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Financial Myopia in Closed Systems: How State Financial Monitoring Systems Can Ignore Local Constraints

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ABSTRACT

We examine how closed-system state financial monitoring can misrepresent local fiscal health by ignoring broader legal and regulatory contexts. Using Texas as a case study, we show that school districts financing debt with renewable energy revenues are penalized under the state's monitoring system due to higher debt-per-pupil levels despite responding rationally to state incentives. This case illustrates a form of financial myopia, where rational financial behaviors are penalized under a monitoring system. We provide causal evidence of this dynamic and argue for an open-systems approach to fiscal monitoring that recognizes the legal and fiscal environments shaping local financial decisions.

1 | Introduction

In recent decades, governments at all levels have adopted performance-based accountability systems to monitor the performance of public organizations (Moynihan 2003; Hannaway and Hamilton 2008; Han 2020; Yu et al. 2025). Public organizational performance, however, has multiple, sometimes conflicting, dimensions (i.e., efficiency, effectiveness, and equity) that are valued and assessed differently by different constituencies, e.g., regulators, employees, or clients (Behn 2003; Amirkhanyan et al. 2014; Song and Meier 2018). These monitoring systems are often designed by one constituency within a closed system without sufficient coordination from other constituencies. As a result, the system may ignore other performance-based accountability metrics, as well as other legal and regulatory regimes, imposed on a monitored government by other constituencies, thus creating conflicting incentives and signals about how local governments should behave.

We revisit the design of performance monitoring systems in the classical debate of closed versus open systems in public administration (Katz and Kahn 1966; Pfeffer et al. 2003; Nelson and Balu 2014). Closed systems view an organization as "sufficiently independent to allow most of its problems to be analyzed with reference to its internal structure and without reference to its external environment" (Trist 1969, 270). By contrast, open systems theory considers organizations to be highly complex and reactive with loosely linked system components, and thus it puts greater emphasis on organizational-environmental connections (Katz and Kahn 1966). We present a case of the failure of performance monitoring systems from the closed-systems perspective and propose an open-systems approach to organizational performance evaluation in the public sector.

We focus on financial monitoring systems, which are popular tools for state governments to monitor the fiscal health of their local governments. While the specifics of these systems vary from state to state, these systems assess the fiscal condition of a local government based on a set of financial and environmental metrics. These indicators, or a composite measure constructed from these indicators, are then compared to peer governments or against a state average (or state-set benchmark). The results of these evaluations are often published on public dashboards. While there are several policy aims of these monitoring systems—to enable legislatures to monitor local governments, to help residents monitor the fiscal health of their specific local government, provide information to external organizations, and so forth—one key aim is to provide local governments with this

Summary

- Closed performance monitoring systems can penalize local governments for financially rational decisions that respond to state law and external incentives.
- When monitoring systems are designed without accounting for rules imposed by other government bodies, local governments may not know how to respond.
- We find that Texas school districts that responsibly issue debt backed by wind energy-expanded tax bases are nonetheless penalized by the State's monitoring system for higher debt-per-pupil levels.
- Financial monitoring systems must adopt an open-systems perspective that accounts for the broader legal, regulatory, and environmental context in which local governments operate.

information so they can make any necessary changes in their financial management and improve their financial condition.

These financial monitoring systems, however, tend to operate as closed systems in which evaluation metrics are generated and assessed internally based on predefined rules or internal performance thresholds set without sufficient consideration for other regulatory regimes or constraints a government must operate under. For example, many state governments limit the ability for local governments to benefit from specific economic development initiatives, or state governments pass laws that incentivize local governments to make certain financial decisions that can negatively impact their perceived fiscal health. We argue that these closed systems can create financial myopia in which financial monitoring systems mismeasure the financial condition of a government that is responding rationally to other opportunities in ways that the monitoring system ignores. Thus, these closed monitoring systems may be blind to the complex realities influencing a government's financial condition.

In this paper, we provide a specific example of this financial myopia in which state law incentivizes certain fiscal and financial decisions of local governments for which these governments are subsequently punished for under the state's financial monitoring system. Specifically, we first demonstrate how, in the U.S. State of Texas, state law incentivizes (and constrains) Texas school districts to use revenue generated from renewable energy installations to finance local debt issuance and increase capital spending rather than increase current spending. Despite the fact that these renewable energy installations increase the local tax base of school districts and improve their financial position (as measured by assets per pupil and total revenue per pupil), we find that the Texas Education Agency (TEA) penalizes these school districts in their financial monitoring system due to higher debt per-pupil levels despite the fact that the taxable property base supporting these bond issues has increased. Thus, the TEA's financial monitoring framework punishes districts for rationally responding to the incentives embedded in state law that governs how these districts can fiscally benefit from renewable energy installations. To demonstrate these findings, we exploit variation in the location and timing of wind energy installations across school districts in Texas.

This paper contributes to the literature on financial monitoring systems and performance management by providing a case study of how a financial monitoring system ignores the legal and regulatory constraints under which many governments operate. The TEA system we examine is very similar in design to many other state and school district financial monitoring systems, and thus our results are generalizable to other states and localities. While previous studies have documented the importance of designing financial monitoring systems to prevent undesirable isomorphic convergence (Gerrish and Spreen 2017), moral hazard (Kim and Park 2023), among other issues, we show that financial monitoring systems designed within closed systems can create financial myopia, or a distorted view of local fiscal conditions in which the oversight system penalizes or overlooks rational financial decisions driven by regulatory requirements, environmental constraints, or emergent opportunities.

Moreover, this paper provides a novel contribution to the larger literature trying to understand the social impacts of wind turbines on communities and host governments. While there is a large literature examining the impact of wind energy on property values and public finances (Hoen et al. 2025; Brunner and Schwegman 2022a, 2022b; Cornaggia and Iliev 2023; Lidberg 2023), this is the first study to examine how the rapid increase in wind energy over the past several decades has impacted the perceived fiscal health of local governments and their ability to meet their financial and service obligations.

The remainder of the paper is structured as follows. We begin by discussing the literature on measuring the fiscal condition of local governments, the effectiveness of state monitoring systems, and the literature on closed versus open monitoring system approaches. We then discuss the Financial Integrity Rating System of Texas (FIRST), the Texas school district-specific financial monitoring system, and Texas state law as it pertains to wind energy installations. We then turn to a description of the data we utilize and our empirical methods before discussing our results and the implications of our findings.

2 | Background

2.1 | Measuring the Financial Condition of Governments

The fiscal condition (or fiscal health) of a government refers to its ability to meet its financial and service obligations in the short- and long-term across a number of different metrics (Gorina et al. 2018; McDonald 2018; Helpap 2016; Maher and Nollenberger 2009). As noted by Wang et al. (2007), Gorina et al. (2018), McDonald (2018), among others, there are four dimensions of fiscal condition: (1) the ability for a government to meet short-term financial obligations (i.e., cash solvency); (2) the ability for a government to meet its financial and service commitments over any particular fiscal year (i.e., budget solvency); (3) the capacity of a government to fulfill its long-term financial (particularly its debt and pension-related) obligations (i.e., long-term solvency); and (4) the ability for the government to maintain essential programs and services as required by law and/or at a level desired by its citizens (service solvency).

While there are many different methods of measuring fiscal condition, most methods can largely be classified into one of two approaches. Some studies, and many state fiscal health monitoring systems, construct a single composite measure (or classification) of fiscal condition (Brown 1993; 1996; Kloha et al. 2005; Maher and Nollenberger 2009; Gorina et al. 2018). Brown (1993) developed a 10-point test to assess the financial condition of small cities by aggregating various financial ratios into a single score. Kloha et al. (2005) later refined this method by incorporating changes over time and comparing cities against fixed benchmarks rather than against each other. The other common approach to measuring fiscal condition is to use disaggregated financial indicators, which can capture various dimensions of fiscal condition (Groves and Valente 1986; Wang et al. 2007; Maher et al. 2020).

Research examining the effectiveness of these state monitoring systems has found mixed results. While some studies highlight the potential benefits of strong fiscal oversight (Coe 2007; Rivenbark and Roenigk 2011; Kang and Chen 2024), Spreen and Cheek (2016) found that Michigan's Fiscal Stress Indicator System had little to no impact on the financial condition of local governments, suggesting that financial managers have limited ability to change fiscal positions in the short run. Benchmarking systems may also promote conformity rather than improvement. Gerrish and Spreen (2017) find that North Carolina's benchmarking tool led to isomorphic convergence toward the mean, rather than widespread financial improvement, as governments adjusted their practices to align with average peer performance. Coe (2008) suggests that while fiscal monitoring should ideally warn local governments of distress and recommend corrective actions, there is little evidence that such efforts consistently lead to better financial outcomes.

2.2 | Measuring Organizational Performance: Closed Versus Open Systems Approaches

Many of these financial monitoring systems are closed systems that consist of internally defined financial indicators and static benchmarks that may not fully account for the legal mandates, contextual limitations, or administrative trade-offs faced by local officials. These closed systems can lead to oversimplifications of the financial reality faced by local governments and public managers. Maher and Deller (2013), Leiser and Mills (2019), Leiser et al. (2021), and Park et al. (2023), for example, document weak associations between objective financial metrics and public managers' subjective assessments of fiscal condition, raising doubts about whether these systems accurately reflect managerial priorities or service realities. Relatedly, Kim and Park (2023) argue that while early warning systems can reduce information asymmetry between states and localities, performance gains are contingent on design—systems that emphasize (or unconditionally facilitate) bankruptcy over proactive engagement may foster moral hazard rather than reform. Together, these studies suggest that closed financial monitoring systems can create financial myopia in which the state (or some oversight body) misjudges a government's financial condition because the closed system overlooks or penalizes rational decisions made in response to external conditions, legal/regulatory mandates, or other opportunities.

More broadly, we propose that financial monitoring systems should adopt an open-system approach to evaluating organizational effectiveness (Kast and Rosenzweig 1972; Cunningham 1978; Martz 2013). The open-systems approach to organizational performance assessment maintains that "performance is best understood in terms of the entire organizational system and management's ability to control the environment" (Martz 2013, 388). Yuchtman and Seashore (1967) argue that a system-resource approach to organizational effectiveness must consider the interdependence between organizations and their environment and use an open-ended multidimensional set of performance measurements. Similarly, Rousseau (1979) argues that an open systems approach to assessing organizational processes should use "measures sensitive to environmental constraints and influences" (540).

This open-systems approach literature, however, has largely focused on private organizations that have significant discretion over their revenue sources and acquisition policies. Public organizations, by contrast, obtain resources mainly from taxes and face a different, more constrained regulatory environment. Therefore, we posit that an open systems approach to organizational performance must be tailored to the public sector to account for the differences between public and private organizations. While private firms can bargain with one another or strategically optimize their resources, public organizations rely on a more rigid set of revenue sources and must respond to regulatory and legal changes that can affect their resources. The performance measurements for public organizations must consider the multiplicity of the regulators, their different goals, and the totality of constraints imposed on a given organization.

2.3 | Our Context: Texas and the Texas FIRST System

To explore the financial myopia that can be created by a specific financial monitoring system, we rely on the Financial Integrity Rating System of Texas (FIRST), which Texas implemented in 2002. FIRST is designed to hold school districts accountable for their financial practices and encourage improvement. It uses audited financial reports and data submitted to the Texas Education Agency to assess areas such as fund balance levels, long-term financial health, audit quality, debt obligations, and compliance with state reporting rules. Based on this information, each district receives a numerical score from 0 to 100 that reflects both certain financial conditions and management practices. The TEA then uses these scores to assign one of four ratings: A (superior), B (above standard), C (meets standard), or F (substandard). An F indicates the district did not meet the minimum financial standards. These ratings are based on a set of fixed indicators, though the score cutoffs can change over time.

The performance ratings can be consequential for school districts. Within two months of releasing a final FIRST rating, a district must "announce and hold a public meeting to distribute a financial management report that explains the rating and its performance" (TEA 2022). The public meetings may draw attention from parents, taxpayers, legislators, and the media. For districts earning top ratings, FIRST can be an opportunity to obtain favorable media coverage or enhance community support. TEA considers FIRST ratings when assigning an accreditation status to a district. Failure to satisfy accreditation criteria or any financial accountability standards can result in various interventions and sanctions for districts. The Texas Education Code requires a district assigned a rating of "F" to submit a corrective action plan to address the financial weakness within one month after the public hearing.

While the FIRST system considers internal metrics like financial management performance, it does not consider (i.e., is closed to) other regulatory and legal constraints placed on school districts. In particular, the FIRST system ignores the constraints and incentives that Texas school districts face when they agree to host a large manufacturing or renewable energy project such as a commercial wind energy installation. Texas is a leader in wind energy development in the United States, and, as of 2022, it accounts for over a quarter of all wind energy generating capacity in the United States (Texas Comptroller of Public Accounts 2023). Importantly, Texas state law allows school districts to approve a property tax abatement agreement, known officially as a Chapter 313 agreement, which allows a temporary 10-year limit on the taxable value of a new wind project.[1] Most Chapter 313 agreements also require wind energy developers to make Payments in Lieu of Taxes (PILOTs) to the hosting school district. However, while the tax abatement limits any increase in the taxable value of property stemming from a new wind project that goes on a school districts tax rolls for maintenance and operations (M&O), the full increase in taxable value goes on a school districts tax rolls for debt service, known as interest and sinking (I&S) fund payments. Thus, even with a property tax abatement in place, school districts can financially benefit from hosting a wind project via an increase in the taxable value to support I&S taxes and thus debt issuance and capital spending (Brunner et al. 2022).

By limiting any increase in the property tax base stemming from the development of a wind energy installation to I&S, the state is incentivizing them to issue debt and increase capital spending. However, the FIRST system specifically penalizes school districts for increasing their debt loads. Thus, using both the numerical FIRST scores and a subset of the financial metrics that factor into these scores, we examine if the design of the FIRST system mismeasures school districts' fiscal condition by failing to account for rational choices made in response to Texas state law about the tax treatment of wind energy installations.

More specifically, we have two related research questions. First, we examine whether the development and operation of a commercial wind energy installation in a school district affects the local fiscal resources and spending behavior of the school districts measured by the local property tax base, the own-source revenue of the school district, long-term debt per pupil, and total assets per pupil.

RQ1: Does the operation of a commercial wind energy installation impact the public revenue and fiscal behavior of hosting school districts in Texas?

This is a first-stage question. It is possible that the hosting of a commercial wind energy installation may impose costs on a school district without providing any increased revenue, or it may provide increase in own-source revenue (and corresponding decreases in state aid) without affecting taxing behavior or changing how the school district allocates public funds. Consequently, if there is no fiscal response, that is, a null effect of wind turbines on local revenues, local tax base, and so forth, then it is unlikely that metrics measured by the FIRST System will be affected. However, if local resources or spending behavior changes, it is likely that this behavior will affect the district's financial condition as measured by the TEA. Thus, our second research question is:

RQ2: Does the operation of commercial wind energy installation impact the fiscal condition, as measured by the FIRST system, of hosting school districts in Texas?

Our final research question is narrowly focused on how wind energy installations impacts the fiscal condition (the numerical score, financial indicators that make up the score, and the letter classifications) of hosting school districts, as measured by the FIRST system. If we find that wind energy installations (1) increase a school district's property tax base and school districts respond by increasing own-source revenues and long-term debt per pupil and (2) the FIRST system penalizes this rational response under state law, then we argue this is an example of financial myopia.

2.4 | Financial Monitoring Versus Academic Accountability Systems

Before proceeding, and in order to avoid any confusion, it is important to note that the FIRST system is a *financial* monitoring system, and it is not focused on evaluating the academic performance of any school district. Like almost all other states (see Kraft et al. 2020 for a broader discussion of these systems), Texas also has an academic monitoring (or "academic accountability") system that monitors student academic achievement (e.g., graduation rates, standardized test performance, etc.), performance differences among various groups of students (e.g., performance disparities between Black and Whites students, etc.), as well as postsecondary readiness. While the state accountability system is similar to the FIRST system in that it evaluates school districts across numerous dimensions[2], there is no formal overlap between these two systems.

Moreover, financial performance and academic performance, at least in Texas, do not appear highly correlated. This may be, in part, because most school districts meet most academic performance and financial metrics. In Appendix A, we regress the different indices used to monitor school district-level academic performance, which is publicly available from the Texas Education Agency, on the district-level FIRST financial scores (described in more detail below) to examine the conditional correlation between these two monitoring systems. As shown in Table A1, we find few consistent relationships between the perceived financial health (as measured by the FIRST system) of a school district and its academic performance (as measured by the TEA).

3 | Data

To answer our research questions, we construct an original school district-by-year panel using data on the universe of wind energy installations in Texas, the FIRST data from the TEA, and data from the National Center for Education Statistics (NCES). We use data from the United States Wind Turbine Database

TABLE 1 | Descriptive table (Base Year = 2008).

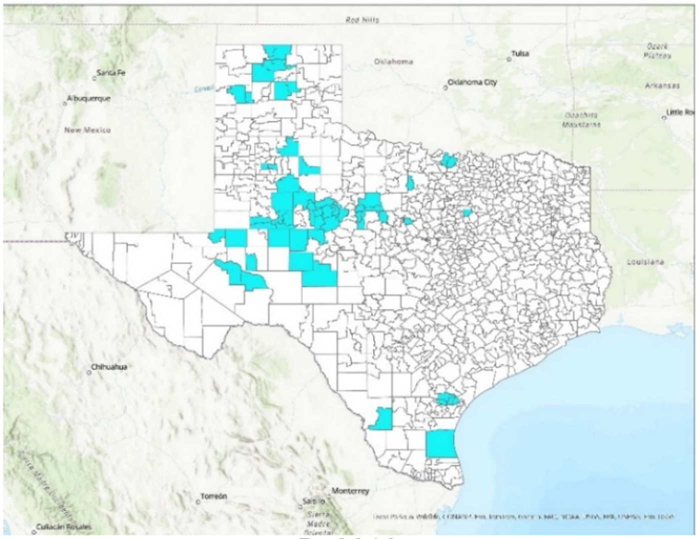
	Districts with no wind energy	Districts with wind energy	Test of significant (p values)
Total Population	249,410	45,659	0.018
Share Hispanic	0.23	0.30	0.023
Share White	0.65	0.61	0.136
Share Black	0.01	0.03	< 0.001
Share 65+	0.14	0.15	0.076
Share 55+	0.23	0.24	0.133
Population density	237.2	49.9	0.008
Real local revenue per-pupil	6154	6805	0.355
Long-term debt EFY per-pupil	12,467	12,904	0.781
Total assets per-pupil	17.827	62.53	< 0.001
Taxable value per-pupil	466,007	1,064,097	< 0.001
FIRST Financial Score	79.9	78.9	0.486
Probability Grade (A ∣ B)	0.98	0.94	0.058
Probability Grade (C ∣ F)	0.02	0.06	0.058
Probability of Grade F	0.02	0.01	0.891
Were debt-related expenditures less than $250.00 per student?	0.64	0.65	0.895
Was the ratio of cash and investments to deferred revenues in the general fund greater than or equal to 1:1?	0.994	1.000	0.521
Was the decrease in undesignated unreserved fund balance less than 20% over two fiscal years?	0.997	1.000	0.619
Was the aggregate total of cash & investments in the general fund more than $0?	0.995	1.000	0.566
Observations	864 (92.4%)	71 (7.6%)	

(USWTDB) to geocode wind energy installations to school district boundaries, creating a yearly measure of installed wind energy capacity per district. We combine these data with detailed annual data on school district revenues and expenditures from the NCES's Local Education Agency Finance Survey (F-33), covering the years 2007–2008 to 2018–19. Using data from the NCES Common Core of Data, we bring in enrollment data to construct per-pupil measures of revenue and spending and deflate all our annual financial measures to constant 2019 dollars using the consumer price index. Lastly, we use data from the 2000 decennial census to control for a range of school district demographic data, including: total population, share African American, share non-Hispanic White, share Hispanic, share of the population over the age of 65, share of the population over the age of 55, and population density. Note that we exclude the small number of school districts that had a wind turbine in operation prior to 2007.

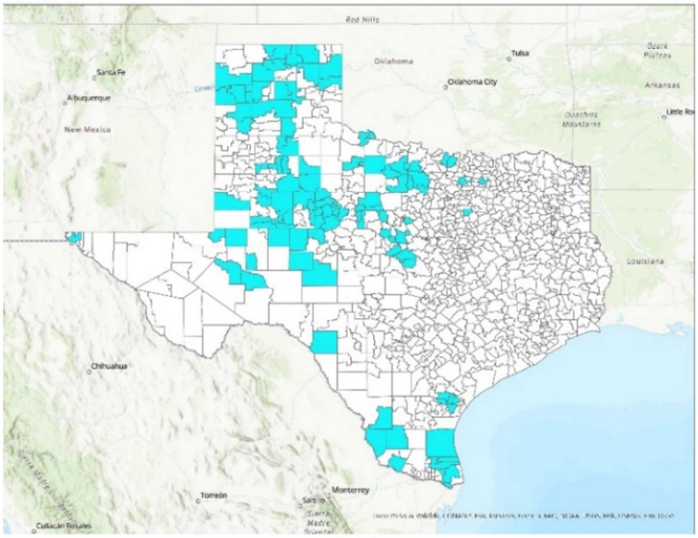
Table 1 provides a summary of the key variables used in our study, including our key spending and revenue outcomes and the Texas FIRST metrics. The summary statistics reported in the table are all based on the first year of our sample time frame, namely 2008, to help illuminate pre-treatment similarities between treated (has a wind energy installation) and non-treated school districts. We provide summary statistics for school districts without any wind turbines in Column 1, the summary statistics for school districts with at least one commercial wind turbine in Column 2, and the p-value of a test between the two columns in Column 3. Given that wind turbines are generally located in more rural areas, we find treated school districts (i.e., those with a commercial wind energy installation) have a smaller population and higher shares of Hispanic and African American residents (compared to the White share) than school districts without wind energy installations. While we find no measurable differences between the districts that ultimately host a wind energy installation and those that do not in terms of local revenue or long-term debt per pupil at baseline, we do find that treated districts have more taxable value and more assets per pupil but are also considered to be less financially healthy (i.e., they have a lower total numerical score at baseline) by the FIRST system. We see no measurable differences between the treated and control districts in our specific financial indicators we examine at baseline.

4 | Empirical Model

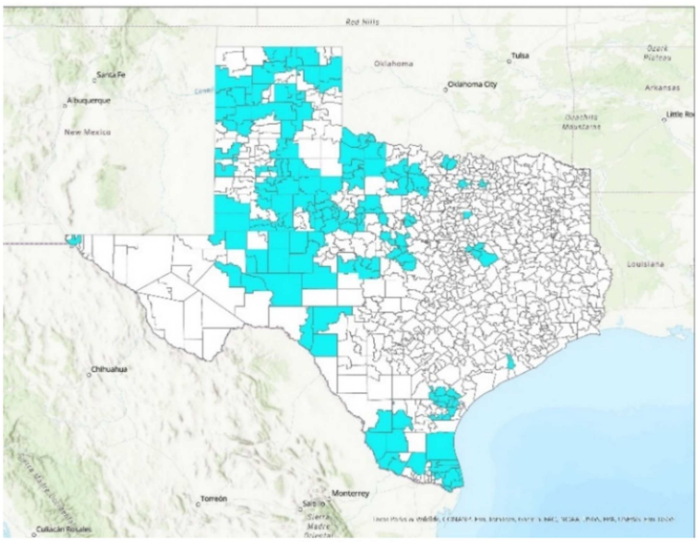
To examine the effect of hosting a wind energy installation on school district fiscal outcomes and financial condition, we exploit variation in the timing of wind energy installations across different school districts within Texas. To get a sense of our temporal and spatial variation, in Figure 1, we plot the growth



In 2010



In 2015



In 2020

FIGURE 1 | Treated school districts in 2010, 2015, and 2020.

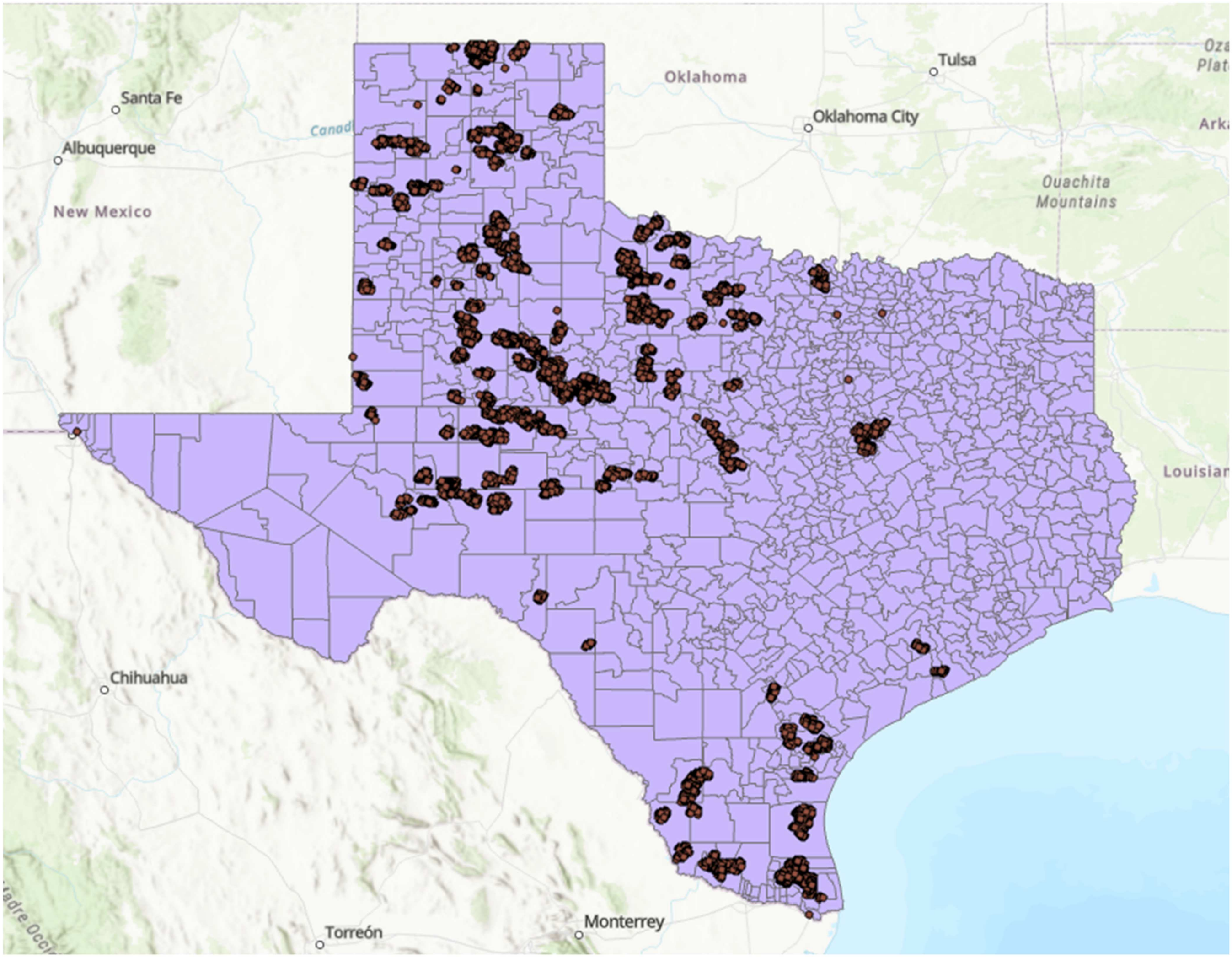


FIGURE 2 | Location of turbines in Texas.

of wind energy from 2010 to 2020. Even in 2010, one could find wind energy in the Northern, Midwestern, and Southern parts of the State. By 2020, more and more school districts had at least one commercial-scale wind energy installation. To give a more detailed overview, we plot the overlay between Texas school district boundaries and wind turbines in Figure 2. We find that wind turbines are spread throughout the center of the state, with some concentration in the southern part of Texas, and very little in the far east or west of the state.

We begin our analysis by estimating non-parametric difference-in-differences event study models of the following form:

$$y_{it} = \sum_{j=-5}^{5} \alpha_j L_{j,it} + \boldsymbol{X}_i \theta_t \kappa + \psi_i + \phi_t + \eta_{it}, \quad (1)$$

where y_{it} denotes an outcome of interest for school district i in year t and $L_{j,it}$ represents a series of lead and lag indicators for when a wind installation becomes operational in school district i. We re-center $L_{j,it}$ so that $L_{0,it}$ equals one in the year the installation became operational. To limit the influence of events too far in the past or future, we limit our temporal window to 5 years before or after a wind turbine becomes operational, and thus we include separate indicators for each of the 5 years prior to and after a wind energy installation becomes operational. The omitted category for our treatment indicators (i.e., the reference year for all estimates) is the year prior to a wind installation becoming operational ($L_{-1,it}$). We include both school district fixed effects (ψ_i) and year fixed effects (ϕ_t), and η_{it} is a random disturbance term. Given that treatment (wind energy installation) occurs at the school district level, in all specifications we cluster the standard errors at the school district level.

The coefficients of primary interest in Equation (1) are the $\alpha'_j s$.The estimated coefficients on the lead treatment indicators (α_{-5}, ..., α_{-2}) provide evidence on whether the parallel trends assumption is likely to hold, while the lagged treatment indicators (α_0, ..., α_{+5}) allow the effect of a wind energy operation on our outcomes of interest to grow over time and in a non-parametric way in the post treatment period. We include a vector of school district control variables ($\boldsymbol{X}_i$), namely total population in 2000, share population white in 2000, share population black in 2000, share population Hispanic in 2000, share of the population that is 65 years or older, share of the population 55 years or older, and the population density all interacted with a linear time trend (θ_t) to allow for differential

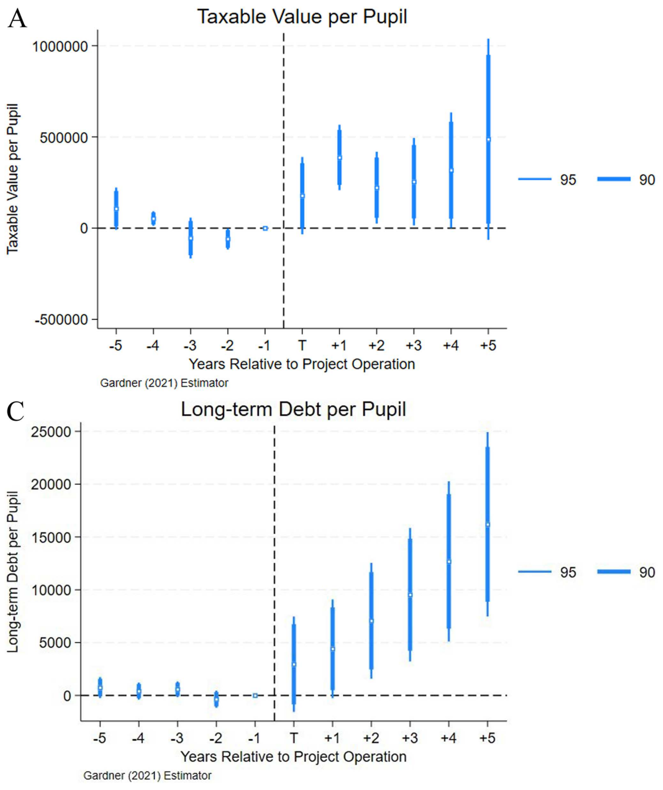


FIGURE 3 | Main Fiscal and Financial Outcomes. (A) Total taxable value base per pupil. (B) Total local revenue per pupil. (C) Long-term debt per pupil. (D) Total assets per pupil.

trending by school districts with different baseline (pre-treatment) values of these characteristics. We do not include time-varying school-district control variables because they could be affected by the installation/operation of wind energy (i.e., endogenous controls).

To improve precision, we complement the event study specification with a single parameter difference-in-differences (DiD) specification:

$$y_{it} = \beta_1 Operation_{it} + X_i\theta_t + \psi_i + \phi_t + \varepsilon_{it}, \qquad (2)$$

where $Operation_{it}$ is an indicator that takes the value of one in all years after an installation becomes operational, and all other terms are as defined in Equation (1). The coefficient of primary interest in Equation (2) is β_1 which represents the DiD estimate of the effect of treatment (wind energy operation) on our outcomes of interest.

Several recent studies have shown that estimates from standard event studies and DiD specifications relying on the staggered timing of treatment for identification may be biased in the presence of heterogeneous treatment effects (Callaway and Sant'Anna 2020; Sun and Abraham 2020; Goodman-Bacon 2021). To address this concern, we employ the imputation estimator developed by Gardner (2022), Borusyak et al. (2024) and Liu et al. (2024). Intuitively, these estimators can be implemented in a two-stage process. In the first stage, one regresses the outcome of interest on the full set of two-way fixed effects using the subsample of untreated observations. In the second stage, the predicted entity and time fixed effect estimates are subtracted from the outcome, and the adjusted outcome is then regressed on the full set of treatment indicators for event studies or the single post-treatment indicator for the standard DiD model.[3]

5 | Results

We begin with our school district fiscal and financial outcomes. Figure 3A presents the event study for taxable value per pupil. Consistent with our expectations, once a wind turbine begins operating, the taxable value in a school district increases. Given these wind turbines continue to operate for *at least* five years, the taxable value per pupil stays elevated. Correspondingly, in Figure 3B, we see that local revenue per pupil, which is largely derived from the property tax, increases by approximately $2000 per pupil two years after operation. Given the constraints imposed on school districts by the state government, we find that long-term debt per pupil increases (see Figure 3C). Interestingly, we also see that assets per pupil[4] increase as well (see Figure 3D). We find no evidence of differential trends prior to the operation of the wind project for any outcome.

In Table 2, we present the DiD results for the full sample in Panel A, for rural school districts (based on the NCES definition of a rural school district) in Panel B, and non-rural school districts in Panel C. For our full sample, the point estimates on all our outcomes are highly statistically significant. In terms of magnitude, we find that, relative to the control mean, total taxable value per pupil increases by 63% following the operation of a wind turbine. Similarly, local revenue per pupil increases by 23%, long-term debt per pupil by 63%, and total assets per pupil by 130% (+ $17.83 per pupil). Consistent with previous studies (see Brunner and Schwegman 2022a, 2022b), our results

TABLE 2 | Impact of wind energy installations on school district fiscal behavior.

	(1) Taxable value per pupil	(2) Local revenue per pupil	(3) Long-term debt, End of FY, per pupil	(4) Total assets per pupil
Panel A: Full sample				
Installation Operational	291,164***	1403***	7859***	23.20***
	(111,211)	(444.12)	(2680)	(7.68)
Observations	11,142	10,927	10,369	10,391
Panel B: Rural school districts				
Installation operational	373,588***	1,778***	10,249***	31.07***
	(141,083)	(549)	(3496)	(10.13)
Observations	7976	7777	7216	7237
Panel C: Non-rural schools				
Installation operational	30,790	233	-345	0.29
	(57,175)	(381)	(1769)	(1.02)
Observations	3166	3150	3153	3154
Control mean	466,007	6154	12,467	17.827

Note: All estimates based on the DiD imputation estimator of Garnder (2021). All specifications include school district and year fixed effects, and the full set of controls enumerated in the paper. School districts with installations prior to 2007 are dropped. Standard errors clustered at the school district level in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

are largely driven by rural school districts (see Panel B), which is where most of the installed wind energy generation is located.

In Figures B1 through B7 of Appendix B, we present event studies for a series of secondary fiscal outcomes. Specifically, we find that the construction and operation of a wind turbine cause an increase in the I&S tax rate (Figure B1) with a corresponding decrease in the M&O tax rate (Figure B2). As a result, the total effective tax rate falls moderately (Figure B3). Nonetheless, we find that total revenue per pupil (Figure B4), total expenditures per pupil (Figure B5), and capital expenditures per pupil (Figure B6) increase significantly while current expenditures decrease slightly (Figure B7). In summary, consistent with Brunner et al. (2024) and Brunner and Schwegman (2022a), we find that wind energy provides a significant financial windfall to the local government.

In Figure 4, we examine the aggregate measures of fiscal condition from the Texas FIRST system. In Figure 4A, we examine the impact on the numerical fiscal score. We find no evidence of differential trends prior to the operation of the wind project, and, following operation, we also see no significant change in the numerical score in the years immediately following operation. If anything, there appears to be a slight downward trend in the numerical score. As shown in Column 1 of Table 3, we find that the numerical score falls by 1.46% points (or 1.8%) following operation of a wind energy installation. In Figure 4B,C, we examine the impact of wind energy on the probability of being classified as an "A or B" school district (Figure 4B), a "C or F" school district (in Figure 4C), and an "F" school district (In Figure 4D) where again "A or B" is considered "superior" or "above standard" achievement," respectively, and "C and F" is considered "meets standard" or "substandard" achievement. We find some evidence that the probability of being classified as an "A or B" school district decreases while the probability of being classified as a "C or F" or an "F" district increases. While these trends are rather noisily estimated in the event study models, we do find, in Column 4 of Table 3, that the probability of being classified as an "F" district increases by 0.013 percentage points (a 81.25% increase from the control baseline). Collectively, we find some evidence that, despite wind projects increasing the financial and fiscal resources of school districts, the Texas Education Agency in the FIRST System is penalizing these districts for responding to the constraints and incentives created by Texas state law.

To examine why the FIRST system seems to penalize school districts with wind energy installations, we next examine various sub-components of the FIRST system. We limit the outcomes we consider to (1) specific financial and fiscal indicators, that are more likely to be directly affected by the installation of a wind project, rather than managerial indicators, and (2) indicators we observe with some consistency throughout the study period.[5] In Figure 5, we examine four subcomponents of the total numerical score that fit these two criteria, and we present standard DiD results in Table 4.

Figure 5A presents event study estimates for the outcome "debt-related expenditures were less than \$250.00 per student".[6] This indicator is a measure of indebtedness and upward movement in this indicator over time is indicative of better fiscal health. Consistent with the results in Figure 3C, we find that this indicator trends downward after a wind energy installation becomes operational, and districts with a significant amount of installed capacity have significant decreases in this metric. This higher debt-to-student ratio, which is considered undesirable under the FIRST System, even if it is largely an artifact of how Texas school districts are limited in their ability to tax wind energy installations, may explain the slight decline in the numerical scores observed in Figure 4. In Figure 5B, we examine the impact of wind energy installation on whether the three-year average "percent of total tax collections (including

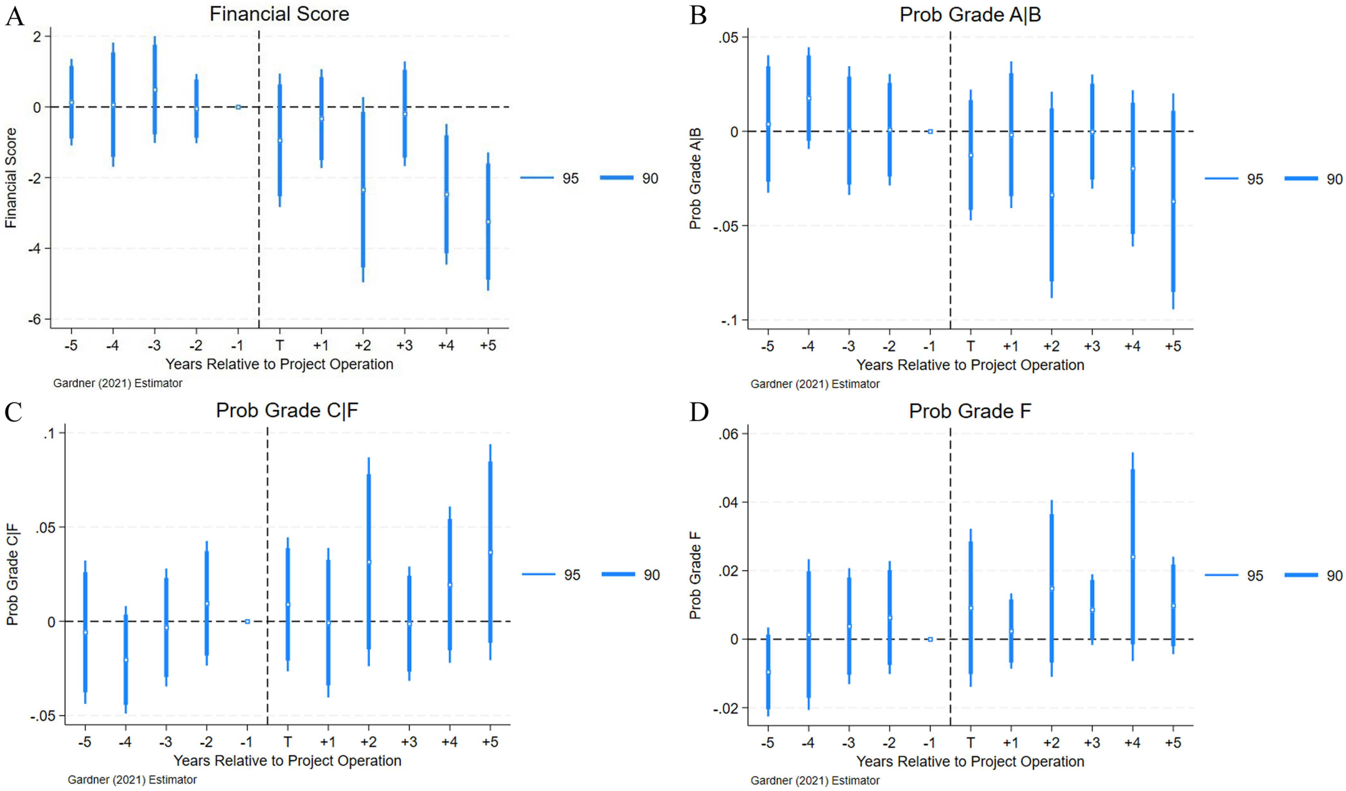


FIGURE 4 | FIRST system aggregate outcomes. (A) Financial score. (B) Probability A | B. (C) Probability C | F. (D) Probability F.

TABLE 3 | Impact of wind energy installations on texas first composite scores.

VARIABLES	**(1) FIRST Financial Score**	**(2) Probability A | B**	**(3) Probability C | F**	**(4) Probability F**
Panel A: Full sample				
Installation operational	−1.46**	−0.016	0.014	0.011*
	(0.664)	(0.013)	(0.013)	(0.006)
Observations	11,143	11,143	11,143	11,143
Panel B: Rural school districts				
Installation operational	−1.7417**	−0.0113	0.0085	0.0121
	(0.7980)	(0.0150)	(0.0153)	(0.0079)
Observations	7977	7977	7977	7977
Panel C: Non-rural school districts				
Installation operational	−0.4918	−0.0332	0.0329	0.0113
	(1.1680)	(0.0290)	(0.0291)	(0.0107)
Observations	3166	3166	3166	3166
Control mean	79.87	0.979	0.021	0.016

Note: All estimates based on the imputation estimator of Garnder (2021). All specifications include school district and year fixed effects, and the full set of controls enumerated in the paper. School districts with installations prior to 2007 are dropped. Standard errors clustered at the school district level in parentheses. $^{***}p < 0.01$; $^{*}p < 0.1$; $^{**}p < 0.05$.

delinquent tax from previous years) is greater than 98%". This indicator measures a school district's ability to collect local taxes (with a 98% minimum standard). Once again there is no meaningful trend in this indicator after the operation of a wind energy installation. In Figure 5C, we examine the impact on whether there was a "decrease in the undesignated unreserved fund balance of less than 20% over the last two fiscal years." This indicator captures whether the district's fund balance is stable, and the district is not using its fund balance for operating expenses. An increase in this indicator is indicative of poor fiscal health and/or financial management practices. There is no clear movement in the event studies—some years post-operation there are increases and decreases, but most of the coefficients are statistically insignificant. Lastly, in Figure 5D,

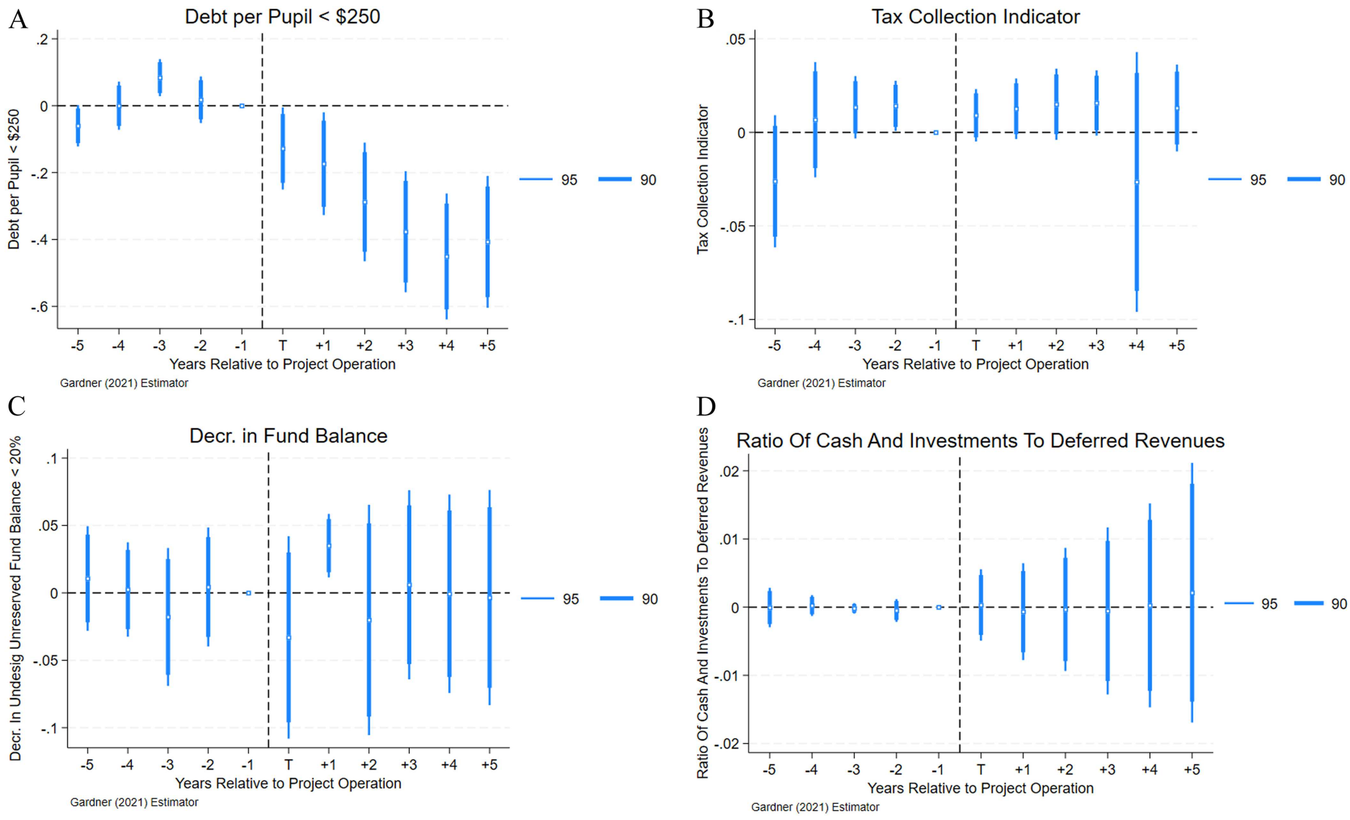


FIGURE 5 | FIRST system specific indicators. (A) Debt per Pupil < $250. (B) Tax collection rate. (C) Decrease in fund balance. (D) Ratio of cash to deferred income.

TABLE 4 | Impact of wind energy installations on Texas First indicators.

	(1) Were debt-related expenditures less than $250.00 per student?	(2) Was the ratio of cash and investments to deferred revenues in the general fund greater than or equal to 1:1?	(3) Was the decrease in undesignated unreserved fund balance less than 20% over two fiscal years?	(4) Was the aggregate total of cash & investments in the general fund more than $0?
Panel A: Full sample				
Installation operational	−0.2831***	0.0002	−0.0051	−0.0026
	(0.0636)	(0.0053)	(0.0237)	(0.0071)
Observations	6504	6504	6504	6504
Panel B: Rural school districts				
Installation operational	−0.3050***	0.0000	0.0122	0.0031
	(0.0772)	(0.0076)	(0.0291)	(0.0090)
Observations	4652	4652	4652	4652
Panel C: Non-rural school districts				
Installation operational	−0.1317	−0.0012	−0.0536	−0.0077
	(0.1083)	(0.0014)	(0.0362)	(0.0060)
Observations	1852	1852	1852	1852
Control mean	0.640	0.994	0.997	0.995

Note: All estimates based on the imputation estimator of Garnder (2021). All specifications include school district and year fixed effects, and the full set of controls enumerated in the paper. School districts with installations prior to 2007 are dropped. Standard errors clustered at the school district level in parentheses. $^{**}p < 0.05$; $^{*}p < 0.1$; $^{***}p < 0.01$.

we examine the impact of a wind energy installation on whether a school district's "ratio of cash and investments to deferred revenues in the general fund is greater than or equal to 1:1." This indicator is essentially a liquidity metric, and it captures whether the district has more cash and investment on hand (and without any constraints) than the dollars that are due as over payments from the State (i.e., the TEA) and the district is not utilizing state funding from the next fiscal year to pay expenses in the current fiscal year. Positive movement in this indicator implies greater fiscal health. We find little evidence that hosting a wind energy installation had any impact on this measure—the estimated coefficients are consistently small and statistically insignificant in the years after operation (with the confidence intervals increasing in later years due to a shrinking sample size due to non-reporting).

In summary, we find evidence of financial myopia in Texas's school financial monitoring system. Wind energy installations increase the local property tax base and local revenues for school districts. Given the constraints and incentives imposed on districts by state law, districts, acting rationally, leverage this increased tax base primarily to issue more local debt for capital investments. However, the FIRST system penalizes this behavior. Despite the districts' enhanced capacity to support debt, the system overlooks these financial resources and instead penalizes districts with more debt on a per pupil basis. Specifically, we observe a 1.8% decline in the numerical financial score and a 70% increase in the likelihood of receiving a failing ("F") designation. This punitive outcome is primarily driven by a FIRST metric that discourages high levels of long-term liabilities, reflecting a narrow focus on debt burdens without accounting for the underlying fiscal context.

6 | Robustness Checks

6.1 | County-by-Year Fixed Effects

As shown in Figures 1 and 2, there is significant regional clustering of wind turbines (in rural central, northern, and southern Texas). To better account for this regional clustering, we re-estimate the main results with school district fixed effects and county-by-year fixed effects. These county-by-year fixed effects flexibly absorb all shocks shared by districts within the same county in the same year, including unobserved changes in local economic conditions, demographic trends, and local policy environments. This change in the fixed effect structure may be particularly important given the known presence of spatially heterogeneous economic shocks, such as those associated with the Great Recession, as well as the Texas state government's response to the Great Recession (which included cuts in state aid) and the uneven recovery from this economic downturn.

In the first section of Appendix C, we replicate our main analysis with this revised fixed effect structure. As shown in Tables C1 through C3, and Figures C1–C12, our results are robust to replacing the year fixed effects with county-by-year fixed effects. Comparing Table 2 and Table C1, we find the magnitudes of the estimated impacts of wind energy on taxable value, local government revenue, and long-term debt is greater when estimated using within-county variation. We continue to find, among rural school districts, a negative impact on the aggregate FIRST financial score; however, the impact on the full sample, while negative, is no longer statistically significant. Importantly, we continue to find no differential pre-trends for any of our outcomes between school districts with a wind installation and districts without an installation.

6.2 | Synthetic Difference-in-Difference

Lastly, as an additional robustness strategy, we use the synthetic difference-in-differences (SDID) method proposed by Arkhangelsky et al. (2021). The SDID estimator uses unit and time weights to match treated districts to a weighted combination of control districts to ensure close pre-treatment trends in outcomes.

We should note that the SDID approach requires strong data assumptions, most notably a strongly balanced panel and a sufficiently long pre-treatment period to reliably construct synthetic counterfactuals. For school districts that were early adopters of wind energy, our pre-treatment period is short. More critically, we do not observe our outcomes for all districts in all years, and thus to implement the SDID approach, we constructed a balanced panel by imputing missing values of the outcomes. This step was necessary to satisfy the estimator's requirements and to allow the SDID algorithm to recover stable unit and time weights. Given these limitations and the imputed values, the SDID estimates should be interpreted with caution.

In section 2 of Appendix C, we present the SDID average treatment effects on the treated (ATT) estimates, as well as complementary event studies. We find that the SDID results are consistent with the main results presented in the preceding section, as well as the findings of the additional robustness check. The ATT estimates (see Appendix Table C4) are similar, albeit somewhat smaller in magnitude, to the results found in Tables 2 through 4 above. Importantly, in Table C4 we find a statistically significant negative relationship of approximately 6 points between hosting a wind energy installation and the overall FIRST Financial Score using the SDID estimator.

In summary, we find that our main analysis is robust to alternative sample selections, counterfactuals, estimators, and fixed effect structures. We consistently find that wind energy installations lead to arguably exogenous increases in taxable value, local government revenues, long-term debt, and total assets. In most analyses, there is also a negative relationship between this expansion of the fiscal resources of treated school districts and the perceived financial health of the school district (consistently driven by increases in per pupil debt). Before concluding, we should note that the magnitude of the estimates, while statistically similar in most analysis, is sensitive to the counterfactual and the estimator use. Thus, we caution anyone from making specific policy conclusions from any one estimate and to consider the range of estimates presented above in the main analysis, as well as the complementary analyses in Appendix C.

7 | Discussion and Conclusion

This paper examines the inconsistencies of "closed" state financial monitoring systems by examining how the Texas Education Agency penalizes local school districts for financial behaviors that are not only rational but also explicitly incentivized under state laws. Specifically, we show Texas school districts are incentivized to use the enhanced tax base that accompanies the hosting of a wind energy installation to finance capital spending through debt issuance, rather than increase current spending. While such decisions improve local financial indicators like revenue and assets per pupil, districts are paradoxically penalized in the TEA′s monitoring system due to elevated debt levels. This creates a form of financial myopia, whereby the monitoring framework fails to account for the increased tax base supporting these bonds and, more broadly, ignores the legal context within which these decisions are made.

Our findings illustrate a broader conceptual flaw in many financial monitoring systems, which are often designed as closed systems that fail to incorporate exogenous constraints and opportunities faced by local governments. Consequently, these systems may generate misleading assessments of fiscal distress or misaligned incentives.

We further find that our results are robust to a variety of alternative estimators and empirical strategies. These include alternative fixed effects specifications as well as the use of a synthetic control difference-in-difference estimator. As noted previously, although the estimates from these alternative identification strategies and the main analysis are statistically similar across most specifications, their magnitudes vary with the choice of counterfactual and estimator. Accordingly, we caution against drawing policy conclusions from any single estimate.

Our study suggests the need to adopt an open-system approach to financial monitoring systems, which emphasizes considering the organizations and their dependence on the resource environment. The organizational environment consists of multiple organizations, which can all impact the resources and performance of a focal organization. If the various organizational actors do not move in a concerted manner, the same performance of the focal organization can be viewed in a conflicting way. For example, both state education, non-education, and, for districts hosting energy installations, energy-related regulatory agencies are critical actors in the organizational environment of school districts. We present a case where school districts are penalized by the performance monitoring systems from the state education agency, even when they rationally respond to legal mandates from the state regulatory agency.

In particular, our findings underscore the critical need for state policymakers to align financial oversight systems with the unique realities facing school districts. Wind energy installations provide a significant boost to local property values, revenues, and capital investment capacity (particularly for rural school districts). State-imposed constraints and conflicting incentives within the FIRST system penalize these districts for rational fiscal decisions, such as issuing local debt for capital improvements. To foster long-term fiscal resilience, states should reevaluate monitoring frameworks like FIRST to avoid punishing districts for effectively leveraging local resources. Creating clearer, supportive incentives and removing contradictory fiscal signals will empower communities to invest in their infrastructure without risking negative financial ratings.

By offering a concrete and policy-relevant example, this paper contributes to the scholarly literature on performance management and fiscal oversight. It supports existing research that warns against poorly designed systems that induce isomorphic behavior or moral hazard, and it adds new insights by identifying the dangers of regulatory blind spots in financial evaluation frameworks. The TEA′s system, while state-specific, reflects common structural elements found in other states' monitoring systems, rendering our findings generalizable. The case underscores the importance of revisiting how these systems are designed to ensure they measure true financial condition rather than penalize rational adaptations to legal and environmental contexts.

Conflicts of Interest

The authors report no conflicts of interest.

Endnotes

[1]The Chapter 313 program expired on Dec. 31, 2022, and was replaced by the Texas State Legislature with a new, but similar, program. Importantly, however, the new program excludes most renewable energy projects. Any existing Chapter 313 agreements that were in place prior to Jan. 1, 2023 remain in effect until their 10-year expiration date.

[2]See the Texas Education Agency for more information on their accountability system: https://tea.texas.gov/texas-schools/accountability. We limit our analysis in Appendix A to 2013 through 2017 because the accountability system changed over time, and the metrics during these years seem relatively consistent over our time frame and had the greatest overlap with available FIRST data.

[3]Our results are robust to using the Sun and Abraham (2020) estimator, which is also free from any contamination and bias that may arise in event study models with staggered timing of treatment and heterogeneous treatment effects.

[4]These data from the NCES F33 files, and we sum the W01 (Assets-sinking fund), W31 (assets- bond fund), and W61 (Assets -other funds) variables into our assets per pupil measure, which include cash, deposits, and government and private securities (such as bonds, notes, stocks, and mortgages).

[5]TEA changed the indicators they collected over the study period, and thus not all indicators used to structure the numerical financial score is available in all years.

[6]This indicator does allow allows fast-growth schools to exceed this cap.

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Appendix A

Comparing the Texas FIRST and Academic Accountability Monitoring Systems

The Texas Education Agency (TEA) evaluates public schools and districts annually to measure academic performance and readiness for the next grade or post-secondary success. This accountability system primarily relies on standardized test results (the "STAAR" test in Texas), graduation rates, and college, career, and military readiness measures. The accountability measures are designed to provide a transparent snapshot of how well schools and districts support student learning and prepare students for life after high school. Like many systems, the metrics used in these systems changed over time and the public facing data is inconsistent from year to year. In our analysis below, we use data available from 2013 to 2017 (it appears the performance system changed after Academic Year [AY] 2018) to examine the conditional correlation between accountability indices and FIRST system index. These data can be found on the TEA's website: https://tea.texas.gov/texas-schools/accountability/academic-accountability/a-f-accountability.

Between 2013 and 2017, the Texas accountability system categorized and measured performance along numerous dimension that were encapsulated into four indices: (1) A student achievement index, which measures student performance across subjects (primarily standardized test performance), (2) a student and school progress index, which measures year-to-year student progress across subjects (to evaluate year-or-year trends and reward schools for advancing toward the established standard); (3) a "closing performance gaps" index, which measures performance disparities between economically disadvantaged students (compared to non-disadvantaged students) and racial/ethnic gaps in performance; and (4) post-secondary readiness, which measures progress towards high school graduation, post-secondary work force development, and tertiary education enrollment. In Table A1, we regress each index (in Columns 1 through 4) and all four indices at once (In Column 5) on the FIRST financial score. In Column 6, we regress the linear combination of these indices on the FIRST numerical score.

TABLE A1 | Conditional correlation between FIRST financial score and the performance indices.

	(1)	(2)	(3)	(4)	(5)	(6)
	FIRST Financial Score					
Student Achievement Index	0.0190				0.0769	
	(0.0302)				(0.0491)	
Student Progress Index		-0.0010			0.0011	
		(0.0142)			(0.0160)	
Closing Performance Gaps Index			-0.0141		-0.0323	
			(0.0169)		(0.0273)	
Postsecondary Readiness Index				-0.0276***	-0.0278***	
				(0.0088)	(0.0088)	
Cumulative Score						-0.0355
						(0.0234)
Observations	4779	4642	4765	4733	4589	4589
R^2	0.9763	0.9768	0.9764	0.9766	0.9770	0.9769
District FE	Y	Y	Y	Y	Y	
Year	Y	Y	Y	Y	Y	

Note: All specifications include data from academic years 2013–2017. The Cumulative Score is a linear combination of the other four indices. Both the financial score and each index are log transformed. Robust standard errors clustered at the school-district level in parentheses. ** $p < 0.05$, * $p < 0.1$. As shown above, the correlations are small and statistically insignificant for the three of the four indices—the student achievement index, the student progress index, and closing the performance gap index. We find a statistically significant negative relationship between the post-secondary readiness index and the FIRST Financial Score, which suggests that increased investment in (or improved performance on) post-secondary outcomes, which is a broad measure capturing post-secondary tertiary enrollment, employment, vocational/technical training, or military enlistment, is negatively correlated with FIRST scores. However, we find no meaningful or statistically significant correlation between the cumulative score and the FIRST score. Given the non-causal nature of these relationships and the inconsistent correlations across different indices, we caution the reader from considering these relationships too deeply. Collectively, while there may be a limited (inverse) relationship between certain aspects of academic performance measures and FIRST scores, we find little relationship between these two systems.; ***$p < 0.01$.

Appendix B

Additional Outcomes for Main Analysis

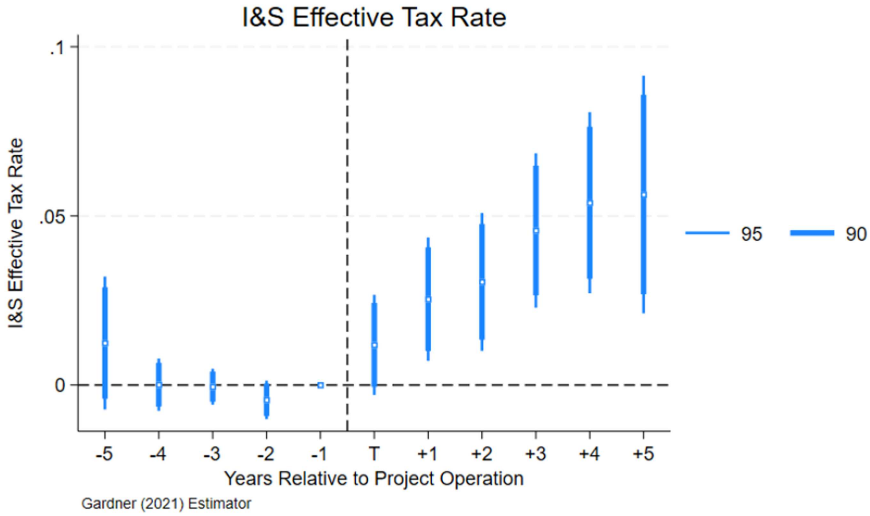

FIGURE B1 | I&S effective tax rate.

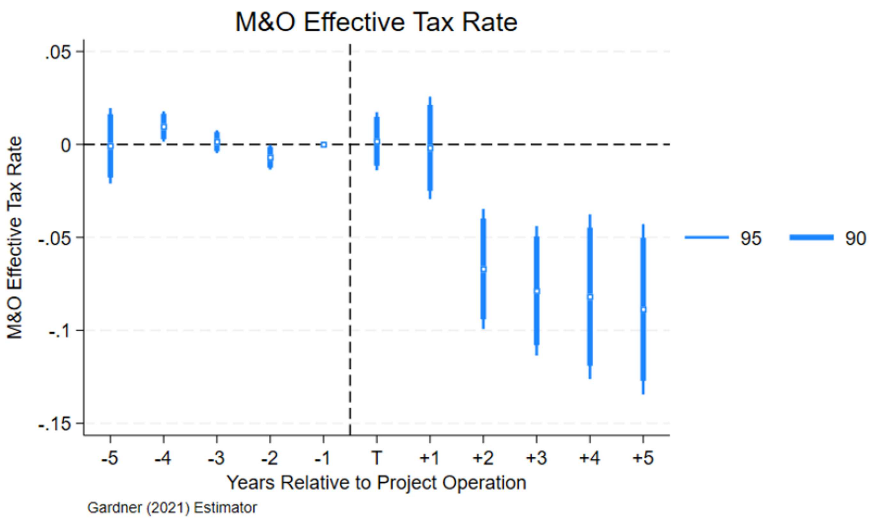

FIGURE B2 | M&O effective tax rate.

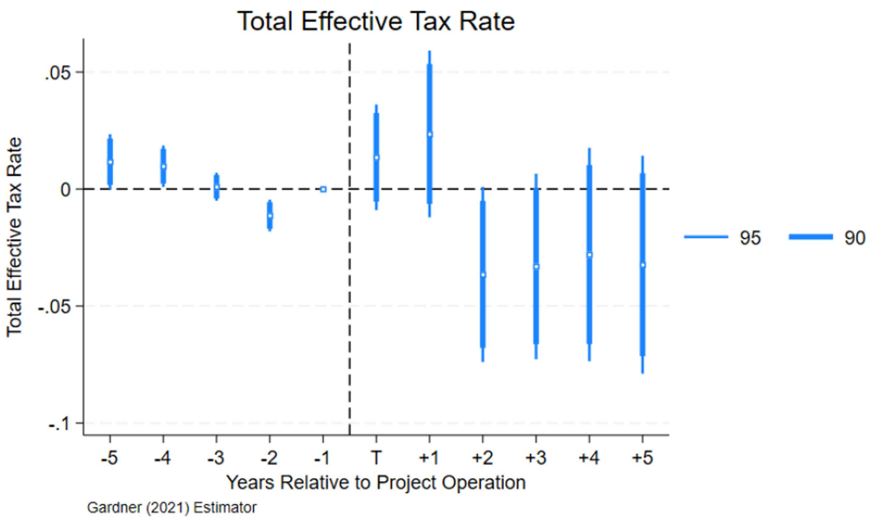

FIGURE B3 | Total effective tax rate.

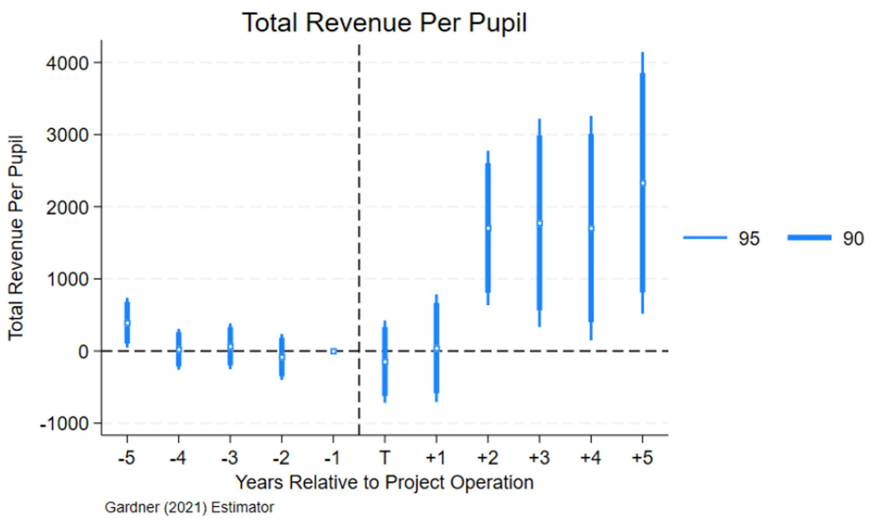

FIGURE B4 | Total revenue per pupil.

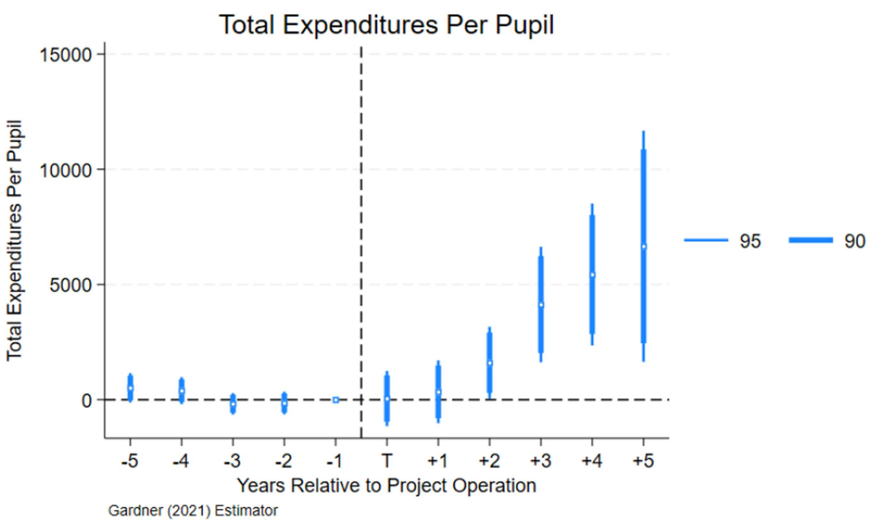

FIGURE B5 | Total expenditure per pupil.

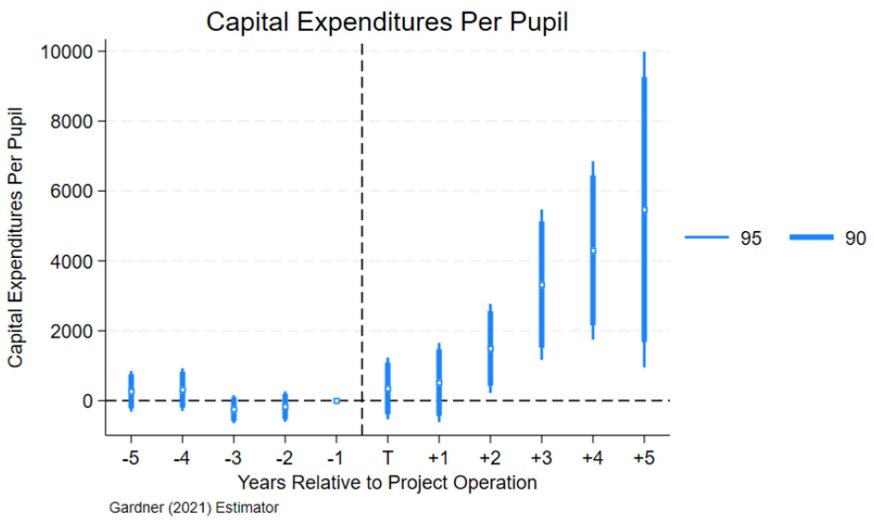

FIGURE B6 | Capital expenditure per pupil.

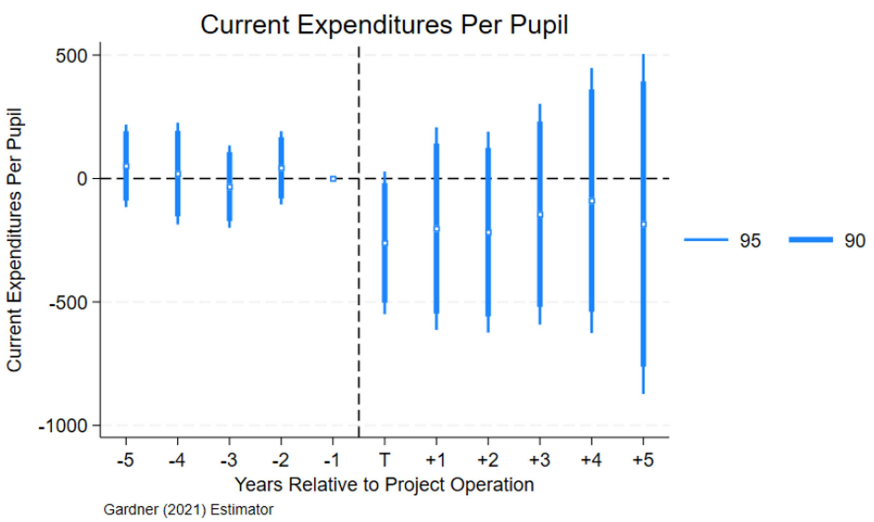

FIGURE B7 | Current expenditures per pupil.

Appendix C

Robustness Checks

This appendix provides additional robustness checks (Figures C1–C24).

Section C1: Alternative Fixed Effect Structure

As noted in the main paper and show in Figures 1 and 2 in the main body of the paper, there is significant regional clustering of wind turbines (in central, northern, and southern Texas). To better account for this regional clustering, we re-estimate the main results with school district fixed effects and county-by-year fixed effects, which strengthens identification by shifting the comparison to within-county variation over time.

As noted in the main body of the manuscript, our results are consistent with the main results presented in Tables 2 through 4. Table C1, Table C2, Table C3, Table C4.

Section C2: Synthetic Difference in Differences:

To further control for baseline imbalances between school districts with a wind installation and school districts without an installation, we use

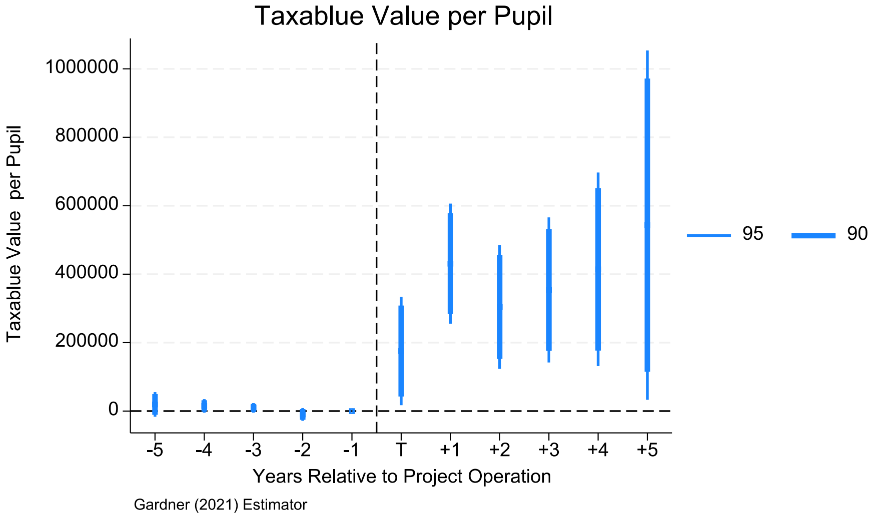

FIGURE C1 | Total market value per pupil – county-by-year FEs.

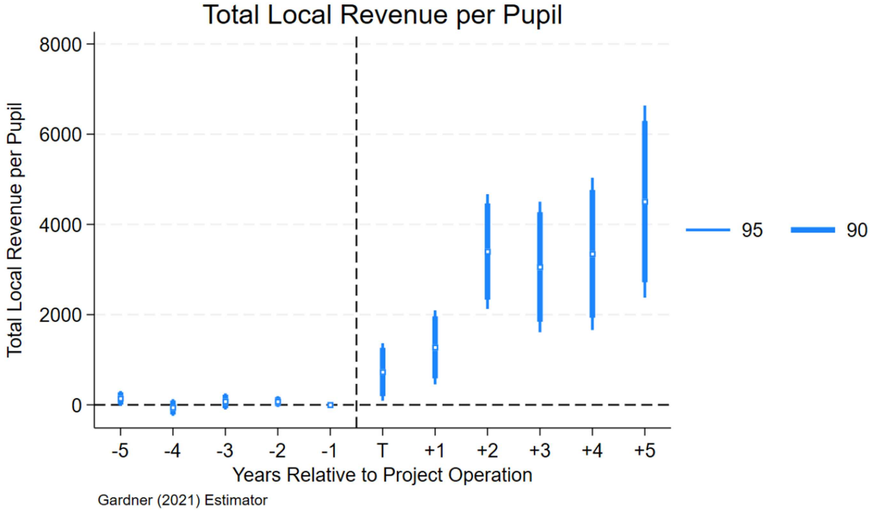

FIGURE C2 | Total local revenue per pupil – county-by-year FEs.

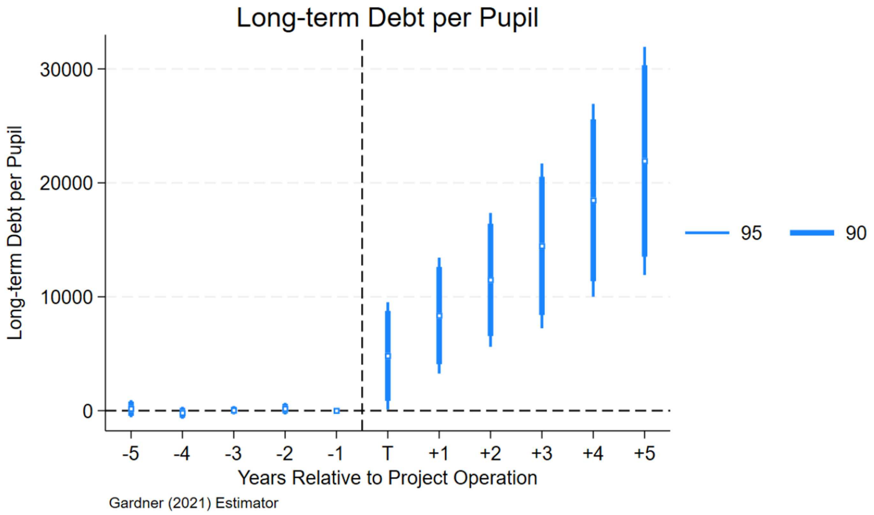

FIGURE C3 | Per pupil long-term debt per pupil – county-by-year FEs.

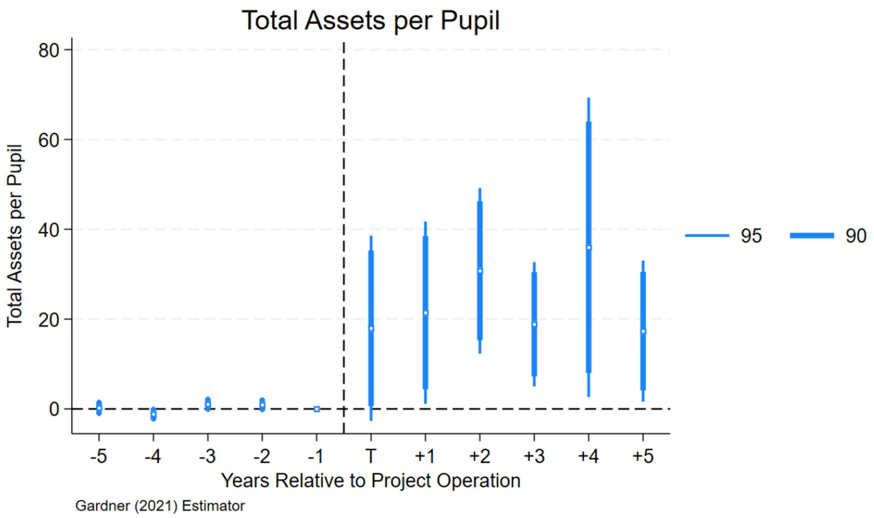

FIGURE C4 | Total assets per pupil – county-by-year FEs.

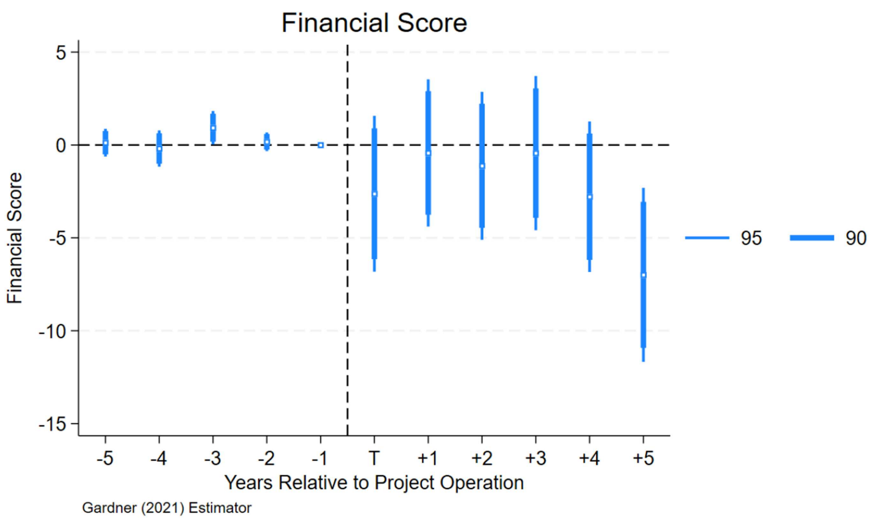

FIGURE C5 | financial score – county-by-year FEs.

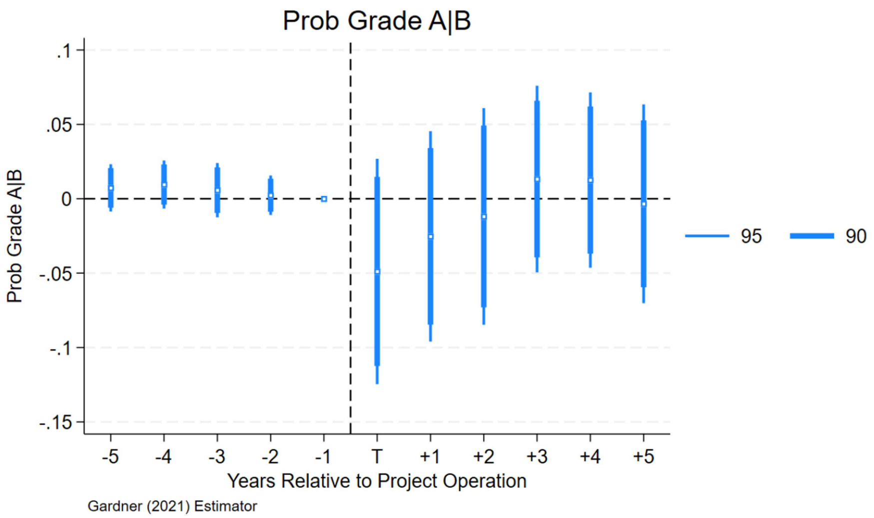

FIGURE C6 | Probability A | B – county-by-Year FEs.

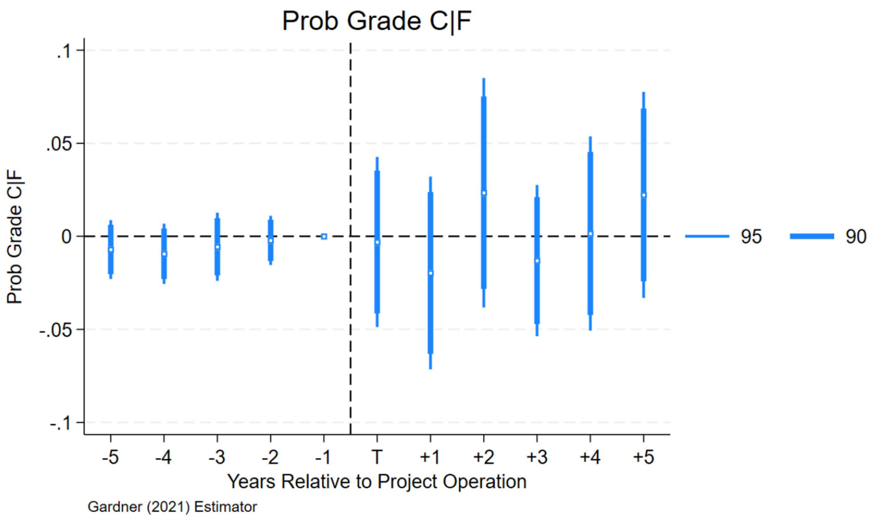

FIGURE C7 | Probability C | F Per Pupil – County-by-Year FEs.

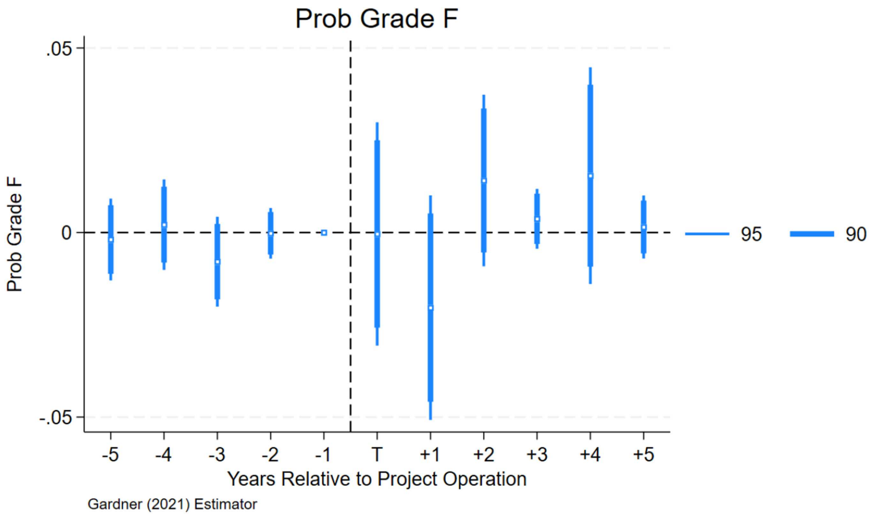

FIGURE C8 | Probability F – County-by-Year FEs.

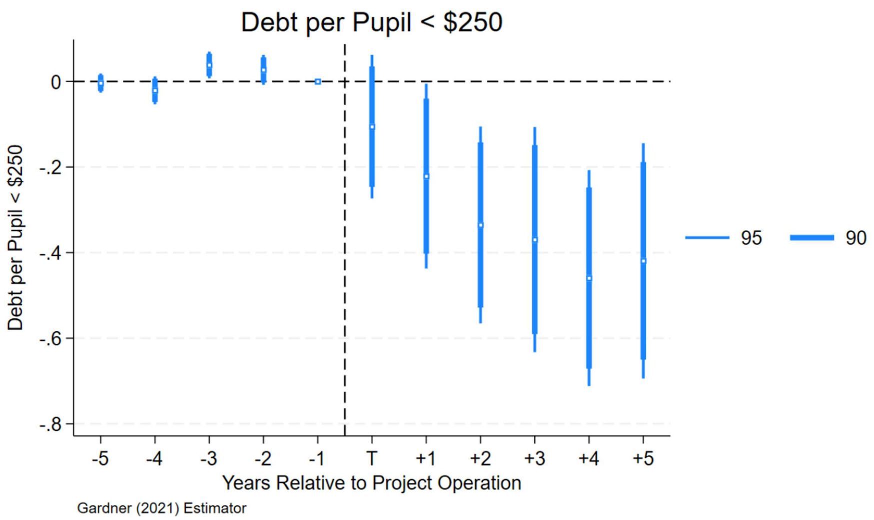

FIGURE C9 | Debt per pupil < \$250 – county-by-Year FEs.

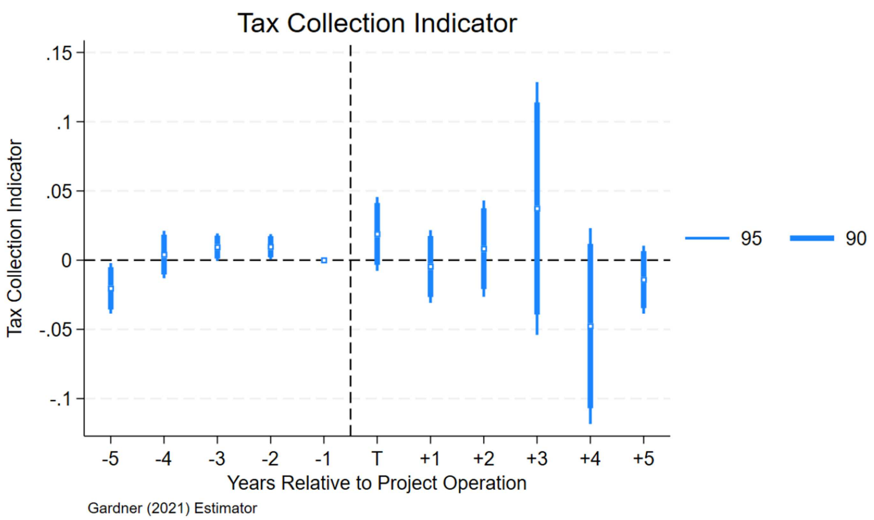

FIGURE C10 | Tax collection rate – county-by-year FEs.

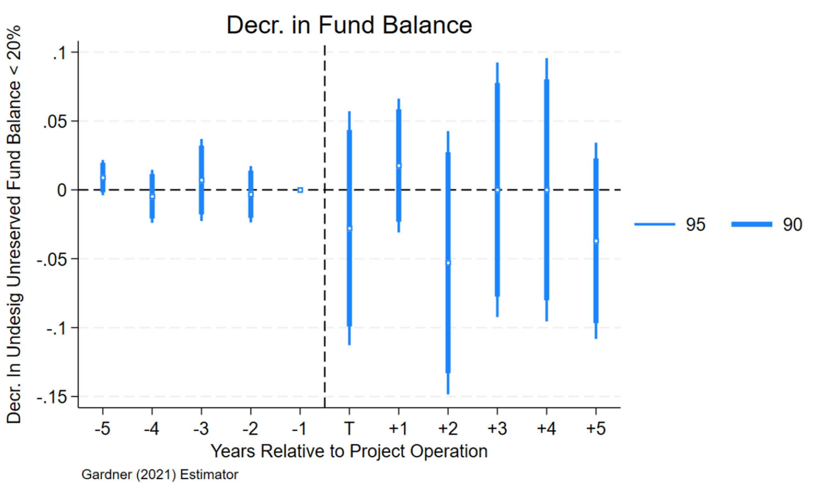

FIGURE C11 | Decrease in fund balance – county-by-year FEs.

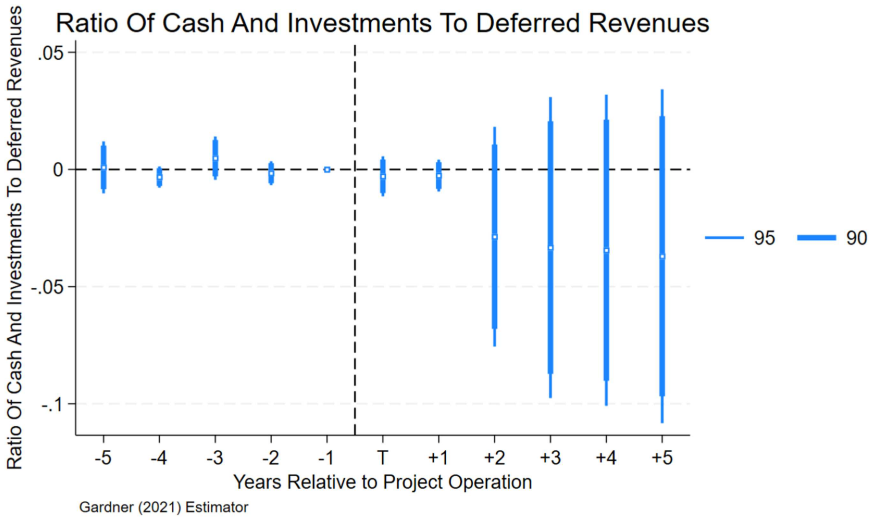

FIGURE C12 | Ratio of cash to deferred income – county-by-year FEs.

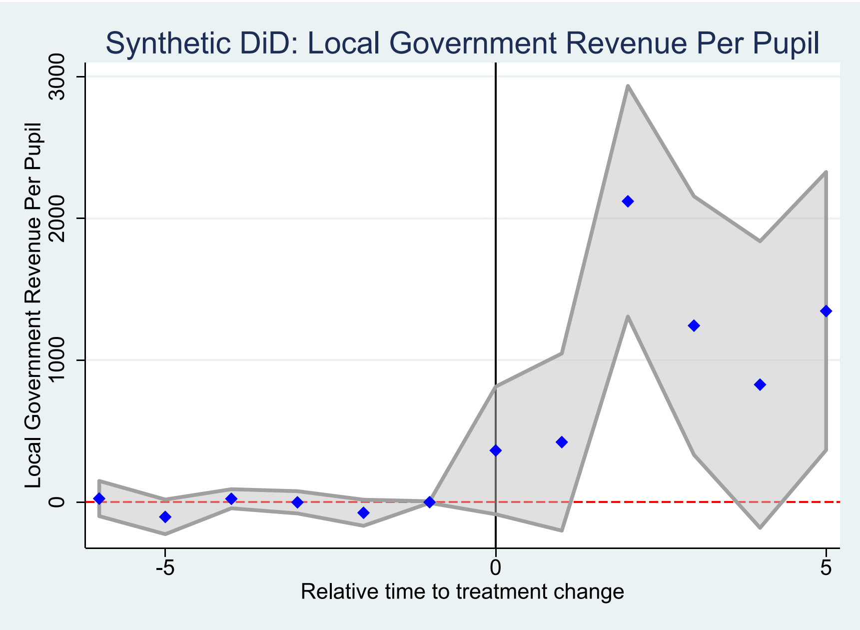

FIGURE C13 | SDID event study for local government revenue.

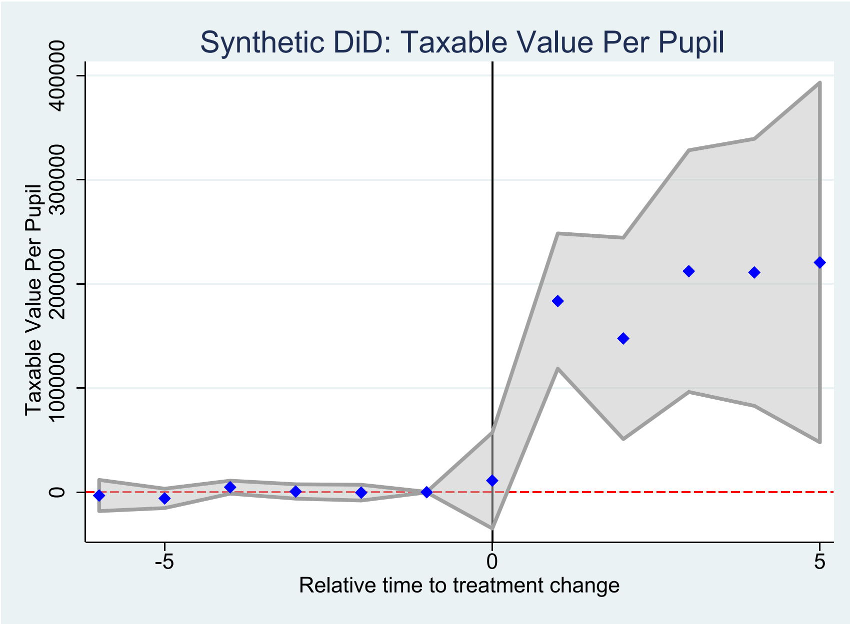

FIGURE C14 | SDID event study for taxable value per pupil.

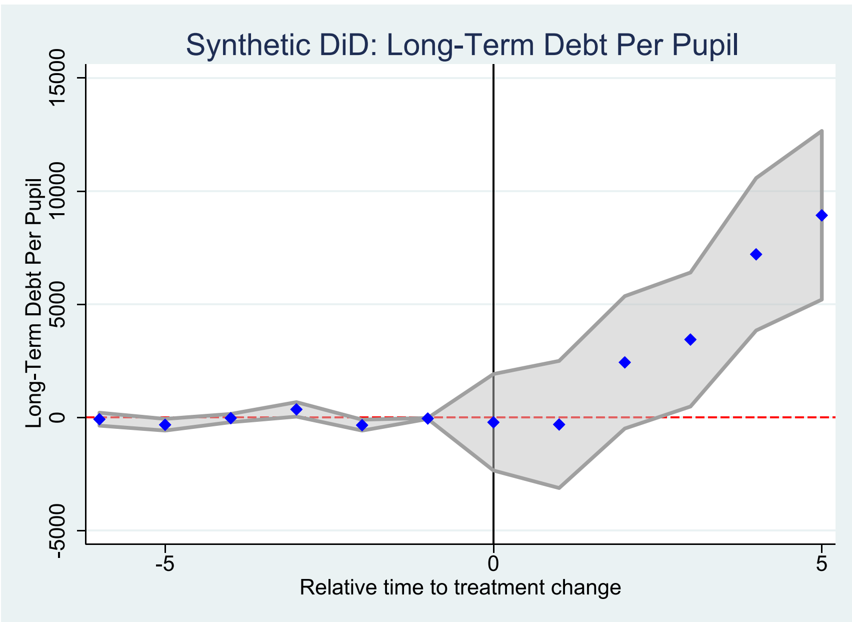

FIGURE C15 | SDID event study for long-term debt per pupil.

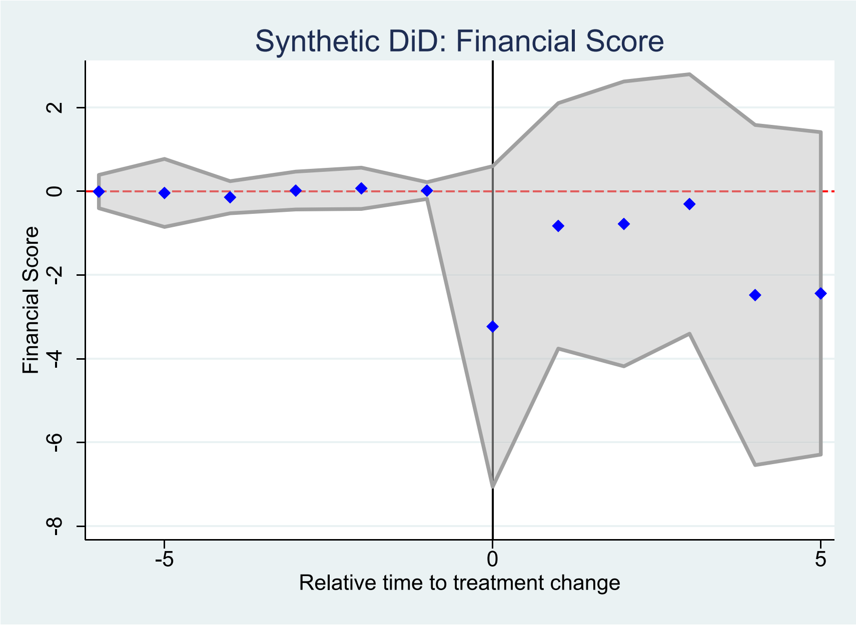

FIGURE C16 | SDID Event Study for Financial Score.

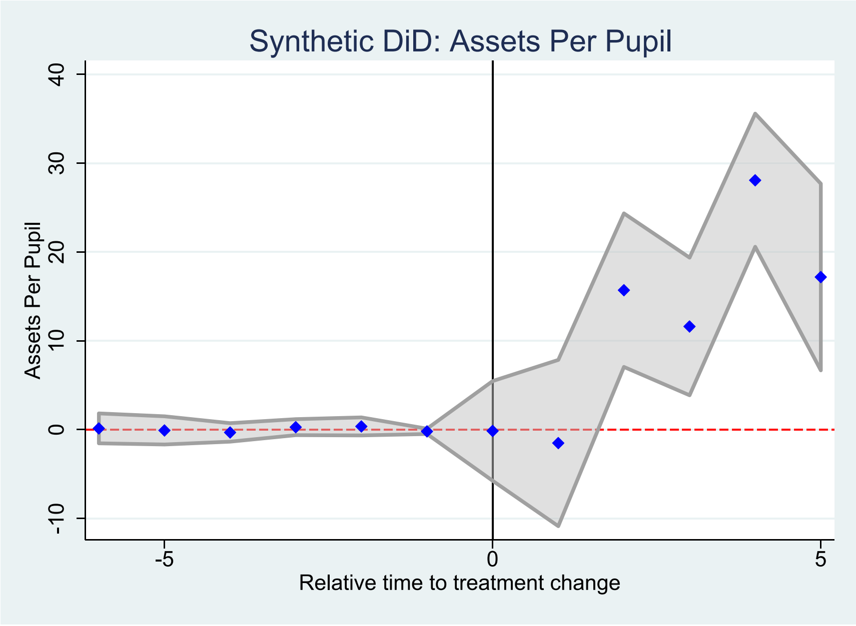

FIGURE C17 | SDID event study for assets per pupil.

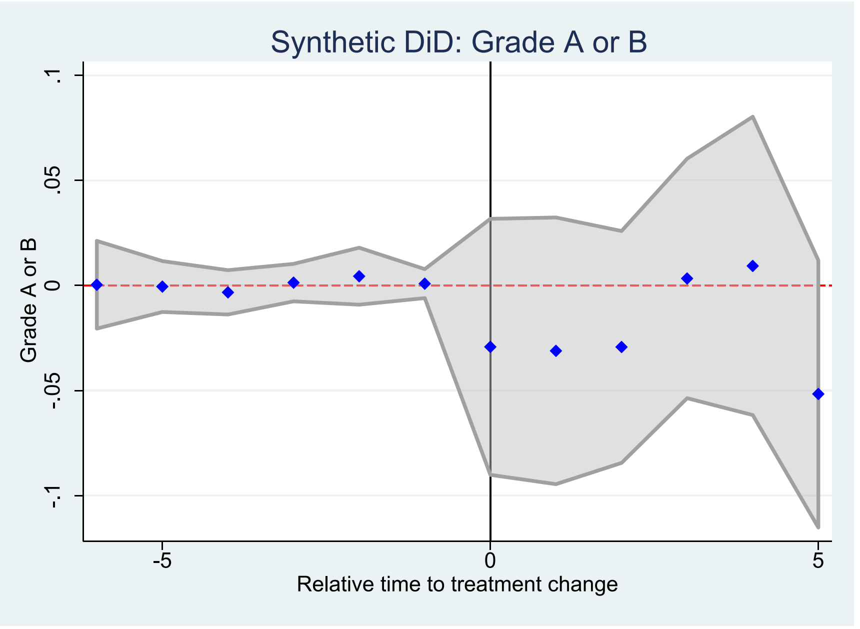

FIGURE C18 | SDID event study for Grade A | B.

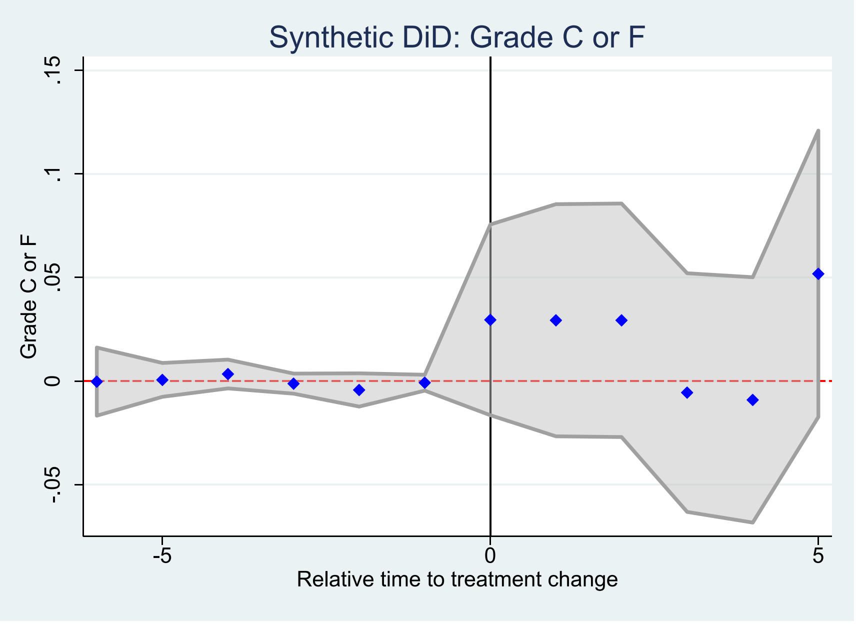

FIGURE C19 | SDID event study for Grade C or F.

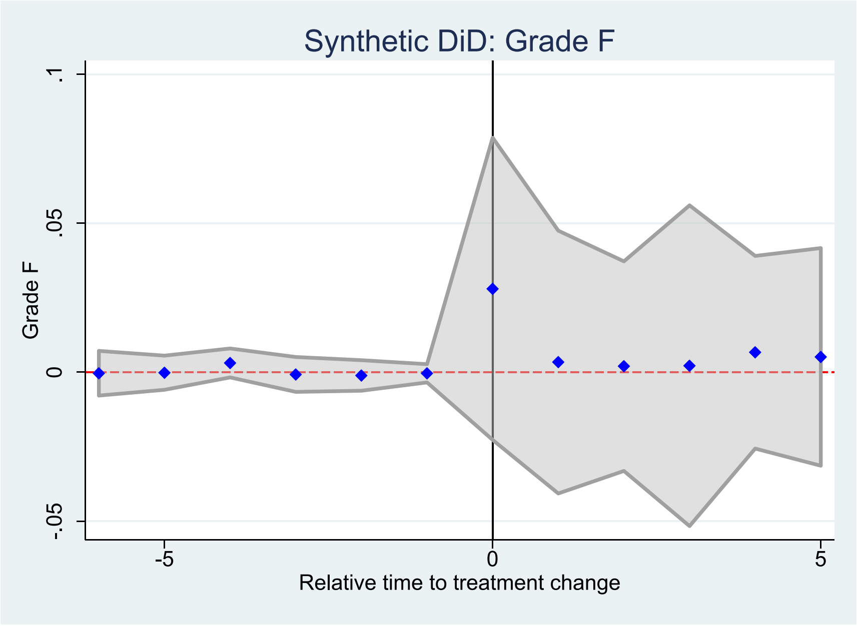

FIGURE C20 | SDID event study for Grade F.

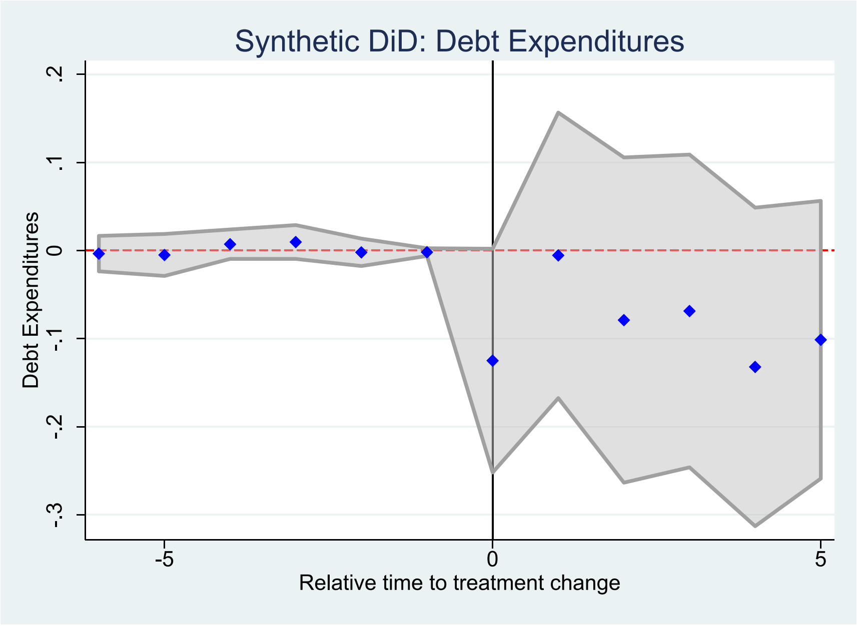

FIGURE C21 | SDID event study for debt expenditures.

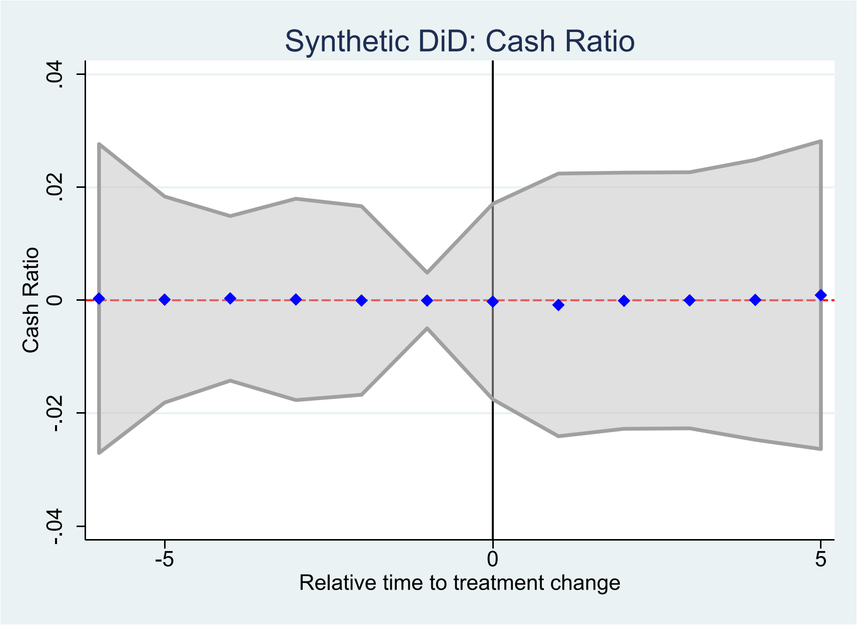

FIGURE C22 | SDID event study for cash ratio.

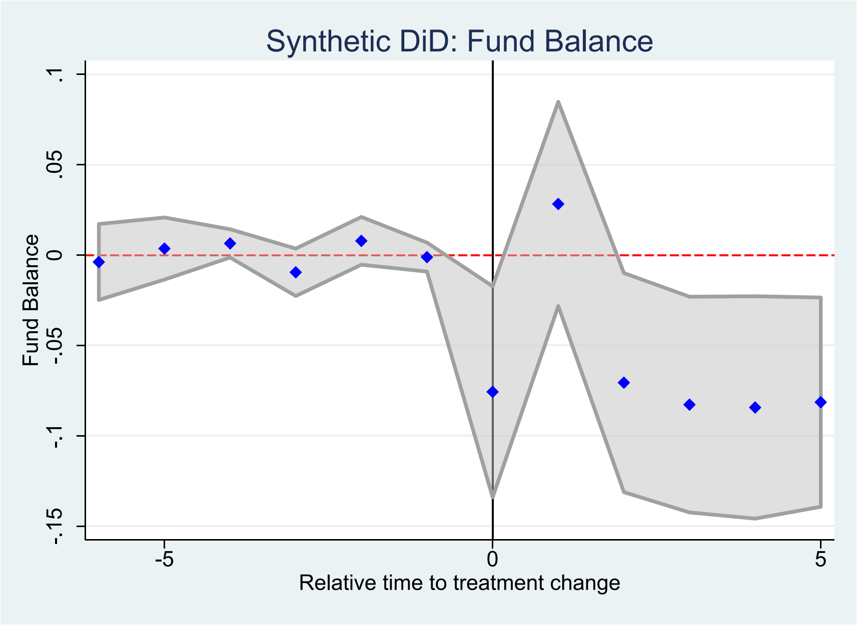

FIGURE C23 | SDID event study for fund balance.

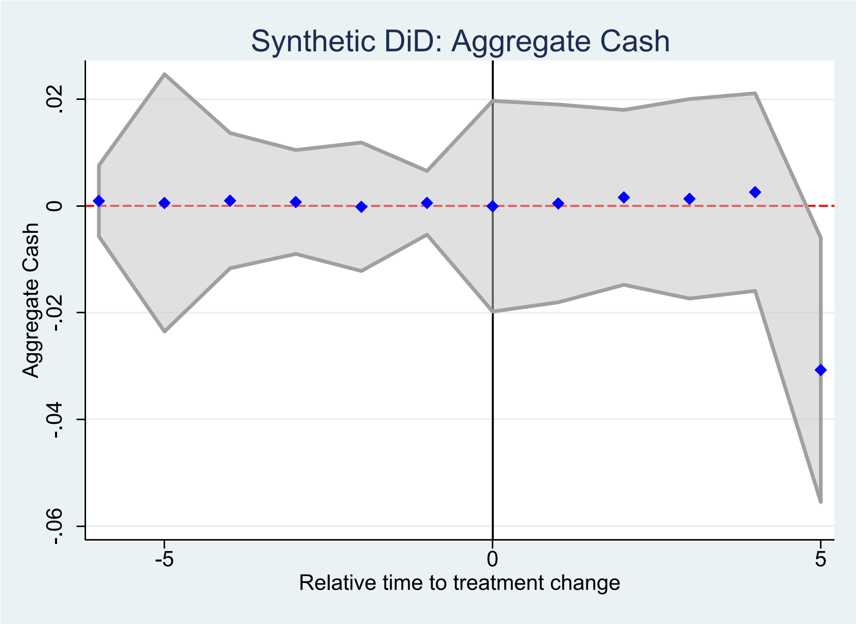

FIGURE C24 | SDID event study for aggregate cash ratio.

TABLE C1 | Impact of wind energy installations on school district fiscal and financial behavior with county-by-year fes.

	(1) Taxable value per pupil	(2) Local revenue per pupil	(3) Long-term debt, end of FY, per pupil	(4) Total assets per pupil
Panel A: Full sample				
Installation operational	368,432***	2505***	11,544***	24.388***
	(100,477.3684)	(504.8288)	(2,803.2346)	(7.042)
Observations	11,142	10,927	10,369	10,391
Panel B: Rural school districts				
Installation operational	623,977***	3,186***	14,615***	27.308***
	(134,099)	(688)	(3534)	(9.223)
Observations	7976	7777	7216	7237
Panel C: Non-rural schools				
Installation operational	24,910	-641	1833	-0.0815
	(43,689)	(446)	(2217)	(1.079)
Observations	3166	3150	3153	3154
Control mean (From Full Sample)	466,007	6154	12,467	17.827

Note: All estimates based on the imputation estimator of Garnder (2021). All specifications include school district and county-by-year fixed effects, and the full set of controls enumerated in the paper. School districts with installations prior to 2007 are dropped. Standard errors clustered at the school district level in parentheses. $^{**}p < 0.05$; $^{*}p < 0.1$; $^{***}p < 0.01$.

TABLE C2 | Impact of wind energy installations on Texas FIRST composite scores with county-by-year FEs.

Variables	(1) FIRST financial score	(2) Probability A|B	(3) Probability C|F	(4) Probability F
Panel A: Full sample				
Installation operational	-2.2847	-0.0081	0.0116	0.0144
	(1.6454)	(0.0254)	(0.0168)	(0.0110)
Observations	11,143	11,143	11,143	11,143
Panel B: Rural school districts				
Installation operational	-3.8991***	-0.0261	0.0064	0.0143*
	(1.4824)	(0.0227)	(0.0159)	(0.0076)
Observations	7977	7977	7977	7977
Panel C: Non-rural school districts				
Installation operational	0.4039	-0.0754**	0.0046	0.0081
	(2.7581)	(0.0346)	(0.0304)	(0.0087)
Observations	3166	3166	3166	3166
Control mean (from full sample)	79.87	0.979	0.021	0.016

Note: All estimates based on the imputation estimator of Garnder (2021). All specifications include school district and county-by-year fixed effects, and the full set of controls enumerated in the paper. School districts with installations prior to 2007 are dropped. Standard errors clustered at the school district level in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

TABLE C3 | Impact of wind energy installations on Texas FIRST indicators with county-by-year FEs.

	(1) Were Debt-Related Expenditures Less Than $250.00 Per Student?	(2) Was The Ratio of Cash and Investments to Deferred Revenues in the General Fund Greater Than or Equal To 1:1?	(3) Was the Decrease in Undesignated Unreserved Fund Balance Less Than 20% Over Two Fiscal Years?	(4) Was the Aggregate Total of Cash & Investments in the General Fund More Than $0?
Panel A: Full Sample				
Installation Operational	-0.2972***	-0.0205	-0.0211	-0.0045
	(0.1010)	(0.0184)	(0.0272)	(0.0047)
Observations	6,504	6,504	6,504	6,504
Panel B: Rural School Districts				
Installation Operational	-0.4508***	-0.0146	-0.0272	-0.0051
	(0.1431)	(0.0148)	(0.0381)	(0.0061)
Observations	4,652	4,652	4,652	4,652
Panel C: Non-Rural School Districts				
Installation Operational	-0.2566*	-0.0000	-0.0588*	-0.0229
	(0.1420)	(0.0000)	(0.0306)	(0.0205)
Observations	1,852	1,852	1,852	1,852
Control Mean (From Full Sample)	0.640	0.994	0.997	0.995

Note: All estimates based on the imputation estimator of Garnder (2021). All specifications include school district and county-by-year fixed effects, and the full set of controls enumerated in the paper. School districts with installations prior to 2007 are dropped. Standard errors clustered at the school district level in parentheses. **$p < 0.05$; *$p < 0.1$; ***$p < 0.01$.

TABLE C4 | Synthetic DiD – average treatment on the treated effect.

Outcomes	ATT Estimate
Taxable Value Per Pupil	174,843***
	(62,487)
Local Revenue Per Pupil	1224***
	(457)
Long-Term Debt Per Pupil	5045***
	(1348)
Total Assets per Pupil	10.07***
	(3.54)
FIRST Financial Score	-6.008***
	(1.594)
Probability A ∣ B	-0.005
	(0.0268)
Probability C ∣ F	0.0274
	(0.0224)
Probability F	0.0077
	(0.0140)
Were Debt-Related Expenditures Less Than $250.00 Per Student?	-0.1243
	(0.0809)
Was The Ratio of Cash and Investments to Deferred Revenues in the General Fund Greater Than or Equal To 1:1?	-0.0001
	(0.0129)
Was the Decrease in Undesignated Unreserved Fund Balance Less Than 20% Over Two Fiscal Years?	-0.0710
	(0.0252)

Note: Averaged treatment effect derived from synthetic difference-in-difference estimator developed by Pailañir, D., Clarke, D., & Ciccia, D. (2024) based on the synthetic control method proposed by Arkhangelsky et al. (2021). All models in this table and event studies below include a treatment indicator, a year measure, standard errors are based on placebo inferences with the default 50 repetitions. $^{**}p < 0.05$; $^{*}p < 0.1$; $^{***}p < 0.01$.

the synthetic difference-in-difference (SDID) method proposed by Arkhangelsky et al. (2021). The SDID estimator identifies treatment effects by jointly choosing unit weights (over control units) and time weights (over pre-treatment periods) to minimize differences between treated units and a weighted combination of controls in the pre-treatment period. SDID explicitly enforces pre-treatment outcome alignment. Formally, SDID solves a regularized optimization problem that balances pre-treatment fit against variance.

Importantly, the SDID algorithm requires a strongly balanced panel and a sufficiently long pre-treatment window so that the synthetic control can closely track treated outcomes prior to treatment, and we rely on placebo methods to estimate standards errors. As we note in the paper, we needed to impute missing dependent variables and modify our sample somewhat to meet the requirements of the estimator. We thus encourage caution when interpreting any specific point estimate. As noted in the main paper, our results are consistent with the main results found in Tables 2 through 4 and the event studies in the main body of the paper.