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Abstract

We investigate whether the local economic effects of niche university actors depend on regional context. Focusing on private university campuses in Germany, we exploit their staggered foundation between 1990 and 2020 and estimate their effects using a conditional staggered difference-in-differences design at the postal-code level. Campus foundations raise local economic activity, but only gradually, with effects becoming statistically significant after about ten years. The effects are strongest in rural and intermediate regions, while urban regions show no significant effects. This pattern supports our argument that niche universities have greater potential to become significant actors in institutionally thinner rural regions.

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1. Introduction

There is significant econometric evidence on the positive effects of public science on local economic development (e.g., Glückler et al., 2015; Schubert and Kroll, 2016, Agassisti et al., 2019; Krieger, 2024; Schubert et al. 2025). Theories in regional science have attributed these effects to the structuration potential of sizeable scientific organizations, which allows them to shape their local environment as place-based leaders (Fonseca et al. 2021; Grillitsch and Sotarauta 2020; Benneworth et al., 2017). Yet, a branch of the literature has recently provided evidence that even the foundation of smaller scientific organizations – campuses of (i) universities of applied sciences in Switzerland (Pfister et al., 2021; Schlegel et al., 2022) and Germany (Lehnert et al., 2022), (ii) colleges in the United States (Lehnert et al., 2024; Andrews, 2023), and (iii) private universities in Japan (Yanagiura and Tateishi, 2024) – has positive effects on the development of their regions, despite the fact that these universities are typically niche actors making it difficult to conceptualize them as place-based leaders. Thus, there is a tension between the conceptual emphasis on place-based leadership exerted by sizeable scientific organizations, and the empirical observation that smaller scientific organizations can have significant positive effects on their region, nonetheless.

To reconcile both perspectives, we make the case that the peripherality of the host region provides important but largely overlooked contextual conditions (e.g., Benneworth and Fitjar, 2019; Nilsen et al., 2022). We argue that smaller universities are indeed limited by their size in assuming roles as place-based leaders. These limits are particularly pertinent in institutionally thick urban regions. In such regional settings, niche actors are unlikely to cause substantial economic effects. However, in more rural, institutionally thin regions (Benneworth and Fitjar, 2019), even smaller universities have the potential to develop a structuring momentum that endows them with a more central leadership role (Kohoutek et al., 2017).

To test our argument, we focus on the foundations of private university campuses in Germany. These campuses can largely be considered niche actors: they are typically (i) relatively young and (ii) relatively small. Moreover, they usually concentrate almost entirely on teaching, with very limited research activities. We rely on a quasi-experimental setting and exploit the staggered foundation of private university campuses in the period between 1990 and 2020, which covers the majority of all private campus foundations in Germany. More precisely, we utilize a conditional staggered extended two-way fixed-effects difference-in-differences approach based on Wooldridge (2025) and Hainmueller (2012) to measure the average economic effects caused by the campus foundations, as well as the time needed for the effects to emerge. Moreover, by allowing the effects to differ between region types, we analyze whether they emerge more strongly across more and less urban regions.

The results demonstrate that the foundation of private university campuses increases local economic activity. These effects do not emerge immediately but build gradually over time and become statistically significant only after about ten years. Additional analyses show that the effects are highly localized and are not driven by spillovers into neighboring postal-code regions. Most importantly, there is pronounced heterogeneity across region types: positive effects arise in rural and intermediate regions, whereas no comparable effects emerge in urban regions. These findings support the argument that the economic effects of smaller university actors depend on the regional context in which they are embedded.

2. Conceptualization

Existing research has examined the economic benefits of scientific activity through impact studies employing a range of methods, including demand-oriented multiplier analyses (e.g., Glückler et al., 2015), regression-based approaches (e.g., Bertoletti et al., 2022; Agasisti and Bertoletti, 2022), and macroeconomic simulation models (e.g., Allan et al., 2022). Across these approaches, literature consistently documents positive economic effects. However, less is known about whether these effects extend across different types of universities and about the regional contexts in which they are most likely to emerge (Benneworth and Fitjar, 2019; Fonseca and Nieth, 2021).

The conceptual question of universities' contextual role in their regional environments has gained prominence, particularly in the economic geography literature. Drawing on structuration theory, this literature emphasizes that universities are not passive agents embedded in existing structures and networks, through which human and financial resources are channeled and whose influence is confined to their internal processes (Kohoutek et al., 2017). Instead, they are active agents of change within broader economic systems that influence the socio-economic structures of their surroundings (Benneworth and Fitjar, 2019; Fonseca and Nieth, 2021).

Through their active engagement with pre-existing networks, universities may improve economic processes in their regional environment, for example, through the provision of knowledge and consulting or by acting as mediators that connect previously weakly connected or unconnected external actors (Fonseca and Nieth, 2021). These effects may persist beyond universities' direct involvement when university-led interactions develop into more durable collaborations among external actors. Universities may thereby strengthen local collaboration structures and the capacity for self-organization of regional economic systems. The underlying argument is therefore that universities generate economic effects not only through direct knowledge transfer, but also through their capacity to structure and coordinate actors in the regional environment, thereby assuming a role of place-based leadership (Benneworth et al., 2017; Grillitsch and Sotarauta, 2020).

Place-based leadership implicitly assumes that universities possess sufficient institutional embeddedness and structuration power to shape their regional environments (Benneworth et al., 2017; Fonseca et al., 2021). However, even though this assumption is generally more plausible for larger and more central universities than for smaller universities in niche positions, a growing empirical literature finds that even smaller and teaching-oriented universities generate positive economic effects across various empirical settings (e.g., Andrews, 2023; Lehnert et al., 2020; Lehnert et al., 2024; Pfister et al., 2021). We argue that the resulting tension between conceptual and empirical evidence reflects insufficient attention to universities' regional context. More precisely, universities' potential to act as place-based leaders depends not only on their own characteristics, but also on the institutional structure of their surrounding regional context.

Urban and rural regions differ not only in geographical location, but also in organizational density, the availability of alternative coordinators, and – as a result – the relative position universities can assume within their regional systems. In more urban regions, universities operate in institutionally thicker environments characterized by a higher density of firms, public organizations, intermediaries, and other knowledge actors, many of which perform overlapping leadership functions (Jolly et al., 2020; Tödtling and Trippl, 2005). In more rural regions, by contrast, universities operate in institutionally thinner environments, with fewer organizations that could assume a comparable leadership role. As a result, smaller and less central universities may attain greater relative size and centrality within a rural, than within an urban context, thereby increasing their potential to act as place-based leaders, and to induce sizeable economic effects (Benneworth and Fitjar, 2019; Petersen and Kruss, 2021; Tödtling and Trippl, 2005).

In sum, the urban–rural distinction captures variation in institutional thickness and in the relative structuration power of universities. Universities appearing as niche actors in an urban context may constitute comparatively central actors in a rural one. Thus, regional peripherality presents a relevant contingency factor for whether universities can translate their presence into place-based leadership and, in turn, into local economic effects.

3. Empirical Setting

3.1. Private Universities in Germany

To test our conceptual arguments regarding the importance of differentiating between more and less peripheral regions for the effectiveness of niche university actors, we focus on the foundations of privately funded and governed universities in Germany. 83 percent of private universities were established after 1990 (Hachmeister et al., 2024) and thus represent a comparatively recent entry of more niche university actors into the German higher education system. At the same time, their campuses are distributed across different types of regional contexts. While the majority of campuses (55 percent) are located in larger cities with more than 500,000 inhabitants, private university campuses are also present in smaller cities (2 percent in cities with fewer than 10,000 inhabitants, 5 percent in cities with 10,000–25,000 inhabitants, and 6 percent in cities with 25,000–50,000 inhabitants) (Hachmeister et al., 2024). This variation across location types allows us to examine whether the effects of niche university actors differ systematically with regional peripherality.

The niche status of German private universities becomes apparent in comparison with German full universities. In 2025, private universities and full universities each accounted for around 28 percent of all higher education organizations in Germany, with 111 and 108 institutions, respectively. At the same time, private universities accounted for only around 14 percent of all enrolled students (approximately 383,000), whereas full universities accounted for around 60 percent (approximately 1,715,000) (Science Council, 2025). The same pattern is reflected in the distribution of student numbers. Whereas most private universities enroll between 500 and 999 students, their student distribution is highly skewed by two large distance-learning institutions with around 100,000 and 47,000 students, respectively. Full universities, by contrast, typically enroll more than 10,000 students exhibit a less skewed distribution. The largest universities in full universities are the FernUni Hagen – a long distance university – with 70,000 students and the LMU München with slightly above 50,000 students. Taken together, this comparison suggests that private universities are appropriately characterized as niche actors, which makes them a particularly informative case for examining how the regional effects of smaller university actors depend on the contexts in which they are embedded.

3.2. Private University Foundations as a Quasi-Natural Experiment

To identify economic effects of private universities, we exploit the staggered foundation of German private university campuses since 1990 using a difference-in-differences design. The core idea is to identify causal effects from changes in outcomes over time in treated relative to untreated regions, rather than from cross-sectional level differences. Thus, it removes time-invariant differences between regions and common shocks over time, thereby isolating the effect associated with campus foundations more credibly.

Difference-in-differences estimators are described as a quasi-experimental approach, while not ensuring causal identification. Since private universities are not founded randomly across space, selection remains a concern. Identification therefore depends on the plausibility of the parallel trends assumption, that is, whether treated and untreated regions would have followed similar outcome trends in the absence of campus foundations. Moreover, in our geographic setting, regional spillovers may pose an additional challenge to the standard assumption that treated and untreated units are mutually independent

3.3. Identification Assumptions

3.3.1. Plausibility of Parallel Trends

The central identification assumption of difference-in-differences estimators is the parallel trends assumption. This assumption is inherently counterfactual, because for treated units the untreated potential outcome after treatment is not observed. As a result, it cannot be empirically tested. Researchers therefore typically examine whether treated and untreated units exhibit similar pre-treatment trends. While such evidence may increase confidence in the design, it is neither sufficient nor necessary for parallel trends to hold after treatment. Its plausibility, therefore, remains an institutional question.

While the parallel trends assumption is difficult to relate directly to real-world selection processes, Ghanem et al. (2022) show that it can be reformulated in terms of more tractable assumptions about treatment selection. In our setting, this means assumptions about the process determining where private universities are located.

Without discussing the formal details of these reformulations, a reasonable assumption in our setting is that the selection process does not depend on post-treatment information, which implies that private universities may choose locations based only on pre-treatment information and on expectations formed from it.[1] Thus, it is admissible that founders choose a region because pre-treatment information –such as economic trends, sectoral growth, or local development plans– suggests, at the time of decision making, that a larger firm is likely to settle there in the future. By contrast, it is inadmissible that founders choose a region because post-treatment information –such as a signed location contract, a finalized but not yet public investment decision, or a binding relocation agreement– establishes, at the time of decision making, that a larger firm will settle there after foundation. While such strategic location selection is theoretically possible, we consider it unlikely and therefore the exception rather than the rule.

To support this assumption, we draw on interview material and on the results of an expert workshop with private university leaders held in LOCATION (to be added after double-

[1] Formally, the relevant distinction is between uncertain expectations based on the pre-treatment information set and information showing that a post-treatment outcome is already effectively determined at the time of treatment selection. Our assumption allows the former but excludes the latter.

blinded peer review) in MONTH YEAR (to be added after double-blinded peer review). These discussions suggest that post-treatment information is not decisive for locational choice. More generally, location decisions do not appear to rest on structured economic assessments of future regional potential. Where economic considerations matter at all, they tend to concern contemporaneous proximity to relevant target groups, for example in social work or health-related professions. Otherwise, universities often follow practical or idiosyncratic opportunities, such as the availability of local licenses or, in the case of art schools, the attractiveness of a particular place.

In the empirical analysis, this assumption is implemented through a conditional difference-in-differences design using entropy balancing following Hainmueller (2012). Specifically, untreated postal-code regions are reweighted such that they match treated regions in the first three moments of the pre-estimation development of predicted standardized logarithmic gross domestic product between 1985 and 1989. Identification therefore no longer relies on unconditional parallel trends across all regions, but on conditional parallel trends among more comparable treated and untreated regions.

3.3.2. Plausibility of the Stable Unit Treatment Value Assumption

Beyond parallel trends, difference-in-differences estimators rely on a set of additional assumptions summarized under the Stable Unit Treatment Value Assumption (SUTVA). In our setting, we treat these assumptions as secondary to parallel trends, because their violation does not necessarily invalidate difference-in-differences estimation, but rather calls for adjustments in the modeling strategy. For our context, SUTVA has two implications that require special attention.

First, SUTVA requires treatment to be stable across treated units. In our setting, this would imply that all campus foundations constitute the same treatment. This assumption is unlikely to hold, because treatment intensity may differ across campus foundations, for example with respect to university size or because more than one private university campus is founded within the same region.

Second, SUTVA requires the absence of spillovers across units. In our geographic setting, however, the spatial reach of private university campuses is unknown a priori. Economic effects may therefore extend beyond the host region into neighboring areas. This concern is particularly relevant because we rely primarily on five-digit postal-code regions, which are comparatively small, with an average area of around 45 km^2. While this helps to measure the effects of comparatively small private university campuses (Lehnert et al., 2024), it increases the likelihood that functional economic areas are subdivided and that spillovers cross regional boundaries.

While our baseline estimators impose SUTVA, we also report results from specifications that relax its two main components. Specifically, we implement estimators that allow treatment intensity to vary with the number of founded campuses. In addition, we account for regional spillovers by including spatial lags of the treatment variable. This allows us to assess the extent to which heterogeneous treatment intensity and spillovers across regions affect our results.

4. Data

4.1. Region Definition

A key aspect of our analysis concerns the geographic definition of the regional unit. This choice is particularly relevant for private university campuses, which are often small, especially in their founding phase. As a result, using larger regional units may dilute their effects (Lehnert et al., 2024). We therefore rely on postal-code regions, of which 8,169 exist in the adopted 2020 classification (Lehnert et al., 2023), compared with 401 NUTS-3 regions (Schubert and Kroll, 2016).

4.2. Databases

To implement our estimations, we rely on three databases: i) one providing estimated GDP at the postal-code level, ii) one identifying the location and foundation year of private university campuses at the same level, and iii) one providing a classification of postal-code regions into more urban and more rural regions.

Administrative GDP data for Germany are unavailable at the postal-code level. The most disaggregated GDP data are at the district ("Kreis") or NUTS-3 level. Thus, we rely on a custom-made dataset, which provides yearly predicted standardized logarithmic gross domestic product for postal-code regions and years in Germany from 1985 to 2020, based on Lehnert et al. (2023) and Lehnert et al. (2024). The measure builds on daytime satellite imagery and complements the widely used luminosity measures in Chen and Nordhaus (2011). It classifies pixels into six surface groups by supervised learning. The six groups are built-up land, grassland, forest, cropland, land without vegetation or buildings, and water. Aggregating these surface shares to the postal-code level yields a stable indicator of regional surface composition available from 1985 to 2020. The approach rests on the insight that the composition and evolution of surface groups co-move with the underlying economy and thus track local activity over long horizons, as established for Germany by Lehnert et al. (2023), which also provides a detailed description of the methodology.

Official university-level data, including data on private universities, are provided by the German Statistical Office (DESTATIS).[2] However, many private universities have more than one campus in more than one postal-code region. Thus, the use of the official data is limited to obtaining a list of all private universities. The years and locations of campus foundations were compiled manually, where available from university websites and otherwise through direct contact with private universities. The resulting series counts active private campuses by postal-code region and year.

The classification of postal-code regions into i) more urban regions, ii) more rural regions, and iii) intermediate regions is based on a scheme developed by the Federal Institute for Building and Regional Planning. Population density defines the thresholds. Urban regions have at least 150 residents per square kilometer, intermediate regions have between 100 and 150, and rural regions have fewer than 100 (Bergholz et al., 2024). Each German district receives one category that remains fixed over time. Postal codes are linked to districts based on their geographical overlap. As a result, one postal code can be linked to more than one district. Therefore, we adapt the typology for the postal-code level as follows:[3]

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[2] Statistisches Bundesamt (Destatis). (2023). Hochschulstatistik: Absolventen nach Hochschulart und Fachgruppe [Dataset]. Wiesbaden: DESTATIS. Provided upon request; received October 26, 2023.

[3] A total of six postal-code regions mixing urban and rural – (urban ∩ rural) ∪ (urban ∩ rural ∩ intermediate) – have been removed from all region type estimations.

A) ***More urban:*** urban ∪ (urban ∩ intermediate)

B) ***More rural:*** rural ∪ (rural ∩ intermediate)

C) ***Intermediate:*** intermediate

4.3. Descriptive Statistics

The private university dataset includes information on the location and foundation year of private university campuses founded before 2020. In total, Germany hosts 111 private universities with 312 campuses, of which 79 campuses are part of four distance-learning universities. We remove campuses from distance-learning universities, as well as 13 campuses from six universities for which no reliable foundation-year information could be retrieved. As a result, the data on private university campus foundations utilized for our analysis cover 233 foundations located in 181 postal-code regions.

Figure 1 displays the rollout of the 233 campus foundations between 1985 and 2020. The phenomenon began with a few campuses founded before the 1990s. Foundations then increased steadily throughout the 1990s and 2000s, culminating in a peak around 2012, when the share of new foundations reached its highest point. After this wave, the pace of foundations declined but remained stable, with campuses continuing to be established. This trajectory underlines the long-run expansion of private universities in Germany, which first gained traction in the 1990s, accelerated around 2010, and has since sustained its relevance.

Moreover, the distribution of the 233 campus foundations across postal-code regions is skewed, as shown in Figure 2. More than four-fifths of all treated postal-code regions host only a single private-university campus, while about one in ten regions hosts two. A minority of regions accommodate three or more campuses, with a maximum observed count of six. This indicates that the treatment is concentrated in the form of single-campus foundations, while multiple-campus clusters are exceptions.

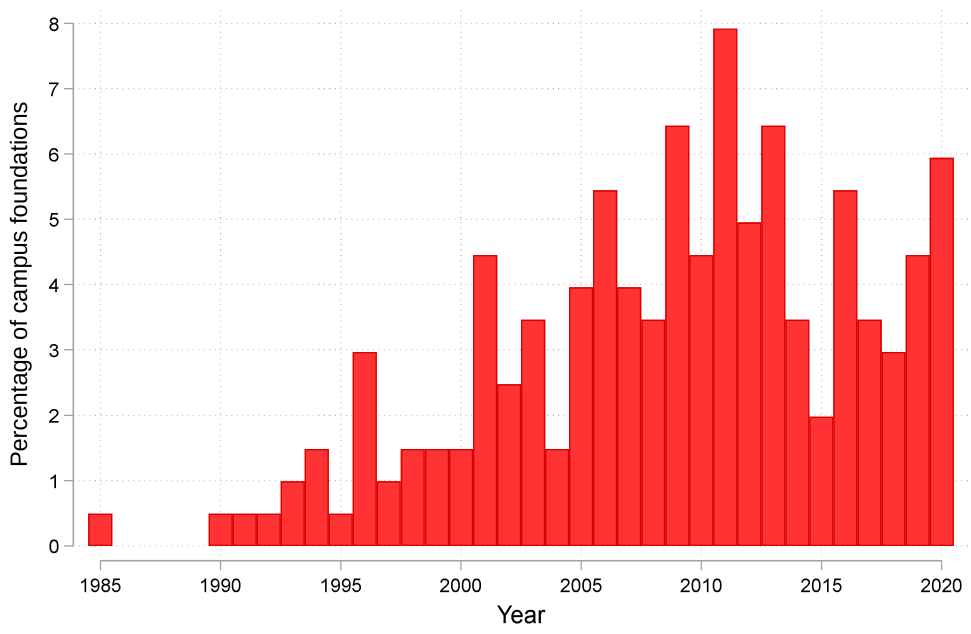

Figure 1: Distribution of Campus Foundations Across Calendar Years, 1985-2020

Figure 1 plots a histogram of the annual percentage share of the 233 private-university campus foundations over 1985–2020. The x-axis shows calendar years; the y-axis shows the proportion of total foundations occurring.

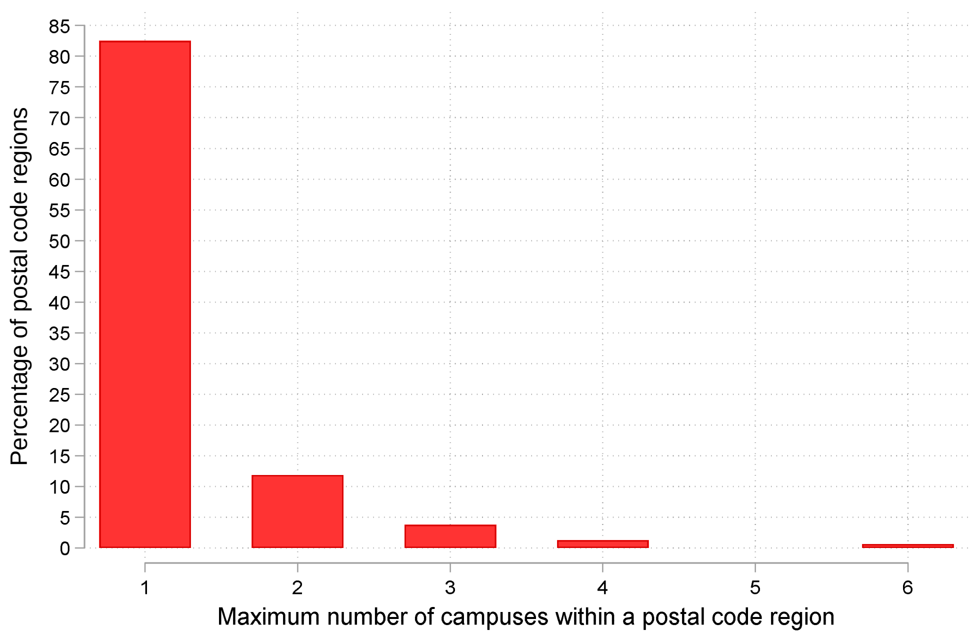

Figure 2: Intensity Distribution of Campus Foundations Across Postal-Code Regions

Figure 2 displays the distribution of the maximum number of private university campuses within a postal-code region across our sample of 233 foundations between 1985 and 2020.

The regional distribution of private university campuses is concentrated in more urban areas. Figure 3, which presents NUTS-3 regions for reasons of visual clarity, shows particularly high campus densities in Berlin, Hamburg, the Rhine-Ruhr area, Frankfurt/Rhine-Main, Stuttgart, and Munich. This pattern is confirmed by the classification of the Federal Institute for Building and Regional Planning: around 80 percent of postal-code regions with private university campuses are classified as more urban, around 18 percent as intermediate, and around 4 percent as more rural. By comparison, postal-code regions overall are distributed more evenly across these categories, with around 27 percent classified as more urban, around 46 percent as intermediate, and around 29 percent as more rural. Private university campuses are thus disproportionately concentrated in urban regions, while not being limited to them.

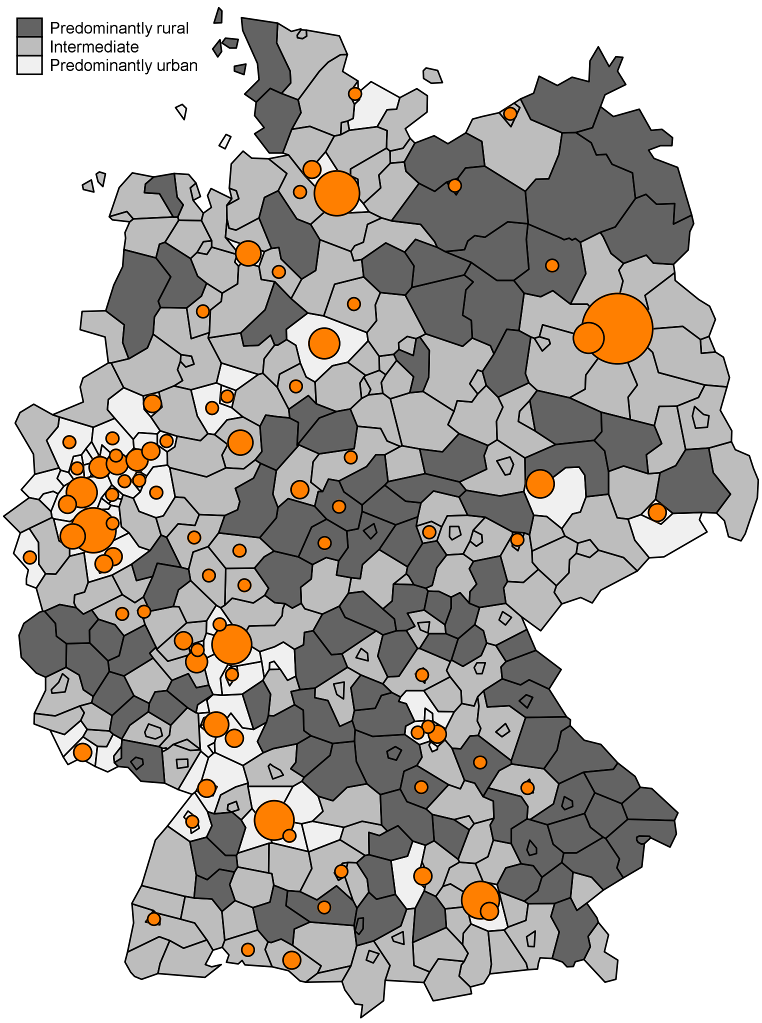

Figure 3: Geographical Distribution of Campus Foundations Across NUTS-3 Regions by Type of Region

Figure 3 displays the distribution of private university campus foundations across Germany for our sample of 233 foundations between 1985 and 2020.

The dataset provided by Lehnert et al. (2023) covers information for 7,493 to 8,134 postal-codes in a given calendar year between 1985 and 2020, instead of the total number of 8,169, due to outlier corrections.

A descriptive comparison between postal-code regions with at least one of the 233 private university campus foundations and those without any campus foundation reveals significant level differences in standardized logarithmic gross domestic product, as shown in Figure 4. The figure plots the annual mean difference between the two groups from 1985 to 2020. Across the full observation period, regions with a campus foundation show consistently higher values. At the same time, the difference remains fairly stable, suggesting that the two groups develop largely in parallel and differ mainly in their average levels.

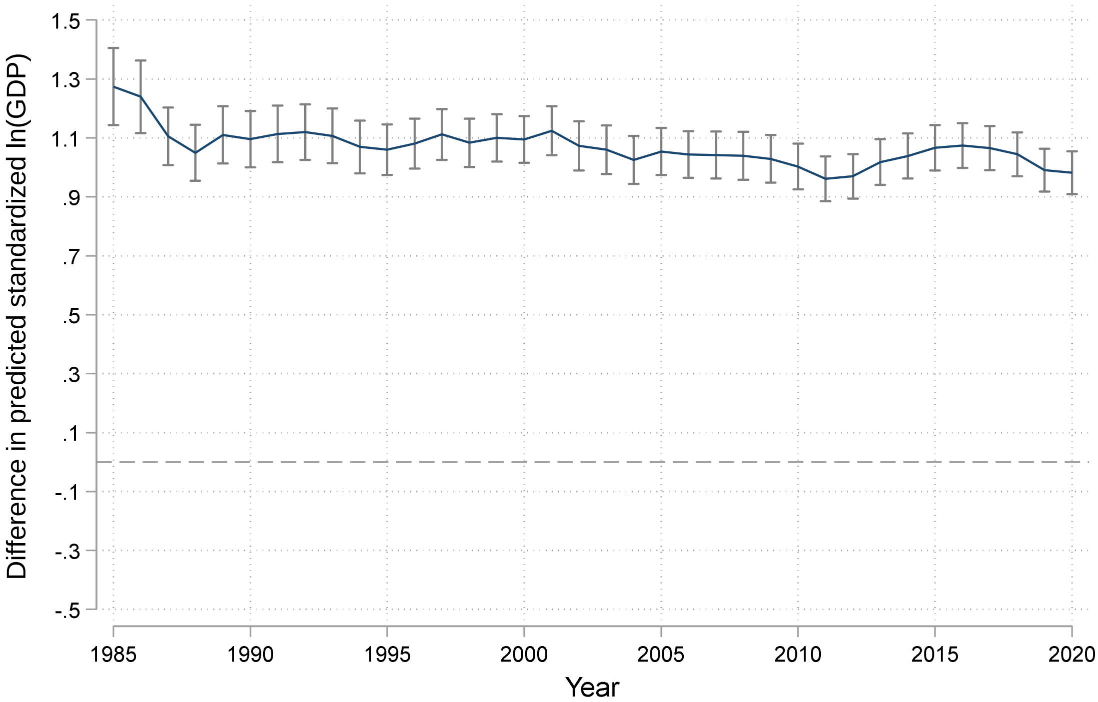

Figure 4: Difference in Standardized Logarithmic Gross Domestic Product Between Postal-Code Regions With and Without Private University Campus Foundations

Figure 4 displays the annual difference in the mean predicted standardized logarithm of gross domestic product between postal-code regions with at least one private university campus foundation and those without any campus foundation. Vertical bars indicate 95% confidence intervals. The vertical scale is based on the minimum and maximum annual group means in the two underlying groups.

Finally, for the baseline estimations, we exclude regions with more than two campus foundations, as repeated campus foundations in these urban regions complicate the identification of clearly defined event-type treatment effects. In addition, our identification strategy –laid out in the next section– requires regions to have no missing values during the period 1985–1989, and no private university campus foundation. Applying these restrictions results in a final estimation sample of 6,956 postal-code regions.

5. Econometric Estimation

The foundation of campuses lends itself to a quasi-experimental analysis of economic effects using a difference-in-differences design. However, because private university campuses are founded consecutively over time, the setting involves staggered treatment timing across cohorts. As shown by Goodman-Bacon (2021), in such designs the conventional two-way fixed-effects estimator can be inconsistent when treatment effects vary across cohorts or evolve over time. While a range of estimators has been developed to address these issues, the Extended Two-Way Fixed-Effects Difference-in-Differences estimator proposed by Wooldridge (2025) is particularly well suited to our setting. Most importantly, it allows treatment effects to be modeled straightforwardly as differing between rural and urban regions. Moreover, compared with alternative staggered difference-in-differences estimators, such as Borusyak et al. (2024), Callaway and Sant'Anna (2021), and Sun and Abraham (2021), Wooldridge's estimator yields equivalent estimates while offering facilitated aggregation of treatment effects, greater efficiency in estimating pre-treatment effects, and better handling of unbalanced panel data (Wooldridge, 2025).

5.1. Extended Two-Way-Fixed Effects Difference-in-Differences

The Extended Two-Way Fixed-Effects Difference-in-Differences estimator is a regression-based estimator that extends the canonical two-way fixed-effects difference-in-differences estimator (e.g., Lehnert et al., 2024) by allowing treatment effects to vary across treatment cohorts and over time since adoption. More precisely, the estimator saturates cohort-by-calendar-year interactions and, in each calendar year, forms comparisons only with regions that are untreated at that time. More formally, Wooldridge (2025) proposes the following estimation equation:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{g=g_0}^{G} \sum_{t=g}^{t=T} \theta_{gt}\, 1(g,t) + u_{it}. \tag{1}$$

where Y_{it} denotes predicted standardized logarithmic gross domestic product for postal-code region i in calendar year t. α_i are postal-code fixed effects and γ_t are calendar year fixed effects. The term $1(g,t)$ is an indicator for a cohort-calendar year cell, g. Cohorts are defined by the fourth calendar year after a private university campus was founded in a postal-code region, to take the average duration of graduates entering the regional market after 3.6 years into account (Lehnert et al., 2024). For a given cohort g, the indicator takes the value one in calendar years t after that cohort's first campus foundation and zero otherwise. The coefficient θ_{gt} is the average treatment effect on the treated for cohort g in calendar year t. It is identified by comparing predicted standardized logarithmic gross domestic product in that cohort–calendar year cell only to postal-code regions that are untreated in calendar year t, namely the not-yet-treated and the never-treated. The index g_0 marks the earliest cohort, G the latest cohort, and T the last calendar year in the panel. u_{it} is the error term.

Equation (1) yields a large number of estimates for the treatment effects on the treated, θ_{gt}, which, however, can be aggregated flexibly into standard average treatment effects on the treated, comparable to those obtained in the canonical setting (cf. Rios-Avila, 2025).

5.2 Conditional Difference-in-Differences

The use of pre-estimation reweighting methods is one possibility to implement a conditional difference-in-differences estimation. Following the argument in Section 3.3.1, we use the entropy balancing method developed by Hainmueller (2012) to reweight our control group. The method stochastically assigns weights to the observations of the control group, postal-code regions without a private university campus foundation, such that the moments of its balancing variables match those of the treated group, postal-codes with at least one private university campus foundation, before estimating average treatment effects on the treated in a subsequent weighted regression. Therefore, using this weighting as a pre-estimation procedure ensures the comparability of the treatment and control groups within the described Extended Two-Way Fixed-Effects Difference-in-Differences design, relaxing the previous unconditional parallel trends assumption toward a conditional parallel trends assumption.

More precisely, we construct weights based on the values of the dependent variable –the predicted standardized logarithmic gross domestic product of a postal-code– observed from 1985 to 1989. We require near-exact balance for the first three moments within each pre-estimation year, namely equality of means, equality of variances, and equality of skewness. Postal-codes already treated during the pre-estimation window are removed, as they represent always-treated units, which do not enter the treatment effect estimation of Wooldridge (2025). The resulting weights enter the Extended Two-Way Fixed-Effects Difference-in-Differences estimator by changing its estimation method from Ordinary to Weighted Least Squares. Accordingly, the weights scale each observation's contribution to the estimation objective, such that control units that achieve closer balance with treated units on pre-treatment outcomes receive greater influence in the regression.

5.3. Implementing the Estimations

5.3.1. Baseline Estimations

We use the Stata command *ebalance* developed by Hainmueller and Xu (2013) to estimate balancing weights, as in Trunschke et al. (2024) and Krieger and Zipperer (2022). The Stata command *jwdid* by Rios-Avila (2025) is used to derive our Extended Two-Way Fixed-Effects Difference-in-Differences estimates, as in García-Vega and Vicente-Chirivella (2024) and Nagengast and Yotov (2025). Thus, each difference-in-differences estimate results from a weighted least squares estimation using the weights from our balancing exercise. Standard errors are clustered at the level of postal-code regions.

5.3.2. Testing Parallel Trends

To test the conditional parallel trends assumption, as discussed in Section 3.3.1, we follow Rios-Avila (2025) and i) extend the cohort-by-year design to include pre-treatment leads alongside post-treatment lags, and ii) only retain never-treated postal-code regions as the control group. More precisely, the estimation equation is:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{g=g_0}^{G} \sum_{t=t_0}^{t=g-2} \theta_{gt}\, 1(g,t) + \sum_{g=g_0}^{G} \sum_{t=g}^{t=T} \theta_{gt}\, 1(g,t) + u_{it}. \quad (2)$$

5.3.3. Testing Stable Unit Treatment Value Assumption

Regional Spillovers – To estimate potential spillovers, we extend our basic specification to account for spatial lags. However, to be able to account for two separate treatments (the treatment of the focal region vs. the treatment of a neighboring region), we must resort to a canonical two-way fixed-effects difference-in-differences estimator (e.g., Lehnert et al. 2024), as the extended estimator does not yet allow for this level of generality. Specifically, we estimate the following equation, while using the weights from our previous balancing exercise:

$$Y_{it} = \alpha_i + \gamma_t + \theta^{plz} * D_{it}^{plz} + \theta^{nb} * D_{it}^{nb} + u_{it}, \quad (3)$$

where all established parameters remain equal, but we differentiate between two separate treatments. D_{it}^{plz} represents the first treatment indicator, which equals one after the first private university campus was founded within the postal-code region i, and θ^{plz} is its coefficient for the average treatment effect on the treated. The second treatment indicator D_{it}^{nb} and its estimate θ^{nb} are defined equally but based on the foundation of private university campuses in the neighboring regions of postal-code i. The empirical results displayed in Section 6.4 indicate that the estimates are conservative in terms of statistical significance.

Treatment Intensity – With respect to treatment intensity, we did not consider the repeated foundation of campuses within a region. Therefore, we repeat our main estimation while taking the number of campuses within a region into account by allowing the treatment effect to change linearly depending on the number of campuses. The highest number of campuses, which is two due to our previous sample limitation described in Section 4, is defined as an intensity of 1, whereas the existence of one campus is defined as an intensity of 0.5 – to fit the treatment intensity interval of [0;1] within the framework of Rios-Avila (2025).

5.3.4. Testing Effect Differences in Rural and Urban Regions

To allow for treatment-effect heterogeneity by covariates, Equation (1) must be extended beyond its cohort-by-year specification. In particular, the treatment effects may differ systematically across values of a control variable, X_{it}. Thus, if the interaction between treatment and the control variable is not modeled explicitly, the resulting average treatment effect on the treated ignores such variation, producing estimates that are misleading for subgroup analysis. Following Rios-Avila (2025), Equation (4) extends Equation (1) accordingly:

$$Y_{it} = \alpha_0 + \alpha_i + \gamma_t + \sum_{g=g_0}^{G} \sum_{t=g}^{t=T} \theta_{gt} \, 1(g,t) +$$

$$\delta X_{it} + \sum_g \delta_g X_{it} 1(g) + \sum_t \delta_t X_{it} 1(t) + \sum_{g=g_0}^{G} \sum_{t=g}^{t=T} \delta_{gt} \, X_{it} 1(g,t) + u_{it}. \tag{4}$$

In this specification, the additional interaction terms ensure that the influence of X_{it} is properly captured:

- $\delta_g X_{it} 1(g)$ allows the effect of X_{it} to differ across cohorts.

- $\delta_t X_{it} 1(t)$ allows the effect of X_{it} to differ across calendar year, and
- $\sum_{t=g}^{t=T} \delta_{gt} X_{it} 1(g,t)$ allows the effect of X_{it} t to vary within cohort–year cells, the level where treatment effects are identified.

The parameter δ_{gt} thus reflects how the covariate modifies the average treatment effect on the treated in a given cohort–calendar year cell. As a result, this specification allows us to estimate heterogeneous treatment effects that vary across covariate values.

We use this extension to estimate the aggregate effects of private university campus foundations within i) more urban regions, ii) more rural regions, and iii) intermediate regions by adding three different indicator variables – each one of them being equal to one if a postal-code region is classified accordingly, and zero otherwise.

6. Results

6.1. Balancing Regions with and without Campus Foundations

As a first step, we use entropy balancing to make treated and control postal-code regions locally comparable in the 1985–1989 pre-period. Pre-weighting, treated regions exhibit higher means, smaller variances, and heterogeneous skewness in standardized logarithmic gross domestic product relative to control regions. After weighting, differences in means, variances, and skewness are virtually zero in each pre-estimation year, as demonstrated in Table 1. This establishes the local comparability of the two groups and supports using the conditional – rather than unconditional– parallel trends assumption in the subsequent Extended Two-Way Fixed-Effects Difference-in-Differences estimations.

Table 1 - Entropy balancing on postal-code region treatment, 1985-1989

Statistic:	Mean			Variance			Skewness		
Group:	Treated	Control		Treated	Control		Treated	Control	
Weighting:		Pre	Post		Pre	Post		Pre	Post
St. ln(GDP_{1985})	1.44	0.21	1.44	0.69	1.03	0.69	0.62	0.66	0.62
St. ln(GDP_{1986})	1.37	0.17	1.37	0.62	0.93	0.62	0.61	0.56	0.61
St. ln(GDP_{1987})	1.20	0.12	1.20	0.38	0.79	0.38	0.37	0.16	0.37
St. ln(GDP_{1988})	1.22	0.19	1.22	0.36	0.76	0.36	0.61	0.12	0.61
St. ln(GDP_{1989})	1.21	0.14	1.21	0.40	0.79	0.40	0.49	0.15	0.49

6.2. Estimating the Economic Effects of Private University Campus Foundations

Next, we turn to the estimation of the main effect, weighted by entropy balancing as described in Section 5.2. The results are reported in Table 2 and show a positive and statistically significant effect of campus foundations (p = 0.027). The aggregated average treatment effect on the treated amounts to 0.022 on the standardized predicted $ln(GDP)$ scale. Following Lehnert et al. (2024), we back-transform this estimate into economically interpretable magnitudes using lower- and upper-bound assumptions for the distribution of district-level GDP across postal-code regions. This implies an increase in local GDP of approximately 1.52 to 2.08 percent.[4] Thus, postal-code regions experiencing a private university campus foundation exhibit higher local economic activity than comparable regions without a campus foundation.

Table 2: Average Treatment Effect on the Treated, 1990-2020

	Coefficient	Standard error	z-statistic	p-value	95% Confidence interval	
ATT - Campus foundation	0.022	0.010	2.210	0.027	0.003	0.042

The number of observations equals 215,616. The number of postal-code regions equals 6,956. The estimate represents the aggregated average treatment effect on the treated derived from Equation (1) and then aggregated over the cohort-specific treatment effects.

6.3. Assessing Parallel Trends During the Absence of Treatment

As argued in Section 3.3.1, the central identifying assumption in difference-in-differences is parallel trends. While we cannot observe the counterfactual path that treated postal-code regions would have followed had they not been treated, we can probe this assumption by examining pre-treatment dynamics in an event-study specification.

Figure 5 reports the dynamic treatment effects of private campus foundations on predicted standardized gross domestic product, as described. The pre-treatment point-estimates and confidence intervals (red bars) lie close to zero and are statistically indistinguishable from it,

[4] Following Lehnert et al. (2024), the coefficient reported in Table 2 for the predicted standarized log outcome is transformed to obtain an interpretable percentage effect: (exp ($\beta_1^{DiD} * s_{l/u}$) - 1)*100. Here, s_l= 0.675 and s_u = 0.919 denote the lower and upper bounds, respectively, for this interpretation.

showing no systematic deviations in the five event years leading up to a campus foundation; and thus supporting conditional parallel trends. Post-treatment estimates (blue bars) gradually increase over time. While estimates are small during the first years after treatment, they turn positive and grow steadily, but they become statistically significant only after more than ten years. It is worth mentioning that after 15 years the effects become more volatile, which is, however, most likely due to the fact that ever fewer treatment cases have such a long observation period. Indeed, when also using treated units before treatment as controls, the effects become more stably positive even after 15 years post-treatment.[5]

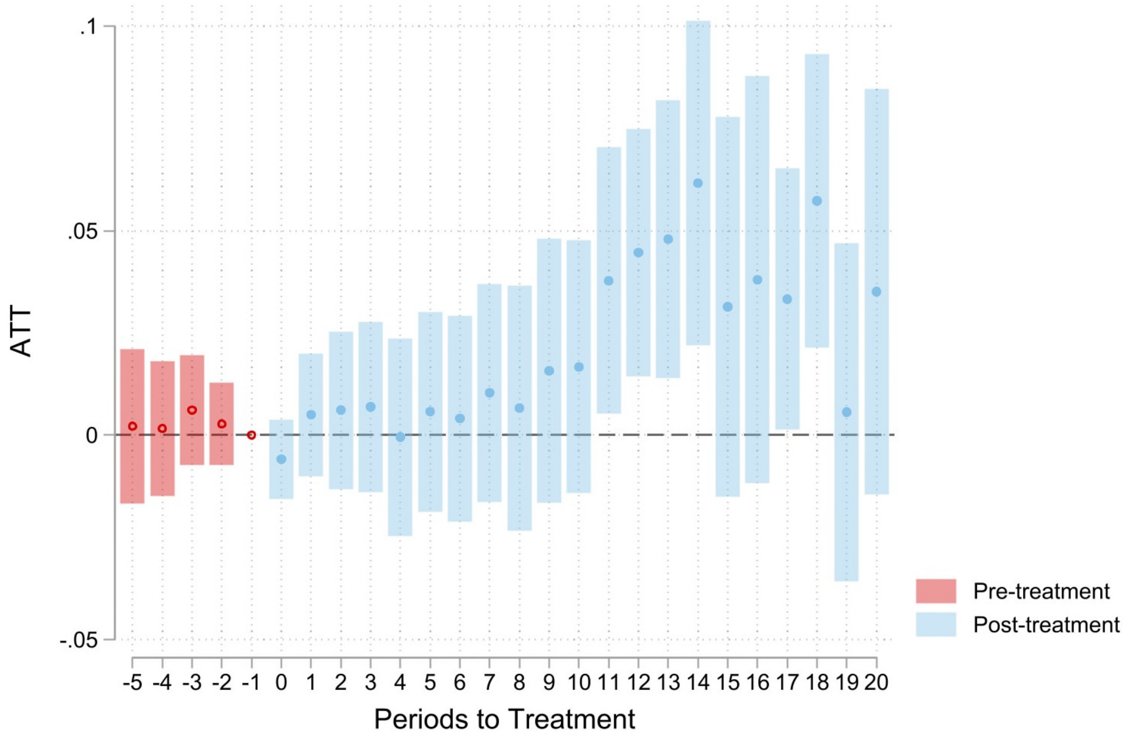

Figure 5: Pre- and Post-Treatment Event-Study Plot – Never Treated Controls

The estimates represent the weighted average treatment effect on the treated for an individual event year. Average treatment effects on the treated are estimated according to Section 5.3.2.

6.4. Assessing SUTVA: Varying Treatment Intensity and Regional Spillovers

The SUTVA assumption requires i) constant treatment intensity and ii) absence of spillovers between treated and untreated units.

[5] The results are available upon request.

With respect to the first assumption, Table 3 demonstrates that the pooled effect of one or two campuses (ATT (1) = 0.021, $p < 0.05$) is essentially in line with the baseline estimate, with negligible differences at the third decimal – confirming robustness. When disaggregating the average treatment effect on the treated by the number of currently existing campuses within a postal-code region, the existence of one campus delivers a significant effect (ATT (2) = 0.021, $p < 0.05$), whereas the existence of two campuses has a similar point estimate but is imprecisely estimated (ATT (3) = 0.021, $p = 0.380$).

This pattern suggests that our previous effects are primarily driven by the establishment of the first campus. While the point estimate for two campuses in a region is virtually identical, the wide confidence interval prevents us from drawing conclusions about any benefits beyond the first foundation. However, the absence of statistical significance for the two-campus case likely reflects the small number of postal-code regions with this group rather than evidence of no additional effect. Therefore, our results underline the robust average treatment effect on the treated of the first campus while leaving open the question of whether further foundations yield additional effects.

Table 3: Average Treatment Effect on the Treated of Multiple Campuses, 1990-2020

	Coeffi-cient	Standard error	z-statistic	p-value	95% Confidence interval	
ATT (1) One ∪ two foundations	0.021	0.010	2.090	0.036	0.001	0.041
ATT (2) First campus	0.021	0.010	2.140	0.032	0.002	0.040
ATT (3) Second campus	0.021	0.024	0.880	0.380	-0.026	0.068

The number of observations equals 215,616. The number of postal-code regions equals 6,956. The ATTs represent the aggregated average treatment effects on the treated derived from Rios-Avila (2025).

With respect to the second assumption, Table 4 shows no statistically significant average treatment effect on the treated for the foundation of private university campuses in neighboring regions (ATT Neighbor = -0.015, p = 0.262). Moreover, the effects of campus foundations within a postal-code region decrease in magnitude and significance but remain largely indicative of our previous findings (ATT focal = 0.018, $p = 0.100$). Thus, jointly, the results indicate the absence of significant spillovers and the robustness of our previous findings. Moreover, the – at this point – weakly statistically significant indications are strongly confirmed in the next section, which demonstrates more significant direct, and less significant indirect effects when differentiating between rural, intermediate, and urban regions.

Table 4: Average Treatment Effect on the Treated; Spatial Lags, 1990-2020

	Coefficient	Standard error	t-statistic	p-value	95% Confidence interval	
ATT – Focal	0.018	0.011	1.64	0.100	-0.003	0.039
ATT – Neighbor	-0.015	0.013	-1.12	0.262	-0.041	0.011

The number of observations equals 215,616. The number of postal-code regions equals 6,956. The ATTs are derived by estimating Equation (3).

6.5 Differentiation between Rural and Urban Regions

The heterogeneous treatment effects reported in Table 5 show that the aggregate effect of campus foundations (ATT = 0.023, p = 0.016) masks regional variation. While the effect for more urban regions is small and statistically insignificant (ATT = 0.007, p = 0.561), both more rural regions (ATT = 0.074, p < 0.001) and regions classified as intermediate (ATT = 0.074, p < 0.001) exhibit larger and highly significant effects. These findings suggest that the economic gains from campus foundations are concentrated outside of urban regions, with rural and intermediate areas experiencing the strongest positive effects.[6]

In addition, to investigate whether the insignificant results for urban regions are due not to a misfit between our region definition at the level of a postal-code and the organizational structure of urban regions, we repeat our previous estimations (entropy balancing and extended two-way fixed-effects difference-in-differences), defining regions at the district-level. In short, all estimates are largely similar in magnitude and statistical significance; only

[6] As a robustness test, we re-estimate our model using five groups, obtained by disaggregating categories A) and B) into their "pure" (urban, rural) and "mixed" (urban ∩ intermediate, rural ∩ intermediate) definitions. In addition, we re-estimate our model using only the "pure" definitions and removing all "mixed" postal-code regions. The results are robust to our aggregate findings. They confirm that effects remain absent in urban areas but are strong in rural and intermediate regions.

the statistical significance for more rural regions decreases to the p-value of 0.078 but remains weakly statistically significant.

Table 5: Average Treatment Effect on the Treated by Region Type, 1990-2020

	Coefficient	Standard error	z-statistic	p-value	95% Confidence interval	
ATT (1) All	0.023	0.009	2.420	0.016	0.004	0.042
ATT (2) More urban	0.007	0.012	0.580	0.561	-0.017	0.031
ATT (3) More rural	0.074	0.012	6.220	0.000	0.050	0.097
ATT (4) Intermediate	0.074	0.012	5.960	0.000	0.050	0.099

The number of observations equals 215,416. The number of postal-code regions equals 6,951. The estimate ATT (1) represents the aggregated average treatment effects on the treated estimating Equation (4), and aggregating them over cohorts. ATT (2) corresponds to the aggregate effect for more urban regions, ATT (3) for more rural regions, and ATT (4) for intermediate regions.

Finally, we repeat our previous analysis on the absence of spillovers while differentiating between region types. More precisely, we repeat the estimations from Section 6.4 separately for each region type. Table 6 shows that positive focal effects remain for more rural regions (ATT = 0.039, p = 0.055) and intermediate regions (ATT = 0.056, p = 0.042), while no significant neighboring effects emerge. Hence, even after differentiating between region types, the economic gains from campus foundations appear to arise primarily within the treated postal-code region itself.

7. Conclusion

This paper documents three main findings. First, the foundation of private university campuses in Germany increases local economic activity by 1.52 to 2.08 percent. These effects emerge gradually and become statistically significant only after about a decade. Second, the effects are largely local and are not driven by spillovers into neighboring postal-code regions. Third, the average effect masks spatial heterogeneity: positive effects are concentrated in rural and intermediate regions, while estimates for urban regions are small and statistically insignificant.

Table 6: Average Treatment Effect on the Treated by Region Type, Spatial Lags, 1990-2020

		Coefficient	Standard error	t-statistic	p-value	95% Confidence interval	
Mostly urban	ATT – Focal	0.006	0.012	0.49	0.625	-0.018	0.030
	ATT – Neighbor	-0.007	0.014	-0.46	0.644	-0.035	0.022
Mostly rural	ATT – Focal	0.039	0.020	1.92	0.055	-0.001	0.080
	ATT – Neighbor	0.029	0.038	0.76	0.449	-0.045	0.103
Inter-mediate	ATT – Focal	0.056	0.028	2.04	0.042	0.002	0.110
	ATT – Neighbor	-0.022	0.023	-0.95	0.341	-0.068	0.023

The number of observations equals 61,479 for mostly urban regions, 55,571 for mostly rural regions, and 96,309 for intermediate regions. The ATT are derived estimating Equation (3) within a separate estimation for each region type.

The main contribution of the paper is to connect two strands of literature that have so far remained weakly integrated. On the one hand, a growing empirical literature shows that smaller and more teaching-oriented university actors can generate positive regional effects (Pfister et al., 2021; Schlegel et al., 2022; Lehnert et al., 2022; Andrews, 2023; Lehnert et al., 2024; Yanagiura and Tateishi, 2024). On the other hand, the place-based leadership literature explains university effects through structuration capacity, coordination, and the orchestration of regional networks (Benneworth et al., 2017; Grillitsch and Sotarauta, 2020; Fonseca and Nieth, 2021; Fonseca et al., 2021). These arguments are difficult to reconcile if leadership is understood independently of regional context, because smaller university actors often lack the scale and embeddedness that leadership-based accounts appear to presuppose, particularly in institutionally thick urban settings (Jolly et al., 2020).

The paper addresses this tension by extending the conceptualization of place-based leadership and by testing this extension empirically. Conceptually, we argue that whether a university can assume a place-based leadership role depends not only on its own characteristics, but also on the institutional thickness or thinness of the regional environment (Benneworth and Fitjar, 2019; Petersen and Kruss, 2021) and on the university's relative size within that environment. In institutionally thinner and more rural regions, even smaller campuses may acquire sufficient relative importance to become coordinators, convenors, and brokers in local systems (Kohoutek et al., 2017; Fonseca and Nieth, 2021). In institutionally thicker urban regions, by contrast, the same actors remain more marginal because they operate alongside a larger set of alternative organizations (Tödtling and Trippl, 2005; Jolly et al., 2020). Empirically, the heterogeneous estimates support this argument: smaller campuses generate positive regional effects primarily in rural and intermediate regions, but not in more urban ones.

This contextualization helps align the existing evidence on smaller universities with the leadership perspective. The findings do not suggest that leadership-based explanations are misplaced. Rather, they suggest that the conditions under which smaller university actors can exercise such a role need to be specified more precisely. What counts as a niche actor in an urban region may become a regionally consequential actor in a more peripheral one.

The delayed build-up of effects is consistent with this interpretation. If the relevant channel runs through coordination, local linkages, and gradual capacity building, effects should not arise immediately. Instead, they should emerge only once new educational pathways, local professional communities, and university–practice interfaces have had time to develop (Benneworth and Fitjar, 2019; Fonseca and Nieth, 2021). In this sense, the temporal pattern of the estimates is in line with the conceptual argument.

The policy implications follow directly. First, private campus foundations should be understood as a place-contingent development instrument rather than as a uniform policy tool. Their contribution appears more likely outside large urban centers rather than within them. Second, if such campuses are expected to support regional development, policy should not only focus on their educational function, but also on their capacity to convene and connect local actors (Fonseca and Nieth, 2021; Petersen and Kruss, 2021). Third, because the estimated effects emerge only gradually, evaluation frameworks should adopt longer time horizons and should not assess regional effects too early.

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