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Do Neighbors Shape the Sticker Price? Spatial Competition and State Funding in Cost of Attendance Reporting Over Time

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Federal law requires U.S. postsecondary institutions to publish a Cost of Attendance (COA) that serves as the legal ceiling on a student's federal financial aid eligibility, yet off-campus living costs are estimated by institutions at their own discretion, with no standardized methodology or external audit. Using a 14-year panel of 2,311 four-year institutions (2010-2023) and externally benchmarked living costs constructed from HUD, USDA, BLS, KFF, and BEA data, we find that roughly half of institution-years report living costs below the benchmark, and this pattern persists across the full 14-year observation window rather than concentrating in any particular year. Spatial analysis reveals significant positive spatial autocorrelation in reporting gaps, and spatial panel models confirm persistent spatial dependence consistent with strategic interaction among geographically proximate institutions, robust to alternative neighborhood definitions, benchmark specifications, and sample restrictions. Public institutions exhibit spatial dependence nearly twice as strong as private institutions, consistent with more direct competition for in-state students within shared geographic markets. A Bartik shift-share instrumental variables design identifies a causal channel through which state fiscal pressure compresses reported living costs at public institutions ($362 per $1,000 funding decline), while a border discontinuity finds no corresponding cross-sectional jump at state boundaries, indicating that the funding-reporting link operates through within-state temporal shocks rather than persistent cross-state level differences. Together, these findings identify discretion in self-reporting, exercised under competitive pressure and state fiscal stress, as a systematic distortion in the cost information that flows into the federal aid system, with implications for federal standardization of living cost methodology.

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Do Neighbors Shape the Sticker Price?

Spatial Competition and State Funding in Cost of Attendance Reporting Over Time[1]

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Abstract

Federal law requires U.S. postsecondary institutions to publish a Cost of Attendance (COA) that serves as the legal ceiling on a student's federal financial aid eligibility, yet off-campus living costs are estimated by institutions at their own discretion, with no standardized methodology or external audit. Using a 14-year panel of 2,311 four-year institutions (2010–2023) and externally benchmarked living costs constructed from HUD, USDA, BLS, KFF, and BEA data, we find that roughly half of institution-years report living costs below the benchmark, and this pattern persists across the full 14-year observation window rather than concentrating in any particular year. Spatial analysis reveals significant positive spatial autocorrelation in reporting gaps, and spatial panel models confirm persistent spatial dependence consistent with strategic interaction among geographically proximate institutions, robust to alternative neighborhood definitions, benchmark specifications, and sample restrictions. Public institutions exhibit spatial dependence nearly twice as strong as private institutions, consistent with more direct competition for in-state students within shared geographic markets. A Bartik shift-share instrumental variables design identifies a causal channel through which state fiscal pressure compresses reported living costs at public institutions ($362 per $1,000 funding decline), while a border discontinuity finds no corresponding cross-sectional jump at state boundaries, indicating that the funding-reporting link operates through within-state temporal shocks rather than persistent cross-state level differences. Together, these findings identify discretion in self-reporting, exercised under competitive pressure and state fiscal stress, as a systematic distortion in the cost information that flows into the federal aid system, with implications for federal standardization of living cost methodology.

Keywords: Cost of Attendance, spatial econometrics, higher education finance, financial aid

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1 Introduction

The costs of attending college remain a key barrier to pursuing and completing a postsecondary credential for many Americans (Gallup Inc & Lumina Foundation, 2024). While substantial discourse has focused on the rising costs of tuition (Archibald & Feldman, 2010; Bound et al., 2019), tuition and fees represent less than half of the estimated costs needed to pursue a college degree (Baum et al., 2023; Kelchen et al., 2017). A growing body of evidence suggests other non-tuition costs, including things like food, transportation, and supplies also present a substantial financial hurdle for many students, with negative impacts on their college experience and ultimate outcomes if students are left unable to foot the bill (Broton et al., 2020; Goldrick-Rab, 2016; Sharp, 2021).

To represent this full range of costs, U.S. postsecondary institutions are required to annually publish an official Cost of Attendance (COA) estimate. The COA includes costs associated with tuition, fees, books and supplies, transportation, food and housing, and other miscellaneous costs (Baum et al., 2023). This published "sticker price" serves two important roles. First, it communicates the full range of potential costs to prospective students. Second, it also sets the legal ceiling on each student's federal financial aid eligibility under Section 472 of the Higher Education Act (Keefe, 2024; Kendall et al., 2020). While most COA components follow well-defined formulas or reflect actual charges from the institution to the student, one stands out: off-campus living costs, which institutions estimate at their own discretion. Federal statute specifies what must be included but not how it should be calculated, and no external body audits the resulting figures (National Association of Student Financial Aid Administrators (NASFAA), 2025a).

This discretion is consequential. If reported living costs fall below what students actually face, the aid eligibility ceiling is too low, and the gap between what students receive and what they need must be covered by work, private debt, or reduced consumption (Broton et al., 2020; Goldrick-Rab, 2016; Scott-Clayton & Minaya, 2016; Shireman et al., 2018). Evidence suggests a disconnect between expected and realized costs has detrimental impacts on students' college experiences, retention, and ultimate success (Broton et al., 2020; Kelchen et al., 2017; Sharp, 2021).

Prior work has established that this discretion produces sizable variation, with differences of at least 20 percent above or below estimated expenses among institutions in the same region (Kelchen et al., 2017). As evidenced by a recent practitioner survey by the National Association of Student Financial Aid Administrators, some of this variation stems from the use of differential data sources and methods, which lack enforced professional guidelines (National Association of Student Financial Aid Administrators (NASFAA), 2025a). However, in a competitive market, institutions are also incentivized to keep their sticker prices low as to not alienate potential students (Goldrick-Rab, 2016). Almost half (43 percent) of financial aid administrators surveyed reported institutional pressures to keep the COA from appearing too high (National Association of Student Financial Aid Administrators (NASFAA), 2025a).

While prior work has documented both the importance of the COA and the potential for institutional distortion in its construction, extant scholarship leaves three questions open. First, the evidence base is predominantly cross-sectional, capturing reporting behavior at a single point in time (Coles et al., 2020; Kelchen et al., 2017; Libassi & Mabel, 2022). Cross-sectional designs cannot identify how reporting accuracy responds to time-varying institutional pressures, such as shifts in state appropriations or enrollment competition. Nor can they tell us whether the patterns identified in these snapshots reflect persistent structural features of the federal aid system or transient institutional decisions that resolve as institutions update their methodologies. The persistence question matters for policy: persistent underreporting points to a coordination failure that voluntary institutional reform is unlikely to resolve, while transient variation may correct itself over time. Second, although the literature hypothesizes that institutions face competitive pressure to keep published costs low (Goldrick-Rab, 2016; National Association of Student Financial Aid Administrators (NASFAA), 2025a), no study has tested whether reporting behavior exhibits the spatial structure that such competition would produce. If institutions are reporting in reference to one another rather than independently estimating local conditions, this strategic interaction should manifest as geographic clustering in reporting patterns. Spatial dependence, if present and robust to time-invariant institutional characteristics, would constitute direct empirical evidence of the competitive mechanism that prior work has only inferred from practitioner surveys. Third, while institutional pressures to keep COA low are well-documented, the causal effect of specific fiscal shocks on reporting accuracy has not been estimated. Whether reporting accuracy declines because institutions face genuine state funding stress, or simply because such stress correlates with other unobserved institutional characteristics, requires a causal identification strategy that the existing literature has not deployed.

This study addresses these gaps by answering the following questions: (1) Across U.S. four-year institutions from 2010 to 2023, how prevalent and persistent is the discrepancy between institutionally reported and externally benchmarked off-campus living costs? (2) Does this discrepancy exhibit spatial dependence consistent with strategic interaction among geographically proximate institutions, in which institutions report in reference to one another rather than independently estimating local conditions? (3) Do exogenous declines in state appropriations causally compress reported living costs at affected institutions? To address these questions, we construct an independent benchmark of local living costs using multiple federal data sources and compare it to institutional self-reports across a 14-year panel of 2,311 four-year institutions. The analysis proceeds in three stages: (1) documenting the magnitude and trajectory of underreporting across 14 years, extending prior cross-sectional snapshots to a longitudinal panel; (2) testing whether underreporting is spatially clustered in ways consistent with strategic interaction, using cross-sectional spatial Durbin models and spatial panel models with institution and year fixed effects; and (3) assessing whether state appropriation funding causally affects reporting accuracy through a border discontinuity design and a Bartik shift-share instrumental variables approach.

We find that roughly half of institution-years report living costs below the benchmark, and that this pattern persists across the full 14-year observation window rather than concentrating in any particular year. Underreporting is spatially clustered: when nearby institutions underreport, a given institution is more likely to do the same. The spatial autoregressive parameter remains positive and significant after absorbing institution and year fixed effects, with public institutions exhibiting spatial dependence nearly twice as strong as private institutions. The Bartik IV shows that exogenous declines in state funding compress reported living costs at public institutions, consistent with heightened competitive pressure strengthening incentives to underreport. A border discontinuity finds no corresponding cross-sectional jump at state boundaries, suggesting that the funding-reporting link operates through within-state temporal shocks rather than persistent cross-state level differences. Together, these findings suggest that the discretion in self-reporting, exercised under competitive pressure and state fiscal stress, systematically distorts the cost information that flows into the federal aid system. Because the spatial structure of this distortion implies that voluntary correction by any single institution would create competitive disadvantage relative to peers, federal standardization of living cost methodology is the most direct available policy lever.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and benchmark construction. Section 4 presents the empirical strategy. Section 5 reports results. Section 6 discusses implications and limitations.

2 Literature Review

2.1 COA as an Information Node in the Federal Aid System

The Cost of Attendance occupies a unique position in federal higher education policy: it simultaneously serves as the institutional sticker price, the basis for need-based aid calculations, and the legal ceiling on total financial aid a student can receive, including how much students may be able to borrow in student loans (Fuller, 2014; Libassi & Mabel, 2022; Smole et al., 2008). Under the Higher Education Act, institutions must include tuition, fees, books, supplies, transportation, and living expenses in their published COA, but Congress has historically prohibited the Department of Education from regulating how individual components are calculated (Goldrick-Rab, 2016). Though professional associations like National Association of Student Financial Aid Administrators (NASFAA) (2025b) offer resources and professional guidelines for financial aid offices as they construct their COA budgets, schools receive relatively little official federal guidance (Coles et al., 2020) and are given substantial latitude in how they approach COA construction.

This institutional self-governance in cost estimation of certain items has produced significant variation. Kelchen et al. (2017) was the first to systematically compare institutional living cost allowances to an external benchmark derived from county-level cost-of-living data. The analysis showed that nearly half of all institutions set off-campus living cost allowances at least 20 percent above or below estimated local expenses, and that institutions in the same geographic area often reported widely divergent figures. This work has since been corroborated by studies across multiple state and system (4-year vs. 2-year) contexts that found inconsistencies in COA calculations, including schools serving the same regions (Baum & Cohn, 2022; Coles et al., 2020; Kendall et al., 2020; Shireman et al., 2018). For example, focusing on living costs, Libassi and Mabel (2022) documented substantial various across 21 metropolitan areas; the difference between 25th and 75th percentiles exceeded $5,000. When looking nationally, accounting for differences in local living costs and student living arrangements explained only 55 percent of the identified variation, suggesting that 45 percent of the variation in estimated living costs was attributable to institutions' discretion in setting budgets. In some extreme cases, cost estimates can even differ by more than $15,000 between colleges less than one mile apart (Coles et al., 2020).

2.2 Impacts of Misaligned COA Estimates

COA estimates that are misaligned with realized costs are more than a reporting issue. A recent survey of students across 5 states found that 79% of students experienced an unexpected indirect expense at least once in the last academic year, with over a third (38%) encountering issues four or more times (Coles et al., 2020). A growing body of work suggests many of these unexpected costs stem from housing and food-based insecurities (Broton, 2019; Broton & Goldrick-Rab, 2016; Coleman-Jensen et al., 2018; Kendall et al., 2020), as available financial aid often fails to cover the full food and housing costs for students (Broton et al., 2020). These inaccurate cost estimates can leave students facing budget shortfalls to obtain books, technology, and transportation needs that preclude their engagement in class (Coles et al., 2020). Studies have also documented students needing to work extra hours to cover unexpected costs, taking on more debt, changing their major plans to graduate earlier, or even stopping out of college all together (Broton et al., 2020; Kelchen et al., 2017; Kendall et al., 2020; Sharp, 2021). Inaccurate cost estimates also distort the institutional accountability systems built on top of them. Federal tools such as the College Scorecard and net price calculators rely on institutional COA reports to compute affordability metrics that students, families, and policymakers use to compare institutions (Kelchen et al., 2017), many failing to provide accurate estimates to students (Perna et al., 2021). When reported living costs diverge systematically from realized costs, these comparison tools convey misleading affordability signals, and institutions that report more accurately appear more expensive than peers that underreport (U.S. Congress. Government Accountability Office (GAO), 2022).

2.3 Structural Drivers of Differential Cost Estimates

There could be multiple mechanisms at play leading to both over-and under-reporting of these indirect expenses, as well as the substantial heterogeneity among institutions in the same regions that should ostensibly have comparable cost estimates. First, COAs may differ purely as a function of the heterogeneous approaches each school uses to collect data, update, and set costs. For example, research highlights varying usage of surveys, focus group data, budget logs, external data sources (e.g., MIT Living Wage Calculator), and anecdotal information from local sources to estimate indirect costs (Coles et al., 2020). Without proper support, it may be difficult for institutions to effectively collect sufficient data to accurately triangulate the costs facing their students (Kendall et al., 2020). Moreover, the data itself might be flawed; for example, schools may leverage student surveys to assess things like off-campus living costs, but evidence suggests such self-reported data may be error prone (Zhen et al., 2009). The National Association of Student Financial Aid Administrators (NASFAA) conducted a mixed-methods study of how institutions construct their COA and found wide differences in methodology, data sources, and update frequency (National Association of Student Financial Aid Administrators (NASFAA), 2025a). Only 73 percent of institutions reviewed off-campus housing costs annually, compared to 98 percent for tuition. The association's own recommended figures are voluntary, and it does not track whether member institutions adopt or modify them. Among survey respondents, only 43 percent expressed high confidence in the accuracy of their own COA, and of those who were less confident, 45 percent believed their figures were too low. Some discrepancies between published COA components and students' realized costs might also be due to student choices. For example, a recent analysis of housing costs documented a 36% difference in cost between the least- and most-expensive on-campus housing options, potentially further complicating students' understanding of their true cost of attendance (Kendall et al., 2020). Such issues are further compounded by how institutions communicate their various COA estimates (Conroy et al., 2021; Walizer, 2018); a recent overview of financial aid offers found that 55 percent of colleges do not itemize key direct and indirect costs in their aid offers, and 91 percent fail to correctly estimate the net price students will actually pay (U.S. Congress. Government Accountability Office (GAO), 2022).

2.4 Strategic Behavior, Market Competition, and Spatial Interaction

However, institutions may also be aligning their COA estimates with other pressures to align schools' costs with state higher education agendas and remain competitive for prospective students (Coles et al., 2020). Higher education operates under economic conditions that differ markedly from standard competitive markets. Winston (1999) showed that the average institution's sticker price covers less than a third of its production costs, with the remainder funded by subsidies that vary dramatically across the institutional hierarchy. In this setting, competition is positional: institutions compete not for profit but for enrollment quality and institutional standing, and pricing decisions serve strategic rather than purely cost-recovery purposes. Hillman (2012) documented one manifestation of this strategic behavior in the public sector, showing that institutions use institutionally funded financial aid as a revenue management tool, effectively manipulating the gap between sticker price and net price to optimize enrollment and revenue. If institutions already engage in strategic pricing for tuition, it is plausible that the discretionary living cost component of

COA is subject to similar pressures Goldrick-Rab (2016). This extension generates a testable implication: reporting behavior should exhibit the same spatial signatures that have been documented for tuition pricing, with institutions positioning their reported costs in reference to geographic competitors. Extant literature shows that estimated indirect expenses within schools' COAs may be systematically lower at less-selective institutions, smaller schools, and at places enrolling large shares of low-income students (Libassi & Mabel, 2022; Shireman et al., 2018), all of which are facing increasing pressures to compete for students.

Practitioner evidence supports this inference directly. The recent NASFAA survey found that institutional pressure to keep COA from appearing too high was the single most frequently cited barrier to accurate COA construction, reported by 43 percent of respondents (National Association of Student Financial Aid Administrators (NASFAA), 2025a). Sixty-five percent of institutions reported reviewing peer institutions' COA figures, suggesting that reporting decisions are made with reference to competitors; one institute reported adjusting their COAs to remain under "psychologicaly significant pricing thresholds" compared to their peers (National Association of Student Financial Aid Administrators (NASFAA), 2025a). Analyses conducted by the Government Accountability Office further corroborate these pressures. Interviewees identified competitive pressure as a key reason colleges do not follow best practices in presenting cost information, noting that institutions following transparency guidelines may place themselves at a disadvantage relative to those that present lower figures (U.S. Congress. Government Accountability Office (GAO), 2022). These competitive dynamics are also operating within a funding environment characterized by cyclical volatility (Delaney & Doyle, 2011), where institutions are having to leverage enrollment and pricing strategies to bolster their coffers via enrollment-based revenue in the face of sporadic state appropriations.

While competitive dynamics in higher education pricing are well established, the spatial dimension has received little attention. The most direct precedent is McMillen et al. (2007), who applied spatial econometric methods to college tuition and found that institutions' pricing decisions are significantly influenced by the tuition levels of geographically proximate competitors. Their work demonstrated that spatial dependence in higher education pricing is not merely an artifact of shared regional conditions but reflects strategic interaction among institutions. However, as Hoxby (2009) documented, the higher education market has partially nationalized over recent decades, with selective institutions drawing students from increasingly broad geographic areas. Off-campus living costs, by contrast, remain inherently local: a student's rent, food, and transportation expenses are determined by the institution's immediate geographic context, not by national market conditions. This makes COA living cost reporting a setting where spatial competition is particularly likely to operate. Whether it does, and whether such spatial dependence persists after controlling for institutional heterogeneity and common time shocks, has not previously been tested.

2.5 Summary of Gaps and Contributions

The preceding review identifies two unresolved gaps in the literature on COA reporting behavior. First, the existing evidence base is predominantly cross-sectional, capturing reporting behavior at a single point in time (Kelchen et al., 2017). A longitudinal view is needed to determine whether the variation documented in prior snapshots reflects persistent structural features of the federal aid system or transient institutional decisions, and to identify how reporting accuracy responds to time-varying institutional pressures such as fluctuations in state appropriations. Second, although the literature attributes COA variation in part to competitive pressure (Goldrick-Rab, 2016; National Association of Student Financial Aid Administrators (NASFAA), 2025a), and although McMillen et al. (2007) established that tuition exhibits spatial competition, no study has tested whether the discretionary living cost component of COA follows a similar pattern, nor whether state fiscal shocks causally shape reporting accuracy. This study addresses both gaps by constructing a 14-year panel of 2,311 four-year institutions and applying spatial econometric and quasi-experimental methods to assess the persistence, spatial structure, and causal drivers of COA underreporting.

3 Data and Construction of Benchmark Living Costs

3.1 Sample and Institutional Data

The analytical dataset is a longitudinal panel spanning academic years 2010 to 2023. This period is chosen because BEA Regional Price Parities reached stable MSA-level coverage by 2010, and 2023 represents the most recent complete IPEDS data year. The sample includes Title IV participating, four-year public and private not-for-profit institutions located in the contiguous United States, drawn from the Integrated Postsecondary Education Data System (National Center for Education Statistics, 2024). We exclude institutions classified as exclusively offering distance education, for-profit institutions, and those in overseas territories.

From the IPEDS Institutional Characteristics (IC) files, we obtain geographic coordinates, sector, locale, self-reported off-campus room and board costs, other expenses, in-state tuition, and acceptance rates. From the Fall Enrollment (EF) files, we obtain total FTE enrollment and racial/ethnic enrollment shares (Black, Hispanic, White, and a combined minority share defined as Black + Hispanic). The IPEDS Student Financial Aid (SFA) files provide the percentage of undergraduates receiving Pell Grants, which serves as an institutional-level proxy for low-income student concentration. After data cleaning, the final panel contains 26,336 institution-year observations across 2,311 unique institutions. Private not-for-profit institutions account for 64 percent of the sample.

3.2 Benchmark Data Sources and Construction

Following Kelchen et al. (2017), we construct benchmark living costs from five federal data sources. Housing costs are based on HUD Fair Market Rents (FMR), which provide county-level 40th-percentile rental benchmarks (U.S. Department of Housing and Urban Development, 2024). Food costs draw on the USDA Low-Cost Food Plan, which provides national monthly food expenditure baselines for young adults (U.S. Department of Agriculture, Center for Nutrition Policy and Promotion, 2026); we adjust these geographically using BEA Regional Price Parities (RPP) at the MSA level for metropolitan institutions and at the state non-metropolitan level for micropolitan and rural institutions (U.S. Bureau of Economic Analysis, 2026). Transportation and miscellaneous personal expenditures are based on national baselines for individuals under 25 from the BLS Consumer Expenditure Survey (U.S. Bureau of Labor Statistics, 2026). Health insurance costs use state-level benchmark premiums from the Kaiser Family Foundation (KFF) for 2014–2023 (Kaiser Family Foundation, 2026); for 2010–2013, national averages from eHealth bridge the pre-ACA period.

The benchmark is estimated under a conservative roommate scenario for a 9-month academic year, maintaining comparability with IPEDS reporting conventions. An alternative single-occupancy specification is used for robustness.

$$\widehat{\text{TrueCost}}_{it} = \underbrace{\frac{\text{FMR}_{\text{2BR},ct}}{2} \times 9}_{\text{Housing}} + \underbrace{\text{USDA}_t \times \text{RPP}_{it} \times 9}_{\text{Food}} + \underbrace{\text{BLS}_{\text{transp},t}}_{\text{Transport}} + \underbrace{\text{BLS}_{\text{misc},t}}_{\text{Misc.}} + \underbrace{\text{KFF}_{st}}_{\text{Health}}$$

Where county-level housing data is unavailable (7.7% of observations), national median housing costs are substituted. Food cost fallbacks use the unadjusted national USDA baseline (8.9%). Health cost fallbacks for 2010–2013 use RPP-adjusted national averages (27.2%, entirely driven by the pre-ACA period).

The primary outcome is the COA reporting gap:

$$\text{COA Gap}_{it} = \text{ReportedLivingCost}_{it} - \widehat{\text{TrueCost}}_{it}$$

A negative value indicates underreporting: the institution reports lower living costs than the benchmark estimate.

3.3 Causal Identification Data

Two additional data sources support the causal identification strategies. For the Bartik shift-share instrumental variables analysis, we use the State Higher Education Finance (SHEF) report published by the State Higher Education Executive Officers Association (State Higher Education Executive Officers Association, 2025). The SHEF dataset provides annual state-level education appropriations and net FTE enrollment for all 50 states and the District of Columbia from fiscal year 1980 through 2024. We compute state appropriation per FTE as the ratio of education appropriations to net FTE enrollment for fiscal years 2010–2023.

For the border discontinuity design, we use the zipcode-to-state-border distance dataset from Knight and Schiff (2019). This dataset records the Euclidean distance in kilometers from each U.S. zipcode centroid to the nearest boundary point of each state boundary line. Each institution is matched to its nearest zipcode, and the minimum distance to a non-home-state border determines the institution's proximity to a state boundary.

3.4 Descriptive Statistics

Table 1 presents summary statistics for the pooled panel. The mean COA gap under the roommate benchmark is −\$190, indicating slight underreporting on average, but with substantial variation. At the 25th percentile, institutions underreport by \$2,280; at the 75th percentile, they overreport by \$1,870. Public institutions report a mean gap of +\$230 (overreporting), while private institutions report −\$430 (underreporting). Tuition averages \$20,200 with substantial dispersion.

Table 1: Descriptive Statistics (2010–2023 Pooled Panel)

	N	Mean	SD	P25	Median	P75
Panel A: COA Variables ($k)						
COA Gap (Roommate)	25,322	−0.19	3.61	−2.28	−0.01	1.87
COA Gap (Alone)	25,322	−2.23	3.92	−4.42	−1.96	0.09
Reported Living Cost	25,322	13.78	4.02	11.25	13.45	15.96
Estimated True Cost	25,322	13.98	2.98	11.42	13.74	15.82
Panel B: Institutional Characteristics						
In-State Tuition ($k)	25,322	20.20	14.10	8.38	15.06	30.50
FTE Enrollment (log)	25,295	7.47	1.53	6.67	7.54	8.51
Acceptance Rate (%)	20,564	69.01	19.61	57.26	71.18	83.38
Panel C: State Funding (SHEEO)						
State Approp. per FTE ($k)	22,176	7.81	3.84	5.07	7.32	9.79

Note: Monetary values in thousands of dollars ($k). Sample sizes vary across variables due to differential reporting requirements in IPEDS: acceptance rate ($N = 20{,}564$) is reported only by institutions with admissions criteria, and state appropriations per FTE ($N = 22{,}176$) is merged to public institutions only for the IV analysis.

4 Empirical Strategy

4.1 Spatial Weights Matrix

We operationalize spatial connectivity using a row-standardized k-nearest-neighbors (KNN) weights matrix $\mathbf{W}$ with $k = 5$. For institutions i and j, the weight w_{ij} equals $1/k$ if j is among i's five nearest neighbors by great-circle distance, and zero otherwise; diagonal elements $w_{ii} = 0$ and each row sums to unity. KNN is preferred to a fixed distance band because institutions are geographically clustered in metropolitan areas but sparsely distributed in rural regions, making a fixed radius yield drastically different neighbor counts. Robustness checks use $k = 3$ and $k = 10$. The formal construction is reported in Appendix A.1.

4.2 Cross-Sectional Spatial Models (2023)

We estimate a hierarchy of spatial models, selected via Lagrange Multiplier diagnostics following Anselin et al. (1996). The Spatial Autoregressive Model (SAR) introduces an endogenous spatial lag of the dependent variable:

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \qquad \boldsymbol{\varepsilon} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}) \tag{1}$$

where $\rho \in (-1, 1)$ captures endogenous spatial dependence. The reduced form implies that each observation is a function of all other observations' covariates through the spatial multiplier $(\mathbf{I} - \rho\mathbf{W})^{-1}$, which generates global feedback effects that decay geometrically with spatial distance.

The preferred specification is the Spatial Durbin Model (SDM), which nests both the SAR and the Spatial Error Model (SEM) by including spatially lagged covariates:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\theta} + \boldsymbol{\varepsilon} \tag{2}$$

The SDM permits likelihood ratio tests against the SAR ($H_0 : \boldsymbol{\theta} = \mathbf{0}$) and the SEM ($H_0 : \boldsymbol{\theta} + \rho\boldsymbol{\beta} = \mathbf{0}$), following the testing hierarchy of LeSage (2008). Because the SDM's $\boldsymbol{\beta}$ coefficients do not directly represent marginal effects due to spatial feedback, we decompose total effects into direct, indirect (spillover), and total components via the partial derivative matrix (LeSage & Pace, 2009):

$$\frac{\partial \mathbf{y}}{\partial x_k} = (\mathbf{I} - \rho\mathbf{W})^{-1}(\beta_k\mathbf{I} + \theta_k\mathbf{W}) \tag{3}$$

Direct effects are the average diagonal elements; indirect effects are the average row sums of off-diagonal elements. Standard errors are obtained via Monte Carlo simulation with 500 draws. The SEM specification and detailed LM diagnostic procedure are reported in Appendix A.2.

4.3 Spatial Panel Models (2010–2023)

To assess whether spatial patterns persist after controlling for time-invariant institutional heterogeneity and common time shocks, we estimate spatial panel models with two-way fixed effects (Elhorst, 2014). The SAR panel specification is:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \mathbf{x}_{it}'\boldsymbol{\beta} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where α_i are institution fixed effects (absorbing time-invariant characteristics such as sector, location, and institutional mission) and γ_t are year fixed effects (absorbing national trends such as inflation, federal policy changes, and housing market cycles). The identifying variation for ρ comes from within-institution, within-year co-movements in COA gaps among spatial neighbors. Time-varying covariates include in-state tuition and log FTE enrollment. We estimate the model using maximum likelihood on a balanced panel of 1,057 institutions observed in all 14 years. The corresponding panel SEM specification, full matrix notation, and software conventions are reported in Appendix A.3.

4.4 Border Discontinuity Design

The spatial models establish spatial dependence but cannot definitively distinguish strategic mimicry from correlated responses to shared local conditions. To move toward causal identification, we exploit the sharp discontinuity in state higher education funding at state borders, following the geographic regression discontinuity framework of Knight and Schiff (2019). The identifying assumption is that institutions located near a state border face similar local economic conditions (labor markets, housing costs, cost of living) but different state-level funding environments.

Define the running variable as the signed distance from institution i to the nearest non-home-state border:

$$\tilde{d}_i = \begin{cases} +d_i & \text{if } \text{Approp}_{s(i)} \geq \text{Approp}_{s'(i)} \\ -d_i & \text{otherwise} \end{cases} \tag{5}$$

where d_i is the Euclidean distance in kilometers, $s(i)$ is institution i's home state, and $s'(i)$ is the nearest neighboring state. Institutions with $\tilde{d}_i > 0$ are on the higher-appropriation side, and the cutoff is $\tilde{d}_i = 0$. The parametric border regression is:

$$\text{Gap}_{it} = \beta_1 \Delta\text{Approp}_{it} + \beta_2 d_i + \beta_3 d_i^2 + \mathbf{x}'_{it}\boldsymbol{\delta} + \mu_{p(i)} + \gamma_t + \varepsilon_{it} \tag{6}$$

where ΔApprop_{it} is the cross-border appropriation difference per FTE in thousands of dollars, $\mu_{p(i)}$ are border-pair fixed effects, and $\mathbf{x}_{it}$ includes FTE enrollment, acceptance rate, and sector. Standard errors are clustered at the state level. The primary bandwidth is 50 km; we also report 25, 75, and 100 km. As a complementary check, we estimate nonparametric local polynomial RD models using the bias-corrected estimator of Calonico et al. (2014) and assess validity through McCrary density and covariate placebo tests; details are reported in Appendix A.4.

4.5 Bartik Shift-Share IV

Even within the border band, appropriation differences may be correlated with unobserved state-level factors that independently affect COA reporting. To address remaining endogeneity in the full panel, we estimate two-stage least squares (2SLS) models using a Bartik shift-share instrument for state appropriation per FTE.

The instrument leverages the idea that each state's current appropriation level is partly driven by national funding trends, weighted by historical exposure to higher education spending. Define state s's base-year (2010) share of national appropriations:

$$\omega_s = \frac{\text{Approp}_{s,2010}}{\sum_{s'=1}^{S} \text{Approp}_{s',2010}} \tag{7}$$

and the leave-one-out national mean appropriation per FTE in year t:

$$\overline{\text{Approp}}^{\text{FTE}}_{-s,t} = \frac{\sum_{s' \neq s} \text{Approp}_{s',t}}{\sum_{s' \neq s} \text{FTE}_{s',t}} \tag{8}$$

The instrument is the interaction of the two:

$$Z^{\text{Bartik}}_{s,t} = \omega_s \times \overline{\text{Approp}}^{\text{FTE}}_{-s,t} \tag{9}$$

The leave-one-out construction ensures that state s's own fiscal shocks do not contaminate the instrument. Conditional on state and year fixed effects, the remaining variation captures how differential base-year shares translate national trends into heterogeneous predicted funding paths. The exclusion restriction requires that, conditional on these fixed effects and institutional controls, the Bartik instrument affects institutional COA gaps only through its effect on own-state appropriation per FTE.

The first and second stages are:

$$\text{First stage:} \quad \text{Approp}_{s(i),t} = \pi_1 Z^{\text{Bartik}}_{s(i),t} + \mathbf{x}'_{it}\boldsymbol{\phi} + \alpha_s + \gamma_t + \nu_{it} \tag{10}$$

$$\text{Second stage:} \quad \text{Gap}_{it} = \beta_1 \widehat{\text{Approp}}_{s(i),t} + \mathbf{x}'_{it}\boldsymbol{\delta} + \alpha_s + \gamma_t + \varepsilon_{it} \tag{11}$$

where α_s are state fixed effects, γ_t are year fixed effects, and controls include FTE enrollment, acceptance rate, and sector. Standard errors are clustered at the state level. Instrument strength is assessed via the effective first-stage F-statistic, with $F > 10$ as the conventional threshold for ruling out severe weak-instrument bias (Stock & Yogo, 2005). A peer-state leave-one-out instrument was also considered and rejected on first-stage strength grounds; details are reported in Appendix A.5.

5 Results

5.1 Patterns of COA Underreporting

Before turning to spatial analysis, Table 2 disaggregates the COA gap across institutional characteristics, establishing the descriptive patterns that motivate the subsequent analysis. Underreporting is more prevalent among private institutions (53.4% of institution-years) than public ones (44.6%), with private institutions reporting a mean gap of −\$451 compared to +\$204 for public institutions. Geographically, institutions in towns show the highest underreporting rate (56.9%, mean gap −\$776), while city institutions are closest to benchmark (47.9%, mean gap +\$94). Larger institutions report more accurately: very large institutions (15,000+ FTE) underreport only 36.5% of the time (mean gap +\$821), while medium-sized institutions underreport 54.7% of the time (mean gap −\$523). Selectivity shows a modest gradient: the most selective quartile underreports less frequently (43.8%) than the open-admission quartile (51.9%). These cross-tabulations reveal that underreporting is concentrated at smaller, less selective, and town-located institutions, suggesting that the discretionary nature of off-campus living cost estimation produces variation that is structured along institutional dimensions rather than randomly distributed.

The aggregate pattern in Table 2 shows that roughly half (50.3%) of institution-years exhibit underreporting; Table 3 reveals that this is a structural feature of individual institutions rather than a sporadic occurrence. The chronic-frequency sample consists of 1,781 four-year institutions observed for at least 10 of the 14 panel years, less restrictive than the 802-institution balanced panel used in the spatial panel models, since institution-level frequency can be assessed from unbalanced data while spatial panel SAR requires complete observations.

Underreporting is nearly universal in the cross-section of institutions. Panel A shows that 83.5% of institutions underreport in at least one year, and 51.0% do so in more than half of the years they are observed. More striking, 34.6% of institutions underreport chronically (in at least 70% of observed years), and 19.6% underreport in every single year of the panel. Panel B confirms that institutions are distributed across the full frequency spectrum rather than concentrated at extremes: 16.5% never underreport, 26.0% do so in 4–7 years, and 11.7% do so in all 14. Underreporting is not produced by transient measurement noise or occasional reporting errors; a substantial fraction of institutions report living costs that systematically fall below external benchmarks throughout the observation window.

The institution-level pattern is more pronounced at private institutions. While the share of institutions ever underreporting is nearly identical across sectors (83.7% private vs. 83.3% public), the depth of chronic underreporting differs substantially: 39.5% of privates chronically underreport in ≥70% of years compared to 26.1% of publics, and 24.9% of privates underreport in every year of the panel compared to 10.4% of publics.

This sector difference in baseline reporting behavior is conceptually distinct from the IV result reported in Section 5.6, which captures the marginal response of public institutions to exogenous changes in state funding rather than the long-run level of underreporting. Privates exhibit higher chronic underreporting in levels but their reporting does not respond to state appropriation cycles (Appendix Table A6), consistent with their negligible exposure to state-funding pressure; publics are closer to benchmark on average but compress reported costs when state funding declines.

Table 2: COA Gap by Institutional Characteristics (2010–2023 Pooled)

	N	**Mean Gap ($)**	**Med. Gap ($)**	**% Under-report**	**Mean Reported**	**Mean Benchmark**
Overall	26,332	−214	−17	50.3	13,730	13,944
Sector						
Public	9,519	204	348	44.6	14,002	13,797
Private Not-for-Profit	16,813	−451	−306	53.4	13,576	14,027
Urbanicity						
City	12,718	94	185	47.9	14,344	14,250
Suburb	6,599	−306	79	48.9	14,095	14,401
Town	4,960	−776	−520	56.9	12,131	12,907
Rural	2,045	−435	−219	53.1	12,642	13,077
Size (FTE)						
Small (< 1,000)	8,100	−433	−359	53.4	13,811	14,243
Medium (1,000–4,999)	11,802	−523	−342	54.7	13,093	13,616
Large (5,000–14,999)	4,409	551	697	38.7	14,607	14,056
Very Large (15,000+)	1,990	821	769	36.5	15,210	14,389
Selectivity (Acceptance Rate Quartile)						
Most Selective (Q1)	5,304	261	428	43.8	14,057	13,796
Selective (Q2)	5,303	−194	20	49.8	13,258	13,452
Less Selective (Q3)	5,303	−279	−49	50.8	13,582	13,861
Open Admission (Q4)	5,303	−218	−123	51.9	14,307	14,525

Note: Gap = Reported Living Cost − Benchmark Estimate (roommate scenario). Negative values indicate underreporting. % Underreport = share of institution-years with Gap < 0. Monetary values in dollars. Selectivity quartiles defined by acceptance rate; Q1 = lowest acceptance rate (most selective).

Table 3: Chronic Underreporting at the Institution Level

	All Institutions ($N = 1{,}781$)	**Public** ($N = 652$)	**Private** ($N = 1{,}129$)
Panel A: Institution-Level Underreporting Frequency			
Ever underreport (≥1 year)	83.5%	83.3%	83.7%
Majority of years (≥50%)	51.0%	44.0%	55.1%
Chronic underreport (≥70% of years)	34.6%	26.1%	39.5%
Always underreport (all 14 years)	19.6%	10.4%	24.9%
Panel B: Distribution of Years Underreporting (out of 14)			
0 years (Never)	16.5%	16.7%	16.3%
1–3 years (Rare)	14.8%	18.4%	12.8%
4–7 years (Sometimes)	26.0%	29.4%	24.0%
8–10 years (Often)	14.7%	16.9%	13.4%
11–13 years (Frequent)	16.4%	12.3%	18.8%
All 14 years (Always)	11.7%	6.3%	14.8%
Median years underreporting (overall)	6 of 14	6 of 14	7 of 14

Note: Each cell reports the percentage of institutions in the column sample satisfying the stated criterion. The sample consists of 1,781 four-year institutions observed for at least 10 of the 14 panel years (2010–2023), of which 652 are public and 1,129 are private not-for-profit; institutions observed for fewer than 10 years are excluded to ensure that frequency-based classifications have statistical credibility.

5.2 Exploratory Spatial Data Analysis

Figure 1 presents the Moran scatterplot for the 2023 COA Gap. Global Moran's $I = 0.132$ ($p < 0.001$), indicating statistically significant positive spatial autocorrelation: institutions that underreport tend to be located near other institutions that also underreport, and vice versa. The positive slope of the regression line (whose gradient equals Moran's I) confirms this pattern, with Low-Low clusters (blue) concentrated in the lower-left quadrant and High-High clusters (red) in the upper-right. The statistic is robust to the choice of k: $I = 0.134$ ($k = 3$), $I = 0.132$ ($k = 5$), and $I = 0.117$ ($k = 10$), all with $p < 10^{-14}$.

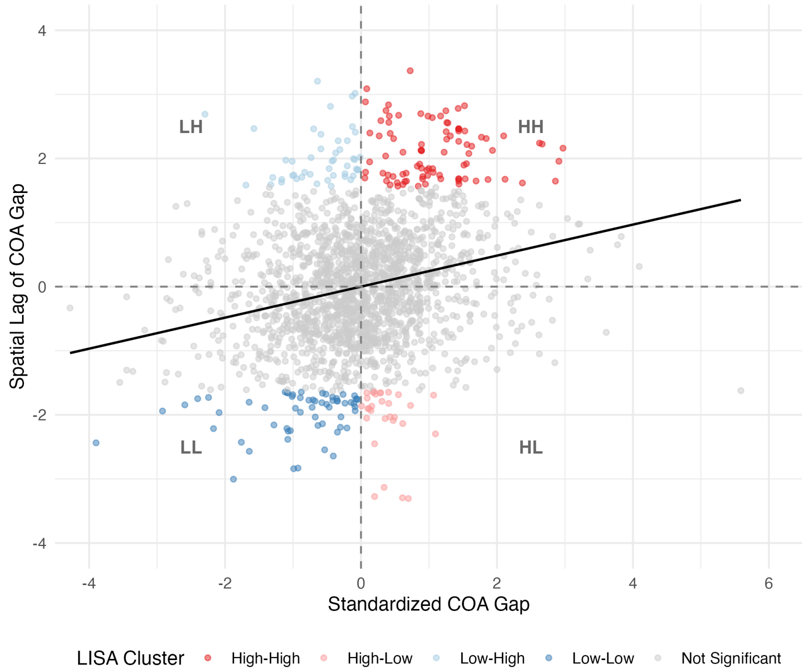

Figure 1: Moran Scatterplot of the COA Gap (2023)

This spatial autocorrelation is not unique to 2023. Figure 2 plots Global Moran's I for each year of the study period. The statistic is positive and statistically significant ($p < 0.001$) in every year from 2010 to 2023, ranging from approximately 0.07 in 2013 to 0.19 in 2018. The increase after 2015 and subsequent plateau suggest that spatial clustering in COA reporting intensified during the mid-2010s and has remained elevated since. This longitudinal pattern provides preliminary evidence that the spatial dependence observed in the cross-section is a persistent structural feature of COA reporting, not a one-time artifact.

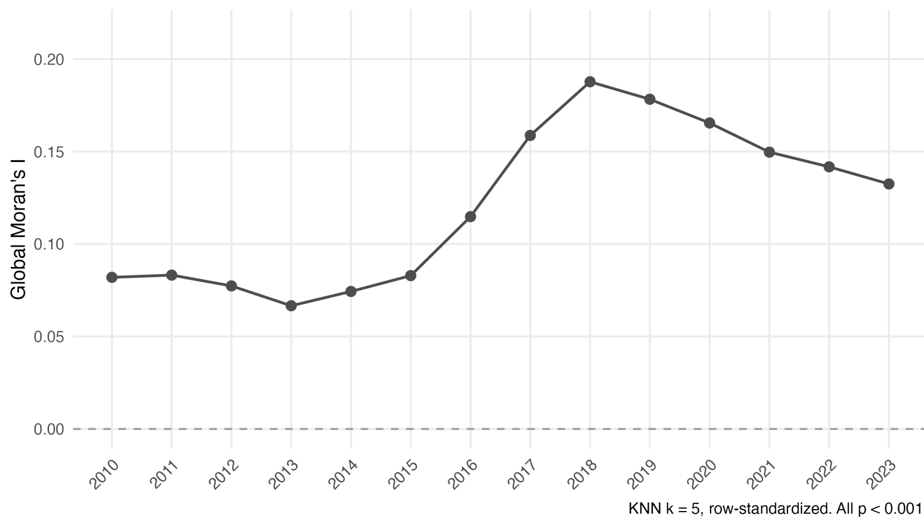

Figure 2: Global Moran's I for the COA Gap (2010–2023)

Figure 3 maps LISA clusters to county polygons for 2023. Low-Low clusters (blue) concentrate in the Northeast, particularly New York and New Jersey, where private institutions face intense competition and high local living costs. High-High clusters (red) appear in the Pacific Northwest, Mountain West, and parts of the Mid-Atlantic, where institutions report living costs above benchmark estimates. The spatial outliers (High-Low and Low-High) are sparse, consistent with the dominant pattern of positive spatial autocorrelation.

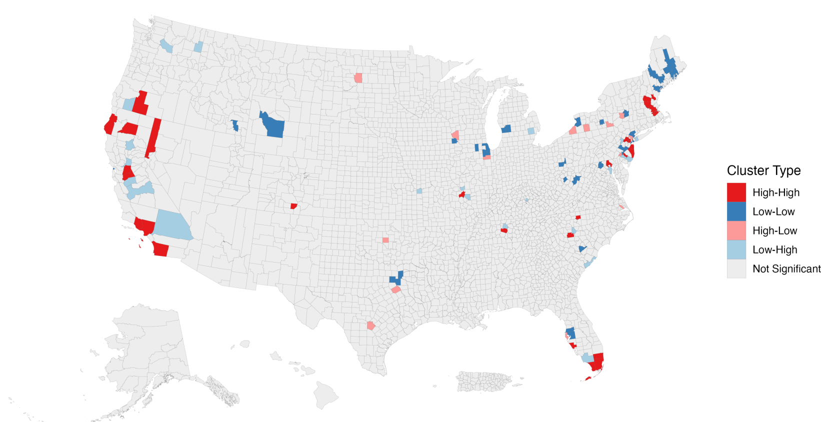

Figure 3: LISA Cluster Map of the COA Gap (2023)

Notes: Institution-level LISA clusters (KNN $k = 5$, $p \leq 0.05$) aggregated to county polygons for visualization. Counties containing at least one significantly clustered institution inherit that cluster designation.

The LISA map identifies where spatial clustering occurs but does not quantify its magnitude or test whether it persists once institutional characteristics are accounted for. We turn next to spatial regression models that formalize these patterns, beginning with the cross-sectional specifications presented in Table 4, whose decomposition into direct and spillover effects is reported in Table 5.

5.3 Cross-Sectional Spatial Regression (2023)

Table 4 presents cross-sectional regression results. LM-lag and LM-error diagnostics both reject OLS ($p < 10^{-16}$), supporting spatial specifications. Across all models, private not-for-profit institutions report COA gaps approximately $1,300 more negative than public institutions, indicating greater underreporting after controlling for tuition, locale, enrollment, and selectivity. The spatial autoregressive parameter is highly significant: $\rho = 0.282$ (SAR), $\lambda = 0.283$ (SEM), and $\rho = 0.274$ (SDM).

Table 4: Cross-Sectional Spatial Regression (2023, $N = 1{,}525$)

	OLS (1)	**SAR** (2)	**SEM** (3)	**SDM** (4)
Tuition ($k)	8.3	8.7	9.3	9.1
Private Not-for-Profit	−1,319***	−1,323***	−1,338***	−1,335***
FTE (log)	−41.6	−38.8	−31.4	−29.1
Acceptance Rate	−4.6	−3.5	−3.0	−2.8
Spatial parameter	—	$\rho = 0.282$***	$\lambda = 0.283$***	$\rho = 0.274$***
Log Likelihood	—	−14,767	−14,768	−14,762

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Locale dummies included but omitted. Dependent variable: COA Gap ($). ρ = spatial lag parameter (SAR, SDM); λ = spatial error parameter (SEM). SDM additionally includes spatially lagged covariates. Sample restricted to institutions with non-missing acceptance rate.

Table 5 reports SDM direct, indirect, and total effects. The key finding is that neighboring rural contexts exert substantial *downward* pressure on COA reporting. Specifically, the indirect (spillover) effect of Rural Fringe (locale 41) is −$3,524 ($p = 0.02$), indicating that institutions whose neighbors are in rural fringe areas report gaps approximately $3,500 lower than otherwise comparable institutions. Similarly, the total effect for Remote Rural (locale 43) is −$3,335, also reflecting significant downward pressure. Private status has a large direct effect (−$1,337, $p = 0.002$) but an insignificant indirect effect, suggesting that an institution's own sector matters more than its neighbors' sectors.

Table 5: SDM Impact Decomposition (2023)

	Direct	**Indirect**	**Total**
Tuition ($k)	9.1	−0.8	8.3
Private Not-for-Profit	−1,337***	−50	−1,387
Locale: Rural Fringe (41)	−1,150*	−3,524**	−4,673***
Locale: Remote Rural (43)	−2,275**	−1,060	−3,335*
FTE (log)	−36.9	−222.2	−259.0
Acceptance Rate	−3.3	−14.2	−17.5

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Simulated p-values based on 500 Monte Carlo draws. Direct effects represent the impact of an institution's own characteristics on its own COA Gap (including spatial feedback). Indirect effects represent spillovers from neighboring institutions' characteristics. Negative values indicate downward pressure on the COA Gap (i.e., toward greater underreporting).

5.4 Spatial Panel Results (2010–2023)

Table 6 presents spatial panel estimates. The spatial lag parameter (ρ) remains highly significant across all specifications ($p < 2.2 \times 10^{-16}$), confirming that spatial dependence in COA reporting persists after controlling for institution and year fixed effects. Tuition and FTE enrollment are both positively associated with the COA gap within institutions: a $1,000 tuition increase corresponds to a $59 increase in the gap, and a one-unit increase in log FTE (approximately 172% enrollment growth) corresponds to a $482 increase.

Table 6: Spatial Panel Models (Balanced Panel, 1,057 Institutions × 14 Years)

	TWFE (M2)	**SAR Panel** (M4)	**SEM Panel** (M5)	**TWFE (w/ accept.)** (M3)
Tuition ($k)	60.8***	59.2***	58.3***	50.2***
FTE (log)	479.6***	481.6***	493.6***	119.9
Acceptance Rate	—	—	—	3.2*
Spatial parameter	—	$\rho = 0.139$***	$\lambda = 0.138$***	—
Observations	14,798	14,798	14,798	11,228
Institutions	1,057	1,057	1,057	802

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All models include institution and year fixed effects. SAR = Spatial Autoregressive lag model (ρ); SEM = Spatial Error Model (λ). M3 uses a smaller balanced panel restricted to institutions with non-missing acceptance rates in all 14 years.

Robustness checks across alternative neighborhood definitions ($k = 3, 10$), benchmark specifications (alone vs. roommate; alternative health benchmarks), and sample restrictions (excluding institutions with < 5 neighbors, excluding 2020 COVID year) confirm the panel SAR result. The spatial autoregressive coefficient remains positive and statistically significant across all specifications, with ρ values ranging from 0.09 to 0.27. Full estimates are reported in Appendix Table A1.

Figure 4 visualizes this robustness. The spatial parameter is positive and significant across all eight specifications, ranging from 0.087 ($k = 3$) to 0.267 (single-occupancy gap). Public institutions exhibit spatial dependence nearly twice as strong as private institutions ($\rho = 0.251$ vs. 0.136), consistent with public universities competing more intensively within shared state funding environments.

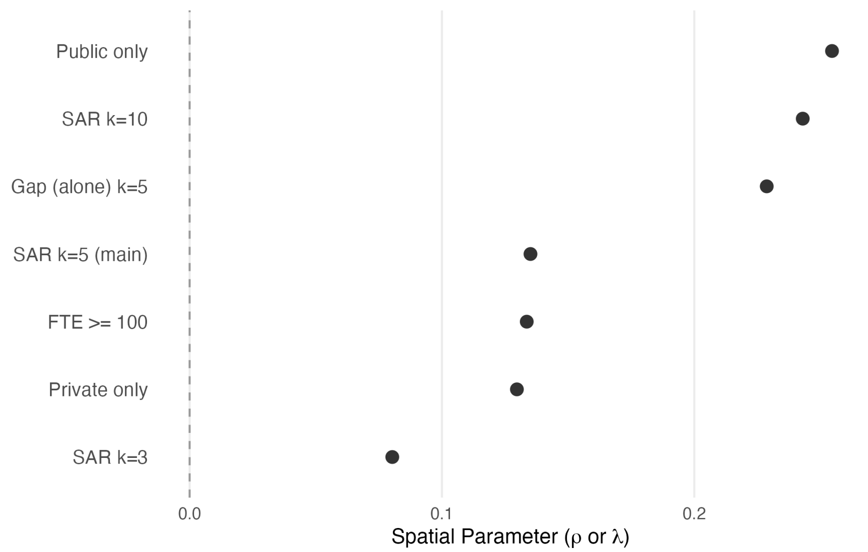

Figure 4: Spatial Parameter Across Panel Specifications

5.5 Border Discontinuity

Table 7 presents results from the border discontinuity design. The sample includes institutions within 50 km of a state border, yielding approximately 29,000 observations across the 14-year panel. The key coefficient is the cross-border difference in state appropriation per FTE, measured in thousands of dollars.

Across all specifications, the appropriation difference has no statistically significant effect on COA gaps. In the preferred specification with border-pair fixed effects, year fixed effects, a distance polynomial, and institutional controls (column 3), a \$1,000 increase in own-state appropriation relative to the neighboring state is associated with a \$7.8 decrease in the COA gap, but the standard error (22.5) renders this estimate indistinguishable from zero. The gap (alone) specification (column 4) and in-state tuition (column 5) are similarly insignificant. Only the estimated living cost outcome (column 6) shows a significant positive effect (\$40.5, $p < 0.05$), reflecting genuine cross-border differences in local costs of living rather than strategic reporting behavior.

Table 7: Border Discontinuity: Cross-Border Appropriation Difference and COA Gap (50 km Bandwidth)

	Gap (Roommate)			**Gap (Alone)**	**Tuition In-State**	**Est. Living Cost**
	(1)	(2)	(3)	(4)	(5)	(6)
Approp. Diff. (\$1K)	−9.4	−13.1	−7.8	−44.6	−24.5	40.5**
	(21.9)	(22.5)	(22.5)	(30.6)	(98.2)	(18.0)
Border Dist. (km)		66.0**	65.8***	88.6***	−19.2	−17.8
		(24.9)	(23.8)	(29.3)	(157.2)	(17.5)
Border Dist.^{2}		−1.0*	−1.0*	−1.4**	0.2	0.4
		(0.5)	(0.5)	(0.6)	(3.4)	(0.3)
Border-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls			Yes	Yes	Yes	Yes
Observations	33,812	33,812	29,262	29,262	29,262	29,262
R^2	0.169	0.175	0.215	0.313	0.634	0.894

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the state level in parentheses. Controls include FTE enrollment, acceptance rate, and sector. Border-pair FE absorb time-invariant differences between each pair of adjacent states. Sample restricted to institutions within 50 km of a state border.

Figure 5 displays the geographic RD plot. Binned means of the COA gap are plotted against signed distance to the state border, with separate quadratic fits on each side. The fitted curves show no sharp discontinuity at the boundary; confidence bands overlap substantially at the cutoff. McCrary density tests fail to reject the null of no sorting at the boundary ($p > 0.05$), confirming that institutional locations are not strategically selected relative to state borders. However, placebo tests on predetermined covariates reveal significant discontinuities in FTE enrollment, acceptance rate, and retention rate at the boundary (Appendix Table A4), reflecting systematic cross-state differences in institutional composition—for instance, states differ in their mix of flagship universities, land-grant institutions, and private colleges. The very narrow MSE-optimal bandwidths selected by the nonparametric estimator (2–8 km) indicate that these differences are sharpest for institutions immediately adjacent to the border. This covariate imbalance is a limitation of the geographic RD approach and motivates the inclusion of institutional controls in the parametric border regressions. The null result on appropriation differences should therefore be interpreted with the caveat that the border design does not achieve full covariate balance, even though the parametric specification conditions on observable differences.

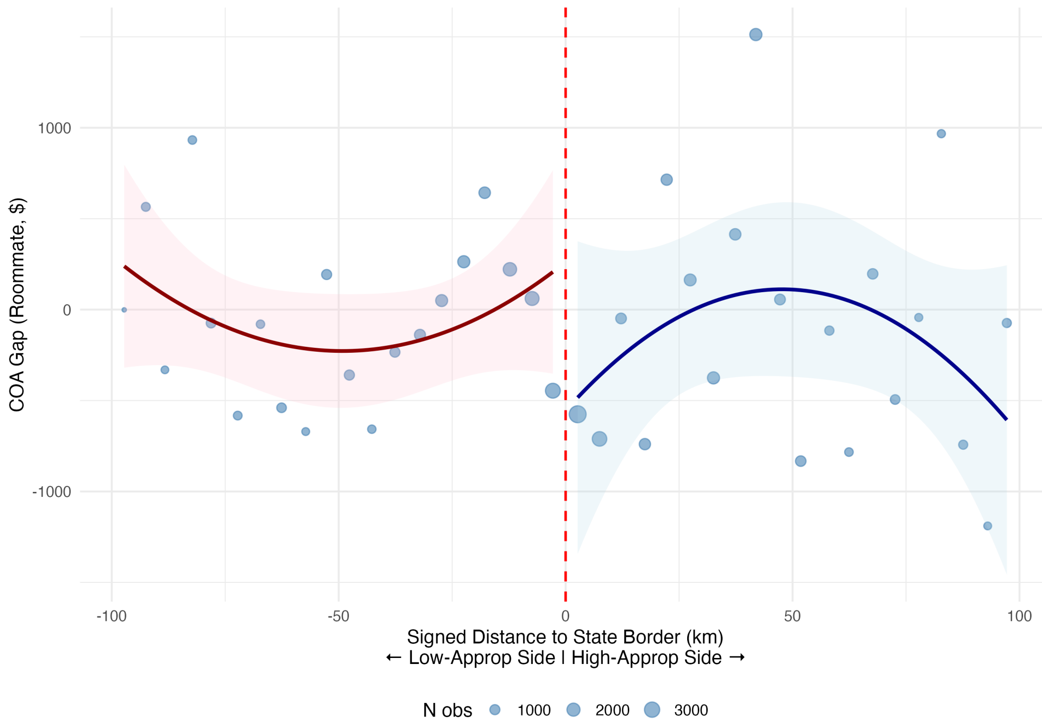

Figure 5: Border Discontinuity: COA Gap (Roommate) by Signed Distance to State Border

Notes: Bins = 5 km. Signed distance is positive for institutions on the higher-appropriation side of the border. Separate quadratic polynomial fits with 95% confidence bands on each side of the cutoff. Size of points proportional to number of observations per bin.

The null result is robust to bandwidth choice. Table A2 in the Appendix reports estimates for bandwidths of 25, 50, 75, and 100 km; point estimates remain small and insignificant at all bandwidths. The border heterogeneity analysis (Appendix Table A3) finds no differential effect for public versus private institutions within the border band.

5.6 State Appropriation IV

State appropriations directly affect only public institutions; private institutions receive negligible direct funding from state higher education budgets and have no theoretical reason to adjust reported living costs in response to state fiscal fluctuations. The IV identification strategy is therefore most coherently interpreted as a public-institution treatment, and we present the public-institution Bartik IV estimate as the primary specification. A private-institution placebo, pooled full-sample estimates, and additional supplementary analyses are reported in Appendix Table A6 and Appendix Figures A2–A3.

The first stage confirms a strong positive relationship between the Bartik instrument and state appropriations per FTE, with first-stage F-statistics far exceeding the conventional threshold of 10 across all specifications (1,015.6 in the primary specification; 662.8 and 1,228.6 in the two robustness specifications). Full first-stage estimates are reported in Appendix Table A5. Table 8 presents the second-stage 2SLS estimates.

Table 8: IV Estimates: State Appropriation and COA Gap, Public Institutions

	OLS	**IV: Bartik (Primary)**	**IV: Excl. Recession+COVID**	**IV: Excl. Extreme States**
Approp/FTE ($1K)	113.9*	361.9**	420.6*	388.1***
	(63.9)	(143.1)	(229.8)	(143.4)
FTE Enrollment	0.032***	0.032***	0.036***	0.032**
	(0.011)	(0.012)	(0.012)	(0.013)
Acceptance Rate	15.154***	14.888***	15.068***	12.470**
	(5.331)	(5.208)	(5.367)	(5.942)
Observations	7,012	7,012	4,700	5,943
First-stage F	—	1,015.6	662.8	1,228.6
R^2	0.313	0.314	0.308	0.298
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the state level (in parentheses). Sample restricted to public four-year institutions. Approp/FTE ($1K) is state appropriations per FTE in thousands of dollars. The dependent variable is the COA gap (roommate scenario), defined as reported off-campus living cost minus externally benchmarked estimate, in dollars. The Bartik shift-share instrument is constructed from base-year (2010) state shares of national appropriations interacted with leave-one-out national mean appropriation per FTE. Column 2 reports the primary specification; columns 3 and 4 report robustness checks excluding 2010–2012 and 2020–2021 (recession and COVID years) and the five highest and five lowest states by appropriation per FTE, respectively. First-stage F-statistics in all IV specifications far exceed the conventional threshold of 10, indicating no weak-instrument concerns. A private-institution placebo, pooled full-sample estimates, and a rolling-window dynamic analysis are reported in Appendix Table A6 and Appendix Figure A3.

Column 1 reports the OLS baseline. The coefficient is positive and marginally significant at $113.9 per $1,000 of state appropriation per FTE ($p < 0.10$, SE = 63.9). Column 2 reports the primary Bartik IV estimate, which is substantially larger at \$361.9 per \$1,000 ($p < 0.05$, SE = 143.1). The IV estimate exceeding the OLS estimate is consistent with attenuation bias in OLS from measurement error in state-level appropriation data and from the endogeneity of contemporaneous fiscal conditions to unobserved economic shocks. Mechanically, the IV estimate implies that a one-standard-deviation decline in state appropriations per FTE (approximately \$3,840) translates into roughly \$1,390 of reported-cost compression at the average public institution, indicating that the effect is economically meaningful as well as statistically significant.

The public-institution result admits a coherent interpretation. When a state experiences an exogenous decline in higher education funding, public universities face intensified competitive pressure: they must attract students in a tighter fiscal environment, strengthening incentives to keep reported costs low. The living cost component of COA, which institutions self-report with full discretion, absorbs this pressure. The net effect is a compression of reported costs relative to what students actually face.

The primary public-institution estimate is supported by two corroborating analyses reported in Appendix Table A6. The private-institution placebo specification yields a coefficient indistinguishable from zero (-3.5, SE = 345.3), supporting the interpretation that the channel operates specifically through state-funding pressure on public institutions rather than through a confound affecting all sectors. The pooled full-sample IV yields a smaller and statistically insignificant estimate (\$135.2, SE = 271.9), consistent with mechanical attenuation when half of the sample is conceptually unaffected by the treatment.

Columns 3 and 4 of Table 8 report robustness checks on the primary Bartik IV specification. Excluding the Great Recession recovery (2010–2012) and COVID period (2020–2021) yields a larger but less precise estimate (\$420.6, $p < 0.10$, SE = 229.8) on a sub-sample of 4,700 institution-years, reflecting both the more conservative within-period variation and the smaller effective sample. Excluding the five highest and five lowest states by appropriation per FTE yields an estimate of \$388.1 ($p < 0.01$, SE = 143.4), tightly clustered around the primary estimate and significant at the 1% level. A rolling-window dynamic analysis (Appendix Figure A3) shows that estimates are stable and centered during normal fiscal periods (2013–2018), with wider confidence intervals during the post-recession and COVID windows when the Bartik instrument loses first-stage power. The convergence of the OLS and IV estimates in direction, the robustness of the IV estimate across alternative samples, and the null result in the private-institution placebo jointly support the interpretation that exogenous declines in state funding causally compress reported living costs at public institutions.

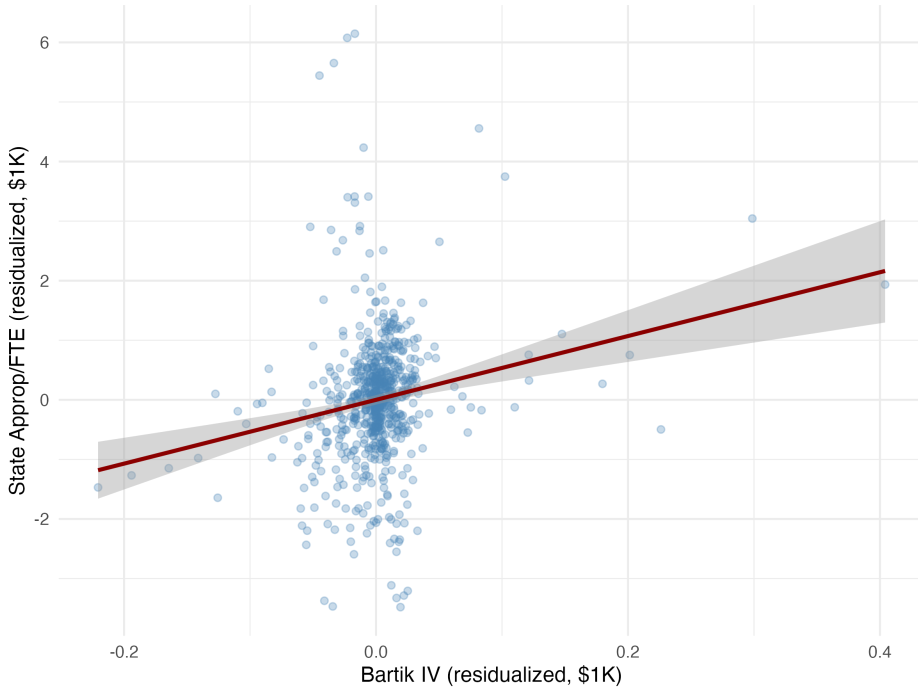

Figure 6: First-Stage Relationship: Bartik Shift-Share and State Appropriation per FTE (Residualized)

Notes: Each point represents a state-year observation. Both axes are residualized on state and year fixed effects. The fitted line shows the first-stage OLS relationship with 95% confidence band. The state-year level relationship displayed here is invariant to whether the second-stage sample is restricted to public institutions.

Figure 6 displays the residualized first-stage relationship. After partialing out state and year fixed effects, the Bartik instrument retains a clear positive linear relationship with actual appropriation, confirming instrument relevance.

6 Limitations

Several caveats warrant acknowledgment. The benchmark relies on assumptions about housing arrangements, academic year duration, and nationally uniform transportation costs, and while robustness checks yield consistent results, the true cost of student living is inherently unobservable. The spatial models cannot definitively distinguish strategic mimicry from correlated responses to spatially shared shocks, though the convergence of evidence across cross-sectional spatial Durbin models, panel SAR specifications, and the public-institution IV result strengthens the strategic interaction interpretation. The border discontinuity faces challenges from cross-state covariate imbalance in institutional composition, partially addressed through parametric controls. The Bartik IV rests on the assumption that national fiscal conditions affect public institutions only through state appropriations; within-state heterogeneity in how appropriations are distributed across institutions introduces additional measurement error, since SHEEO data capture aggregate state-level funding rather than institution-specific allocations. Despite these limitations, the convergence of evidence across multiple identification strategies provides a more comprehensive picture of COA reporting behavior than any single method alone. The consistency of the spatial dependence findings across alternative neighborhood definitions, benchmark specifications, and sample restrictions further strengthens confidence in the central conclusion that underreporting is a persistent and competitively structured feature of the federal aid system.

7 Discussion

Measuring the costs of college attendance is not merely a technical exercise; it is a policy-consequential information problem with distributional stakes (Winston, 2000). Discrepancies between estimated budgets and actual student costs lead to unexpected financial burdens; limits on students' use of financial aid to afford the full cost of attendance; and ultimately, to suboptimal student outcomes and experiences (Keefe, 2024; Kelchen et al., 2017; Kendall et al., 2020). This study expands our understanding of the disconnect between published COAs and potential student costs along three dimensions. It documents that underreporting is a persistent feature of the federal aid system rather than a transient anomaly, providing the first longitudinal evidence at a national scale. It shows that reporting behavior exhibits the spatial signatures of strategic interaction among geographically proximate institutions, evidence that prior work had inferred from practitioner surveys but not directly tested. And it identifies a causal channel through which state fiscal pressure compresses reported living costs at public institutions.

7.1 Summary of Findings

Three findings emerge from the analysis. First, approximately half of institution-years report off-campus living costs below the externally benchmarked estimate, and this pattern persists across the full 14-year observation window rather than concentrating in any particular year. The cross-sectional variation that Kelchen et al. (2017) documented in a single-year snapshot is a structural feature of the federal COA construction process rather than a transient anomaly.

Second, underreporting is spatially clustered. The spatial autoregressive parameter is positive and significant across all specifications ($\rho = 0.09$–0.27) and remains so after absorbing institution and year fixed effects, with public institutions exhibiting spatial dependence nearly twice as strong as private institutions ($\rho = 0.251$ vs. 0.136). The result is robust to alternative neighborhood definitions, benchmark specifications, and sample restrictions. Third, exogenous declines in state appropriations causally compress reported living costs at public institutions ($362 per $1,000 decline, $p < 0.05$), while a border discontinuity design finds no corresponding cross-sectional jump at state boundaries. Taken together, the IV and border results indicate that the funding-reporting link operates through within-state temporal shocks rather than persistent cross-state level differences.

7.2 Implications for Policy and Practice

Our findings point to multiple implications for policy and practice. At the highest level, if competitive pressures from among neighboring institutions is potentially discouraging accurate reporting, and creating a coordination failure (Winston, 1999), federal policymakers should consider playing a stronger oversight role in the construction of COAs. There are tradeoffs to standardizing this process, as students' ultimate expenses will depend on their own individual choices. However, we echo others (Baum et al., 2023) by emphasizing that some level of standardization, particularly for indirect and off-campus living expenses, in COA construction would be helpful in offering more accurate cost estimates to potential students and families. For example, the Department of Education could mandate the inclusion of additional considerations like regional costs, living arrangements, or family make up which can aid in getting a fuller picture of the range of non-tuition expenses students may face (Baum et al., 2023; Shireman et al., 2018). With or without additionally mandated criteria, federal policymakers should consider offering financial aid offices additional support as they strive to communicate costs to students. For example, leveraging federal resources to vet lists of standardized data sources or offering analytic assistance in surveying students to create robust and relevant measures of realized costs (Coles et al., 2020; National Association of Student Financial Aid Administrators (NASFAA), 2025a, 2025b). Such standardization would not wholly address the competitive pressures schools face to keep COAs in line with peer regional institutions (Goldrick-Rab, 2016), but linking COA to externally auditable benchmarks, and offering analytic support for data collection, would offer aid offices much needed support to fill this important function, while eliminating some of the discretion that enables strategic underreporting and remove the coordination failure that prevents any single institution from unilaterally correcting its figures. It may be particularly helpful to complement these efforts with more robust oversight of other cost estimation tools (e.g., net price calculators, aid award letters; see Perna et al., 2021) to ensure that the communication of the COA is also transparent and easy to understand. Because underreporting clusters geographically, federal accountability tools that aggregate institutional COA reports without external adjustment systematically overstate affordability in regions where peer institutions collectively suppress reported costs. Embedding a regional benchmark cross-check into the College Scorecard and net price calculator templates, in which institutional figures are compared against county-level external data sources, would correct this distortion at the presentation layer even before institutional reporting practices change.

The differential strength of spatial dependence by sector further informs the design of federal standardization. Public institutions exhibit spatial reporting interdependence nearly twice as strong as private institutions ($\rho = 0.251$ vs. 0.136), indicating that the competitive coordination failure federal standardization seeks to address is more pronounced in the public sector. A uniform regulatory framework would therefore deliver its largest marginal benefits at public institutions, though applying it uniformly across sectors preserves the simplicity and external credibility of a single national standard.

State policymakers also have a role to play. As our IV results suggest, state appropriation cycles introduce invisible variation in the accuracy of published costs, with public institutions compressing reported living costs by approximately \$362 per \$1,000 decline in funding. Because students cannot observe the relationship between fiscal shocks and reporting behavior, they are exposed to fluctuations in cost-information accuracy that are entirely beyond their control. However, state leaders must recognize that failing to offer robust state funding naturally forces schools to pull other levers to accrue resources, including leveraging pricing strategies to manage enrollment-based revenues (Bound et al., 2019; Hillman, 2012). Constraining institutional latitude in cost estimation and communication strategies without stable state investments could unintentionally harm the institutions in a costly, competitive market.

However, addressing the calculation and communication of the COA is only part of the issue. Policymakers and institutional leaders also need to combat the real affordability crisis facing students by subsidizing more than tuition and fees. Schools could consider subsidizing housing costs, particularly in expensive areas; addressing food insecurity; or subsidizing child-care and transportation (Broton et al., 2020; Coles et al., 2020), which would reduce the negative impacts of unforeseen non-tuition costs serving as significant barriers to student success. Absent an investment in direct financial support, school leaders should minimally ensure relevant staff are equipped to support students as they navigate these needs. Recent analyses suggest financial aid staff may be less familiar with the availability of non-tuition related supports (e.g., subsidized childcare, emergency housing) on their campuses (Conroy et al., 2021). Ensuring that this information is readily available and accessible for staff and students would at least help individuals leverage pre-existing resources that may be going overlooked.

7.3 Future Directions

Our work also points to avenues for future research. For example, future research could address the limitations outlined by this analysis by using network-based weights matrices that incorporate institutional peer relationships beyond pure geography to refine the spatial mimicry tests. Institution-specific appropriation data, where available from state higher education boards, could sharpen the IV identification. Scholars should also consider expanding the scope of this COA interrogation to include two-year and for-profit institutions. These schools serve disproportionately low-income populations; observing their cost estimation trends would provide a more complete picture of COA reporting behavior across the postsecondary sector and for this important student population. Given that at least some gaps between expected and realized costs are still likely to occur even amidst a standardization of COA calculation, future qualitative work would also be helpful in identifying how financial aid officers and other frontline staff can support students as they navigate unforeseen expenses.

Appendix

A.1 Detailed Construction of Spatial Weights Matrix

This appendix presents the full construction of the spatial weights matrix $\mathbf{W}$ used throughout the spatial analyses. For institutions i and j, the binary connectivity indicator is:

$$w_{ij}^* = \begin{cases} 1 & \text{if } j \in \mathcal{N}_k(i) \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

where $\mathcal{N}_k(i)$ denotes the set of k institutions with the smallest great-circle distance to institution i. The great-circle distance is computed as:

$$d_{ij} = R \cdot \arccos\bigl(\sin\phi_i \sin\phi_j + \cos\phi_i \cos\phi_j \cos(\lambda_j - \lambda_i)\bigr) \tag{13}$$

with (ϕ_i, λ_i) denoting latitude and longitude in radians and $R = 6{,}371\,\text{km}$. The matrix is row-standardized so that each row sums to unity:

$$w_{ij} = \frac{w_{ij}^*}{\sum_{j=1}^{N} w_{ij}^*}, \qquad w_{ii} = 0 \tag{14}$$

Under row-standardization, the spatial lag $\mathbf{Wy}$ for institution i equals the simple average of its k nearest neighbors' outcomes. The primary specification uses $k = 5$; robustness checks reported throughout the paper use $k = 3$ and $k = 10$. KNN is preferred to a fixed distance band because institutions are geographically clustered in metropolitan areas but sparsely distributed in rural regions; a fixed radius would yield drastically different neighbor counts across institutions and would leave isolated institutions disconnected from the spatial structure.

A.2 Spatial Error Model and LM Diagnostic Procedure

The cross-sectional analysis selects among OLS, SAR, SEM, and SDM specifications using a hierarchical Lagrange Multiplier diagnostic procedure. This appendix presents the SEM specification and the diagnostic procedure in full.

Spatial Error Model (SEM)

The Spatial Error Model posits spatially correlated disturbances rather than endogenous spatial dependence:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}, \qquad \mathbf{u} = \lambda \mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \tag{15}$$

where λ captures spatial autocorrelation in unobserved factors. Unlike the SAR, the SEM does not attribute spatial dependence to strategic interaction among institutions; rather, it reflects spatially correlated omitted variables such as regional housing market shocks or local labor market conditions. The reduced form is $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + (\mathbf{I} - \lambda\mathbf{W})^{-1}\boldsymbol{\varepsilon}$.

LM Diagnostic Procedure

We begin model selection with OLS:

$$y_i = \mathbf{x}_i'\boldsymbol{\beta} + \varepsilon_i \tag{16}$$

where $\mathbf{x}_i$ includes tuition, sector, locale fixed effects, log FTE enrollment, and acceptance rate. The robust LM tests of Anselin et al. (1996) evaluate two forms of spatial dependence in the OLS residuals: LM-lag tests $H_0 : \rho = 0$ (no endogenous spatial lag), and LM-error tests $H_0 : \lambda = 0$ (no spatially correlated errors). When both LM-lag and LM-error statistics reject the null, the robust versions of each statistic indicate which form of dependence is dominant. In the present application, both forms are present and the SDM nests both, motivating the SDM as the preferred specification (Equation 2 in the main text).

The LM-lag and LM-error statistics for the 2023 cross-sectional sample are reported alongside the cross-sectional spatial regression results in Table 4 of the main text.

A.3 Panel SEM Specification and Matrix Notation

This appendix presents the matrix notation for the panel SAR specification and the corresponding panel SEM specification not reported in the main text.

Matrix Notation for Panel SAR

The panel SAR specification in Equation 4 of the main text can be written in stacked matrix form across all T time periods:

$$\mathbf{y} = \rho(\mathbf{I}_T \otimes \mathbf{W})\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + (\boldsymbol{\iota}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + (\mathbf{I}_T \otimes \boldsymbol{\iota}_N)\boldsymbol{\gamma} + \boldsymbol{\varepsilon} \tag{17}$$

where $\otimes$ denotes the Kronecker product, $\boldsymbol{\iota}$ is a vector of ones, $\boldsymbol{\alpha}$ stacks the institution fixed effects, and $\boldsymbol{\gamma}$ stacks the year fixed effects. The Kronecker structure $\mathbf{I}_T \otimes \mathbf{W}$ implies that spatial dependence operates within each year (the same weight matrix applies to each time period) but not across years.

Panel SEM Specification

The panel SEM replaces the spatial lag with spatially correlated errors:

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \alpha_i + \gamma_t + u_{it}, \qquad u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \tag{18}$$

The parameter λ captures spatial correlation in unobserved time-varying shocks. The panel SEM provides a useful comparison to the panel SAR because a finding that $\hat{\rho}$ in the SAR remains significant while $\hat{\lambda}$ in the SEM is small would strengthen the strategic interaction interpretation against the alternative that residual spatial dependence reflects spatially correlated unobservables.

Software Convention

The `splm` package in R labels the spatial lag coefficient as λ in its output. Throughout this paper, we follow the more common convention in the spatial econometrics literature: ρ denotes the spatial lag parameter (in SAR and SDM specifications) and λ denotes the spatial error parameter (in SEM specifications), regardless of software labeling.

A.4 Nonparametric RD Estimation and Validity Tests

This appendix presents the nonparametric local polynomial RD estimator used as a complement to the parametric border discontinuity design (Equation 6), along with details of the distance construction and validity tests.

Distance Construction

Using the Knight and Schiff (2019) zipcode-to-border distance dataset, we match each institution to its nearest zipcode and inherit that zipcode's distance to each state boundary. For each institution, we exclude its home state and identify the state boundary that minimizes d_i. This yields the nearest neighboring state $s'(i)$ and the border pair identifier $p(i) = \{\min(s, s'), \max(s, s')\}$, used as fixed effects in the parametric specification.

Nonparametric Local Polynomial RD

As a complementary approach to the parametric border regression, we estimate nonparametric local polynomial RD models using the bias-corrected estimator of Calonico et al. (2014):

$$\hat{\tau}_{\text{RD}} = \hat{\mu}_+(0) - \hat{\mu}_-(0) \tag{19}$$

where $\hat{\mu}_+(0)$ and $\hat{\mu}_-(0)$ are local polynomial estimates of $E[y_i \mid \tilde{d}_i = 0^+]$ and $E[y_i \mid \tilde{d}_i = 0^-]$, respectively, using a triangular kernel with MSE-optimal bandwidth selection. The bias-corrected estimator and robust variance estimator follow the procedure implemented in the `rdrobust` package.

Validity Tests

Two sets of validity tests evaluate the RD identifying assumptions. First, a McCrary density test (McCrary, 2008) examines whether the density of the running variable exhibits a discontinuity at the cutoff, which would indicate manipulation (i.e., institutions sorting across the border in response to appropriation differences). Second, placebo tests examine whether predetermined institutional covariates (FTE enrollment, acceptance rate, retention rate) exhibit discontinuities at the border. Significant covariate discontinuities would suggest that cross-border differences in institutional composition confound the estimate of the appropriation effect. Placebo results are reported in Appendix Table A4.

A.5 Peer-State Leave-One-Out Instrument

In addition to the Bartik shift-share instrument presented in the main text, we considered a peer-state leave-one-out mean instrument as an alternative identification strategy. The peer-state instrument defines, for each state s in year t, the average appropriation per FTE of all other states:

$$Z_{s,t}^{\text{Peer}} = \frac{1}{S-1} \sum_{s' \neq s} \frac{\text{Approp}_{s',t}}{\text{FTE}_{s',t}} \tag{20}$$

The identifying logic is that national funding trends, captured by the peer-state mean, predict state-level appropriations through political and fiscal contagion across states, while remaining plausibly exogenous to any individual state's local conditions after absorbing state and year fixed effects.

The first-stage F-statistic for this instrument was below conventional thresholds ($F \approx 7.8$), indicating insufficient identifying strength. The coefficient on the peer-state instrument was also negative, reflecting the near-zero-sum structure of cross-state appropriation deviations after absorbing year fixed effects: when most other states experience above-average funding in a given year, the within-year deviations from the year mean must on average cancel, and the residual variation in peer-state mean conditional on year fixed effects becomes mechanically negatively correlated with own-state appropriation in a way that does not reflect economic substance.

For these reasons, the Bartik shift-share design presented in Section 4 (main text) is the preferred IV specification. Full peer-state IV estimates are reported in Table A7.

Table A1: Robustness of Spatial Panel Results

Specification	$\boldsymbol{\rho}$	**Tuition**	**FTE (log)**	**N (inst.)**
Main: SAR $k = 5$	0.139***	59.2***	481.6***	1,057
SEM $k = 5$	0.138***[a]	58.3***	493.6***	1,057
Gap (alone) $k = 5$	0.267***	54.5***	364.9***	1,057
SAR $k = 3$	0.087***	60.1***	488.9***	1,057
SAR $k = 10$	0.251***	56.9***	463.6***	1,057
FTE ≥ 100	0.151***	57.7***	554.9***	992
Private only	0.136***	85.7***	315.2***	636
Public only	0.251***	82.6**	885.5***	417

Notes: All models are spatial panel with two-way (institution + year) fixed effects. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All spatial parameters significant at $p < 2.2 \times 10^{-16}$. [a]SEM row reports the spatial error parameter λ rather than the lag parameter ρ.

Table A2: Border Discontinuity: Bandwidth Sensitivity

Bandwidth	25 km	50 km	75 km	100 km
Approp. Diff. ($1K)	−11.2	−7.8	−5.1	−4.8
	(31.2)	(22.5)	(19.4)	(17.9)
Observations	14,628	29,262	38,440	44,026

Notes: All specifications include border-pair FE, year FE, distance polynomial, and controls. State-clustered SE.

Table A3: Border Discontinuity: Public vs. Private Heterogeneity (50 km Bandwidth)

	Public	**Private**
Approp. Diff. ($1K)	−27.1	1.7
	(38.8)	(25.3)
Observations	10,582	18,680

Notes: Border-pair FE, year FE, distance polynomial, and controls. State-clustered SE.

Table A4: Placebo RD: Predetermined Covariates at State Border

	FTE	**Accept**	**Retention**	**Est. Cost**
RD Estimate	3,942***	−9.15***	6.89***	40.5**
Bandwidth (km)	2.2	3.5	7.7	50.0

Notes: Nonparametric local polynomial RD with MSE-optimal bandwidth (Calonico et al., 2014). Significant placebo effects indicate covariate imbalance at state borders.

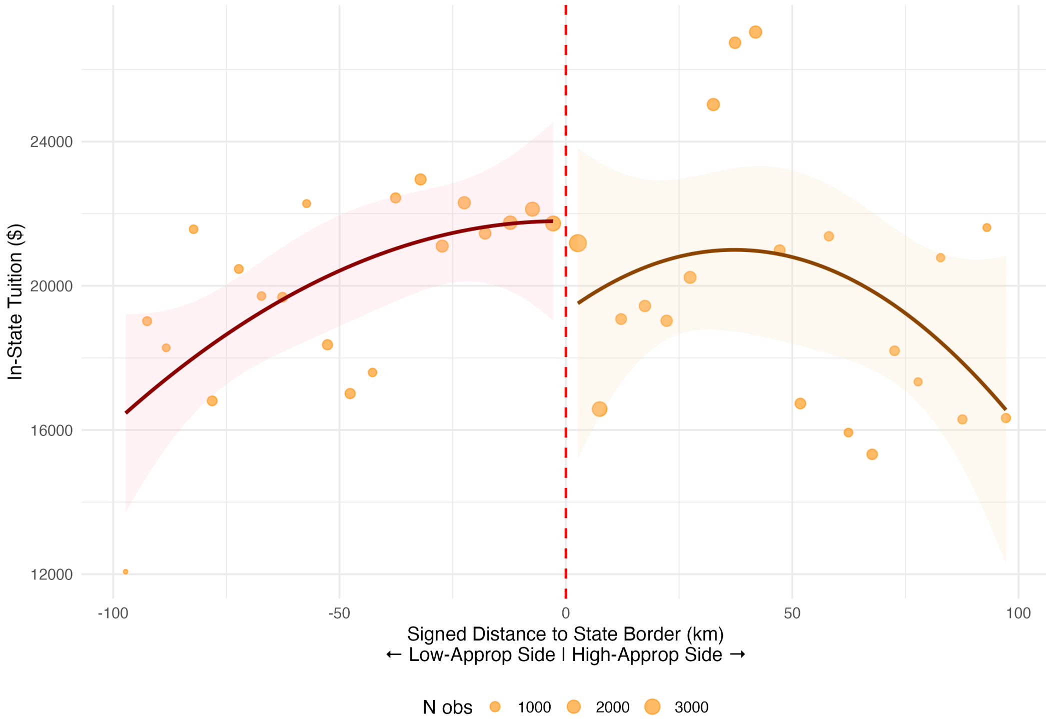

Figure A1: Border Discontinuity: In-State Tuition by Signed Distance to State Border

Table A5: First Stage: Bartik Shift-Share Instrument

	Public-Only (Primary)	**Full Sample**
Bartik IV ($1K)	6.083***	6.659***
	(1.492)	(1.400)
FTE Enrollment	−0.000	−0.000
	(0.000)	(0.000)
Acceptance Rate	−0.001	−0.001
	(0.001)	(0.000)
Private (=1)	—	−0.031**
		(0.014)
Observations	7,012	20,614
R^2	0.916	0.922
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the state level (in parentheses). The dependent variable is state appropriation per FTE in thousands of dollars. The Bartik shift-share instrument is constructed from base-year (2010) state shares of national appropriations interacted with leave-one-out national mean appropriation per FTE. Column 1 reports the first stage for the primary specification reported in Table 8, restricted to public four-year institutions. Column 2 reports the first stage for the pooled full-sample specification reported in Appendix Table A6. Both first stages yield strongly significant coefficients on the Bartik instrument, with F-statistics far exceeding the conventional threshold of 10 (1,015.6 for the public-only specification; reported in Table 8). The Private dummy in Column 2 indicates that private institutions on average report $31 lower state appropriations per FTE than public institutions in the pooled sample, consistent with their negligible direct state funding.

Table A6: Supplementary IV Estimates: Private Placebo, Pooled Full Sample, and Robustness

	OLS	**Bartik IV**
Panel A: Private-Institution Placebo (Private Institutions Only)		
Approp/FTE (\$1K) → Gap (Roommate)	—	−3.5
		(345.3)
Panel B: Pooled Full Sample (Public + Private)		
Approp/FTE (\$1K) → Gap (Roommate)	44.7	135.2
	(46.6)	(271.9)
Approp/FTE (\$1K) → Tuition (\$1K)	0.198**	0.157
	(0.087)	(0.194)
Panel C: Pooled Full-Sample Robustness (Bartik IV, Gap Roommate)		
Excl. Recession + COVID	—	190.3
		(329.9)
Excl. Top/Bottom 5 Appropriation States	—	177.7
		(269.6)
State FE, Year FE	Yes	Yes
Controls	Yes	Yes

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the state level (in parentheses). Controls include FTE enrollment, acceptance rate, and sector (where applicable). Panel A restricts the sample to private institutions and tests for any reporting response to state appropriations; the null estimate supports the interpretation that the primary effect (Table 8) operates specifically through state-funding pressure on public institutions. Panel B reports pooled full-sample estimates combining public and private institutions. The pooled IV estimate is mechanically attenuated relative to the public-only primary estimate because private institutions are conceptually unaffected by the treatment. The OLS coefficient on tuition (0.198, $p < 0.05$) appears counterintuitive but reflects within-state correlations between appropriation and tuition cycles in the two-way fixed-effects framework; the IV estimate (0.157) is positive but insignificant. Panel C reports robustness checks on the pooled estimate.

Table A7: Peer-State Leave-One-Out IV (Supplementary)

	Bartik IV	**Peer LOO**
Bartik IV (\$1K)	900.2	
Peer LOO (\$1K)		−256.2
First-stage F	11.4	7.8

Notes: State-clustered SE. Controls include FTE enrollment, acceptance rate, and sector. The Peer LOO reduced form is significant but should be interpreted cautiously given weak first-stage relevance.

Table A8: Reduced Form: Instruments and COA Gap (Roommate)

	Bartik	**Peer LOO**
Instrument ($1K)	900.2	−256.2
	(591.7)	(117.2)
Observations	20,614	20,614

Notes: State and year FE. State-clustered SE.

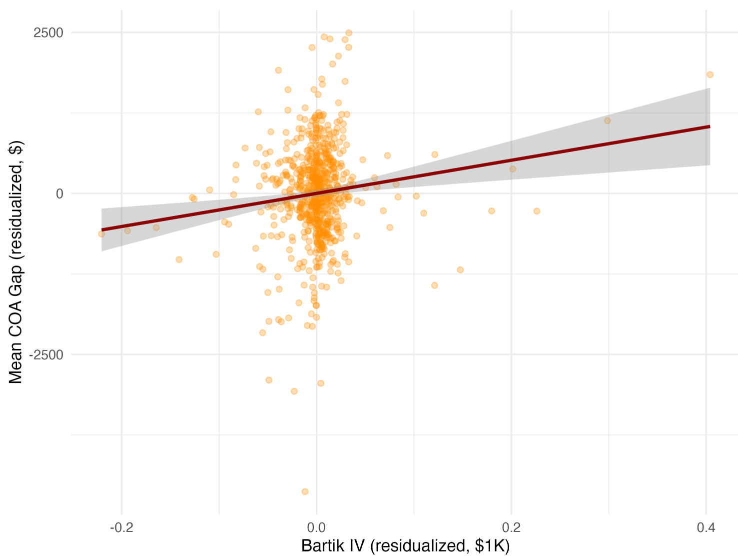

Figure A2: Reduced Form: Bartik IV and COA Gap (Residualized)

Notes: Each point represents a state-year observation. Both axes are residualized on state and year fixed effects. The positive slope indicates that states receiving negative Bartik shocks (funding declines) tend to have more compressed COA gaps (more underreporting), though the relationship is noisy and the reduced-form coefficient is insignificant ($p > 0.10$).

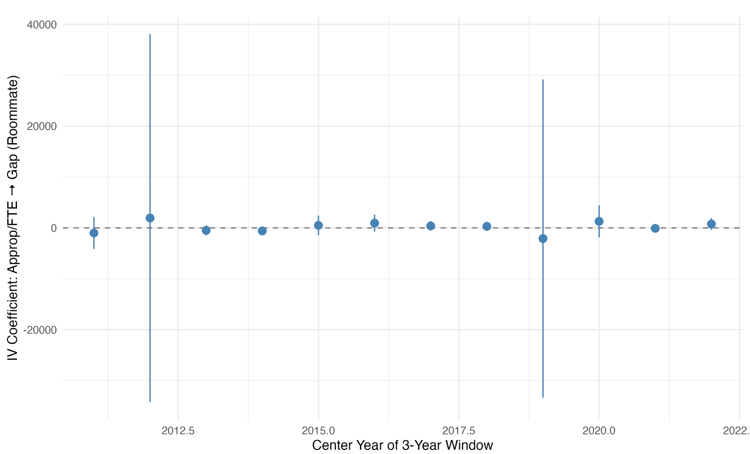

Figure A3: Dynamic IV Estimates (3-Year Rolling Window, Bartik Shift-Share)

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