Our paper aims to answer a compelling and perennial question about the relationship between higher education access and regional economic activity, employing a proxy for economic activity developed by Lehnert et al. (2023) using daytime satellite imagery. Because existing administrative data only exist annually at the county level back to the year 2000 and decennially prior to 2000, this proxy offers three primary advantages: (1) the data can be disaggregated at the sub-county level; (2) the data are available beginning in the year 1984; and (3) the data are available annually. We combine these satellite data with data on branch campus openings in Tennessee and Texas to provide estimates of the impact of branch campus openings on local economic activity. Overall, we find positive and statistically significant estimates.

Though we believe our work contributes to the existing literature on higher education's impact on the economy, much additional work remains in this space. Our analysis includes just two states due to lack of publicly available data on branch campus locations and opening dates. Expanding this analysis to include additional states in different regions of the United States with different political contexts may help bolster the external validity of these results. Additional data on these branch campus locations (e.g., enrollment and graduate counts, information about programs and classes offered, counts of faculty and staff resources) would also provide unique insight into the role of these campuses within the larger higher education system. Finally, though we have anecdotal evidence about how branch campus locations are chosen, a more thorough qualitative investigation of branch campus site selection would help us better understand how these decisions are made by institutions and policymakers.

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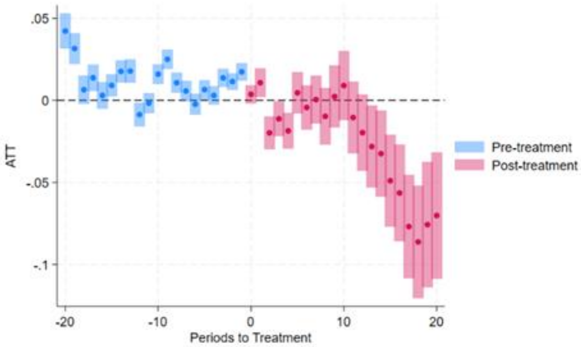
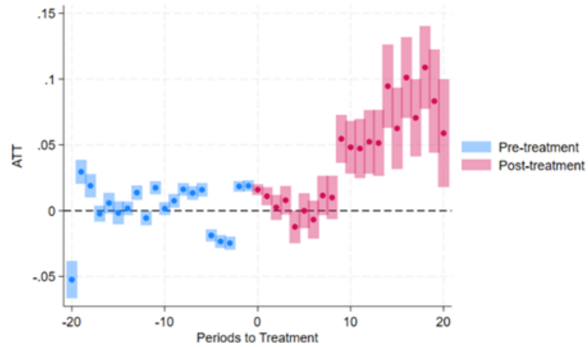
Appendix

Figure A1: Callaway and Sant'Anna DD Estimates of Effects within 10-Mile Radius of Impact in Tennessee and Texas

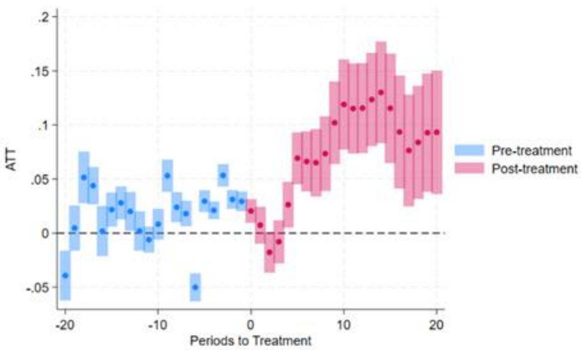


A. Tennessee

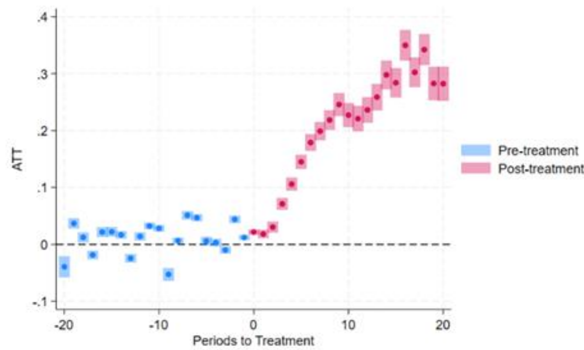


B. Texas

Figure A2: Callaway and Sant'Anna DD Estimates of Effects within 40-Mile Radius of Impact in Tennessee and Texas



A. Tennessee



B. Texas

Table A2: DD Estimates of Branch Campus Effect on Economic Activity within 10-Mile Radius of Impact in Tennessee and Texas

	Tennessee		Texas	
	(1)	(2)	(3)	(4)
Any Branch Campus	0.003		0.025**	
	(0.011)		(0.010)	
Two-Year Branch Campus		0.016		-0.007
		(0.012)		(0.014)
Four-Year Branch Campus		-0.049**		0.037***
		(0.016)		(0.013)
Observations	62,630	62,630	251,680	251,680
Number of tracts	1,701	1,701	6,875	6,875
Within-R^2	0.204	0.205	0.175	0.175

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. The treatment variables are lagged four years so that we estimate the economic impact of a branch campus four years after its opening date. All models include constant, census tract FE, and year FE. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A2: DD Estimates of Branch Campus Effect on Economic Activity within 40-Mile Radius of Impact in Tennessee and Texas

	Tennessee		Texas	
	(1)	(2)	(3)	(4)
Any Branch Campus	0.043***		0.217***	
	(0.006)		(0.007)	
Two-Year Branch Campus		0.047***		0.103***
		(0.006)		(0.008)
Four-Year Branch Campus		-0.002		0.210***
		(0.009)		(0.008)
Observations	62,630	62,630	251,680	251,680
Number of tracts	1,701	1,701	6,875	6,875
Within-R^2	0.207	0.207	0.205	0.210

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. The treatment variables are lagged four years so that we estimate the economic impact of a branch campus four years after its opening date. All models include constant, census tract FE, and year FE. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A3: IV Estimates of Branch Campus Effect on Economic Activity within 10-Mile Radius of Impact in Texas

	(1)	(2)
Any Branch Campus	0.199***	
	(0.043)	
Two-Year Branch Campus		0.577***
		(0.069)
Four-Year Branch Campus		0.334***
		(0.034)
First first-stage F-value of instruments	432.21***	212.88***
Second first-stage F-value of instruments		497.11***
Observations	251,680	251,680
Number of tracts	6,875	6,875
Within-R^2	0.165	0.098

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. The treatment variables are lagged four years so that we estimate the economic impact of a branch campus four years after its opening date. All models include constant, census tract FE, and year FE. Robust standard errors in parentheses. ****p*<0.01, ***p*<0.05, **p*<0.1.

Table A4: IV Estimates of Branch Campus Effect on Economic Activity within 40-Mile Radius of Impact in Texas

	(1)	(2)
Any Branch Campus	0.133***	
	(0.034)	
Two-Year Branch Campus		0.104***
		(0.018)
Four-Year Branch Campus		0.254***
		(0.024)
First first-stage F-value of instruments	611.11***	3,708.38***
Second first-stage F-value of instruments		1,526.02***
Observations	251,680	251,680
Number of tracts	6,875	6,875
Within-R^2	0.201	0.209

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. The treatment variables are lagged four years so that we estimate the economic impact of a branch campus four years after its opening date. All models include constant, census tract FE, and year FE. Robust standard errors in parentheses. ****p*<0.01, ***p*<0.05, **p*<0.1.

Table A5: IV First Stage IV Estimates for Table 2

	Any Branch Campus (1)	2-Year Branch Campus (2)	4-Year Branch Campus (3)
ln(Avg. Distance to 5 Closest Branch Campuses)	0.056		
	(0.047)		
ln(Avg. Distance to 5 Closest Branch Campuses) × Taxing District	-0.661***		
	(0.047)		
ln(Avg. Distance to 5 Closest 2-Year Branch Campuses)		-0.601***	-0.255***
		(0.015)	(0.018)
ln(Avg. Distance to 5 Closest 2-Year Branch Campuses) × Taxing District		0.100***	-0.251***
		(0.016)	(0.019)
ln(Avg. Distance to 5 Closest 4-Year Branch Campuses)		0.483***	-0.710***
		(0.027)	(0.048)
ln(Avg. Distance to 5 Closest 4-Year Branch Campuses) × Taxing District		-0.100***	-0.240***
		(0.027)	(0.050)
F-value of instruments	458.99***	2,183.95***	3,268.45***
Corresponding second stage in Table 2	(1)	(2)	(2)
Observations	251,680	251,680	251,680
Number of tracts	6,875	6,875	6,875
Within-R^2	0.409	0.393	0.411

Notes: The dependent variable is the binary indicator for a branch campus opening and is lagged 4 years. All models include constant, census tract FE, and year FE. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.