The Role of Large Firm Locations in Shaping U.S. Public School Finance*

Rahul R. Gupta
Georgetown University

Viviana Rodriguez
University of Texas at San Antonio

November 2022

Abstract

With over a third of school district funds coming from property taxes levied on households and firms, changes to the local property tax base affect revenues and budgeting priorities for public schools. Arrivals of Million Dollar Plants (MDP) into a county may increase school district revenue by increasing property tax collections. However, because local governments offer companies tax incentives to locate facilities in their jurisdictions, the effect of the arrival of a large firm to a community on school district finance is ambiguous. We uncover this relationship by linking information of public school district finance with firm arrivals and comparing school districts in counties that win a MDP to those in counties that were considered runners-up. We find that the arrival of a MDP increases school district property tax collections, compared to counterfactual counties, which are spent mainly on hiring new teachers. Furthermore, we find that school districts where the MDP locates does not see revenue increases. Rather, the gains are concentrated in districts adjacent to the MDP's, suggesting a transfer from the district where the plant locates to adjacent school districts.

*We would like to thank Cameron Anglum, Cailin Slattery, participants at the IZA Workshop on the Economics of Education, the Association for Education Finance and Policy, the UTSA Economics Brown Bag, and the CBCSE Brown Bag for helpful comments and suggestions. All remaining errors are our own. Contact information: rahul.gupta@georgetown.edu and viviana.rodriguez@utsa.edu.

1 Introduction

The commentary surrounding modern company towns in the popular press motivates studying the relationship between the companies that dominate a community's landscape and the quality of its local institutions. While a growing body of literature investigates the role of local subsidies and tax incentives in luring firms to a state or city, we know of no study that directly links firm arrival to a community to changes in school decision-making at a granular level.[1] To shed light on this relationship, this paper evaluates the impact of large firm arrivals on public school district finance.

Public schooling in the United States is heavily reliant on the structure of the local tax base with 92% of school district funding coming from either state or local sources and over a third of this amount attributable to property tax collections within the school district itself (NCES, 2020). Expansions by large firms into a county may increase property values through agglomeration benefits that are capitalized into land and housing prices or through increases in the size of taxable base through migration and greater employment opportunities. However, because local governments offer companies tax incentives to locate facilities in their jurisdictions, often in the form of property tax abatements, it is unclear whether the arrival of a large firm to a community increases or decreases revenue school districts have available to them (Bartik, 2017; Slattery and Zidar, 2020).

To understand the effect of large firm arrivals on public school districts, we exploit cases where firms announced the location "winning" a large facility and the next best site it considered at the end of its search process.[2] Under a dynamic difference-in-differences (DiD) empirical strategy, we identify the impact of large firm location decisions on school district revenues and expenditures by comparing changes over time of school district outcomes in winning counties to districts in runner-up counties before and after the plant opening announcement.

We draw on two main sources of data for our study. The first data set was built by Gupta (2020) and consists of *Site Selection* magazine articles between 1990 and 2015 that document the site search processes for corporate real estate for the opening of new major business locations. Crucially, these articles not only mention the town or county the company selected for its new facility, but also the next best site the company considered in the final stages of their search process. We use these "winning" and "runner-up" locations as treatment and control groups in our DiD estimation. School district-level outcomes are taken through the U.S. Department of

[1] On a related note, some have discussed the relationship between corporate offices and endowments of local charities and nonprofits such as Card et al. (2010).

[2] Following convention as first described by Greenstone and Moretti, 2003 and Greenstone, Hornbeck, and Moretti, 2010, we refer to these facilities as "Million Dollar Plants" (MDPs) and we discuss sample construction in Section 2.

Education's Common Core of Data (CCD) which provides budget line item breakdowns of school district expenditures by object, revenue by source, and staffing.

We find that Million Dollar Plant (MDP) arrivals lead to an increase in school district revenues beginning two years after the MDP announcement. School districts in counties where MDP open see an increase in their revenues of around \$500 per enrolled pupil, which represents an increase of 4% compared to school districts in runner-up counties. Growth in total revenue is driven exclusively through higher school district property tax collections, which increase by 9%.

Next, we ask how districts allocate these surplus funds across a number of budgetary line items. Conceivably, the additional revenue could be used to invest in idiosyncratic facilities upgrades depending on the district, hiring more staff to reduce class sizes, or can be spent on new programs that are influenced by a potential inflow of new families after the arrival of the MDP. We find that school districts spend nearly the full amount of the additional revenue on instruction by a magnitude of \$400 per pupil (6% increase) after the MDP announcement relative to those in counterfactual counties. The increase in instruction expenditures is driven by the hiring of additional teachers *per pupil* rather than increases in teacher pay. School districts gradually increase the size of their per pupil full-time equivalent teaching staff (teacher FTE) over the seven years following the MDP announcement. By year 7 after the announcement, per pupil teacher FTE is approximately 7% greater than the year prior to the MDP announcement.

Finally, in unpacking these results, we find stark heterogeneity of school district revenue gains by proximity to the MDPs. By geocoding the locations of the Million Dollar Plants, we match each plant to a specific school district within the county and recover its distance to the new plant. This allows us to test whether potential tax abatements these firms receive *reduce* revenue in the most proximate school district, but have positive spillovers to other neighboring districts in the county that result in our large county-wide effects. Prior literature such as Qian and Tan (2021) show that the arrival of a MDP alters the gradient of property values in a county that is based, in part, on commuting patterns of workers in the entering firm. If, for example, a county is divided into multiple school districts, then the firm may receive a property tax abatement to locate in one specific district and its worker elect to commute from other neighboring districts. Our results indicate that the district where the MDP arrives sees no gains in property tax revenues whereas neighboring school districts that receive the inflow of new workers to the area experience an increase in property values without forgoing tax revenue through the incentive packages.

Our study makes several contributions to the literature. First, our study contributes to the literature examining changes to local school finance driven by economic shocks. While, there is a vast literature examining the effects of school funding reform on school district finances (Hoxby, 2001; Murray et al., 1998) and student outcomes (Jackson et al., 2015; Lafortune et al., 2018; Brunner et al., 2020). Other types of revenue shocks or policies can affect school funding. For example, the Great Recession has been found to have had an important impact on school finance by increasing inequality across school districts and leading to increases in student test gaps across income and race (Evans et al., 2019; Jackson et al., 2021). Furthermore, recent work by Brunner et al. (2022) shows how wind energy installations in the U.S. lead to increases in school district capital outlays with no effect on student achievement. This paper contributes to this literature by examining the effect of a novel source of revenue shock, firm arrival. We show how firm arrivals increase the revenue school districts have available to them, mainly driven by higher property tax collections, and how districts choose to allocate these additional dollars towards teacher hiring.

Second, our paper contributes to the literature on the "flypaper" effect. This literature examines whether intergovernmental transfers and exogenous increases of revenue "stick where they hit" rather than being crowed out by local responses, such as reallocation of funds to different projects or towards property tax relief. While some studies find that local governments strongly crowd-out exogenous revenue increases (Knight, 2002; Gordon, 2004; Steinberg et al., 2016), others find strong evidence of flypaper effects (Brunner et al., 2022; Hines and Thaler, 1995).[3] Given the large and sustained increases in local revenue driven by the arrival of the MDPs, our paper provides evidence of a strong flypaper effect of a MDP arrival to a county.

Finally, this study contributes to the literature that examines Million Dollar Plants from a public finance perspective. The initial body of MDP literature used MDPs as a means for understanding agglomeration spillovers and local productivity (Greenstone et al., 2010; Bloom et al., 2019; Gupta, 2020). A more nascent strand of literature in public economics seeks to understand MDPs themselves through estimating the size and scope subsidy deals that are offered by local officials to firms (Slattery, 2018; Slattery and Zidar, 2020). Since MDPs involve large investments, often exceeding a quarter billion dollars and employ over 2,000 employees, we see MDPs as a positive shock to local economic factors that improve the size and value of the local tax base. However, because subsidies are often offered, the impact of the MDPs arrival to a community on local public finance is ambiguous. Our paper therefore focuses on how MDPs impact the quality of local public

[3]Furthermore, there is evidence that suggests that local institutions play a key role in determining whether revenue will "stick where it hits" rather than being crowded out (Brunner et al., 2020; Cascio et al., 2013; Brooks and Phillips, 2010)

services by focusing on a context where the size and value of the local taxable base directly influences the quality of a critical local public good, public education. Our paper quantifies the effect that large firm arrivals have on public school district revenue and educational expenditure. We further uncover stark spatial heterogeneity of these effects that suggest districts where the plant locates potentially subsidize adjacent school districts.

Of primary concern to our research design is possible bias introduced by heterogeneity in treatment arising from different timing associated with each case. Borusyak et al. (2022), Callaway and Sant'Anna (2021), and Goodman-Bacon (2021) discuss disproportionate loading into the DiD estimator from certain treatment groups and time periods when treatments are administered at different times. Our estimation sample allows us to force the DiD estimator to be identified within plant opening cases and not across cases. We provide the full treatment panel and for each of the 94 MDP cases provide time dummy interactions and show parallel trends for each of the 5 years preceding the MDP announcement and the 7 years following.[4]

In the next section, we describe the institutional setting of the Million Dollar Plant site selection process and construction of the event sample. Section 3 describes the Common Core of Data (CCD) which provides information on school districts and enable construction of our main outcomes of interest and final regression sample. We then provide an overview of sampling timeframe, cleaning procedure, and empirical strategy in Section 4. Next, we present and describe a number of figures that show how treated school districts see a change in their financing streams, instructional expenditures, and staffing after a firm arrival in Section 5. Section 6 presents heterogeneity results across school district proximity to the MDP firm. Finally, Section 7 presents robustness checks, and we conclude with our a summary of results and pathways for further research in Section 8.

2 Institutional Setting

While local policymakers use subsidies to create an environment attractive to targeted firms, firms similarly exert influence over the communities in which they locate upon receiving these subsidies. In the most extreme cases, company towns form where small cities organize about a focal firm. While the explicit organization of towns or cities about a firm like Pullman in the early 20th century have all but disappeared in the United States, large firms still shape the communities as taxpayers, employers, and other non-market means of influence.

[4]We refer to Bloom et al. (2019) and Gupta (2020) for discussions on how these MDP events perform under a variety of robustness checks on identifying assumptions.

In some cases as with Boeing in 1970s Seattle, the influence is through direct involvement of employees on school boards and shaping public school policy that potentially contributed to the attraction and development of a talented workforce (Glaeser, 2011). In other instances, anecdotes describe evolution of a community's social and political life through the rise and fall of its local industry as with poultry factories in Albertville, AL over the course the 1990s and early 2000s (Glass, 2017). More recently, as Amazon solicited subsidy deals for its second Headquarters office (HQ2), community development officials sought to market their communities as investing heavily in public schooling that would make their districts attractive for families and potentially for grooming future Amazon employees. The economic development authority that put together the winning deal, HQNoVa, explicitly mentions in its report the intent of the company to "double Virginia's tech-talent pipeline, beginning in K-12 schools" prompting critics to lament the growing influence of U.S. corporations in shaping public education (Bryant, 2020).

These examples, while anecdotal, describe changes that occur in a community in the presence of large firms. More rigorous studies have shown how large firms enhance local firm productivity (Greenstone et al., 2010), improve management practices locally (Bloom et al., 2019), and increase welfare for landowners (Qian and Tan, 2021). However, these effects plausibly influence the provision, availability, and quality of public goods as well. In this paper, we focus on understanding how the location of large establishments shapes the administration of public schools. One key channel through which firm locations drive public school administration is through their contribution to the local tax base. Public school finances in the United States are heavily reliant on revenue sources in the area of the school district with 92% of school district funding coming from either state or local (e.g., county, city, and district) sources and over a third of this amount attributable to property tax collections within the school district itself (NCES, 2020).

On the surface it would appear that expansions by large firms into a county may increase public school funding through positive impacts on local property values. However, local governments generally offer companies tax incentives to locate facilities in their jurisdictions. Thus, it is unclear whether the arrival of large firm to a community necessarily increases the resources school districts have available to them. Tax abatements, cuts in property tax rates (also referred to as school tax rates in some jurisdictions), and other special incentive programs that limit the ability of school districts to levy taxes and fees from their communities are often offered to companies in the form of incentive packages. For example, some estimates suggest city and state governments award approximately $60 billion in subsidies annually (Bartik, 2017) that are largely in the form of property tax abatement (Slattery and Zidar, 2020).

To understand this trade-off, our study is restricted to independent school districts, which are administratively and fiscally independent of any other parent government, and are able to collect property tax directly. We link these school districts to a sample of large and generally Fortune 500 sized companies that are featured in *Site Selection* with details about their site searches to examine how these large firm locations influence outcomes in local school districts.

Site Selection magazine is a publication by the corporate site search consultancy firm Conway Analytics. The focus of the magazine is to provide insights on major corporate location decisions including real estate markets, local business environment, and subsidy offers for location searches. Throughout its history, the magazine has published articles under headings including "Million Dollar Plants", "Location Reports", "Blockbuster Deals", and "Top 10 Deals" that document the final stages of companies' location searches. These articles describe the company, the purpose of the new facility, and the leading factors driving the company's ultimate destination. Crucially, these articles often also listed a set of finalist sites that the company considered in addition to the ultimate chosen location.[5]

To identify the causal effect of large firm locations on public school administration and finance, we utilize a subset of plant opening events that were first data collected by Gupta (2020). These data were collected via a mix of archival collection through microfiche, physical magazine copies, and searches of the magazine's website for more recent events.[6] Altogether, Gupta (2020) recovered data on 240 "cases" from 1990 through 2015 where a company name, industry, winning county, and at least one runner-up county are identifiable and verified through LexisNexis and Google searches. Industry (NAICS) are assigned using descriptions of the opening facility in the articles which often describe the product being manufactured or characteristics of the facility.[7]

[5] Greenstone, Hornbeck, and Moretti (2010) were the first to propose that these *Site Selection* articles can be used in a difference-in-differences style empirical analysis whereby researchers compare outcomes for firms in winning counties to those in runner-up counties.

[6] See Gupta (2020) for more details on the data collection process.

[7] The sample of plant openings overrepresent the manufacturing sector and are generally large Fortune 500 companies. However, plant openings in R&D labs, telecommunications services, financial institutions, and corporate management offices appear frequently as well. Geographically, the U.S. southeast is overrepresented reflecting the gradual migration of manufacturing firms from north to south, though states with the largest numbers of cases are distributed across the west coast, midwest, and mid-Atlantic. All but six states are found in the hand-collected magazine sample.

3 Common Core of Data

Our main data source is the Common Core of Data (CCD). A statistical division housed within the U.S. Department of Education, the National Center for Education Statistics (NCES) created the CCD as the agency's primary instrument for collecting, tabulating, and disseminating statistical information on primary and secondary public schools and school districts in the United States. Because of the degree of local autonomy of public schools, the Department of Education established the CCD to harmonize and facilitate analysis on the functioning of schools for maximum comparability across states. The CCD is ideal for this study because it allows researchers to construct a panel of all school districts in the United States.

To compile the CCD, the NCES administers four surveys each year to state-level education authorities for information on all public primary and secondary schools as well as state and local education agencies. Crucial to our study, is the School District Finance Survey (F-33). The F-33 collects data at the school district-level on all financial transactions associated with revenues by sources, expenditures by function and object, indebtedness, and assets. These data allow us to disaggregate district revenue into their federal, state, and local components, as well as school district expenditures of important categories such as instruction expenditures and teacher salaries.

Of the three broad revenue sources (”Federal”, ”State”, and ”Local”), Federal revenue is the smallest category and on average accounts for just 8% of total school district funding in the U.S. Generally, these funds are transferred to school districts through specific programs or earmarked purposes.[8] State revenue sources account for approximately 48% of total revenue for the average school district. These budget amounts are generally set by state statutes and calculated based on school district size.

For our study, we focus most carefully on components related to local revenue that sum to the remaining 44% of total district revenue. These monies are often levied by the school district itself and are most sensitive to local economic conditions, particularly for independent school districts. Examples of local revenue sources that can individually be identified in the CCD property taxes, general sales taxes, public utility taxes, and individual and corporate income taxes.[9] Property

[8]Examples of these federal programs include the Child Nutrition Act, Title I, Individuals with Disabilities Education Act, and for the years 2008-2013 the American Recovery and Reinvestment Act. The CCD also shows federal funding that is earmarked for specific purposes such as ”safe and drug-free schools” or ”math, science, and teacher quality.”

[9]The database further provides the amount, if any, the school district collects from school lunch, interest earning accounts, private contributions, transfers between school districts, textbook sales, fines and tuition levied, and other smaller and idiosyncratic fees levied on students or district residents in special circumstances.

tax revenue account for nearly 60% of total local revenue. The second largest local categories are miscellaneous sources and transfers between school systems which each account for just 7%.

The structure of expenditure reporting is simpler because expenses are incurred at the discretion of the school district itself. The CCD itemizes total expenditures into subcategories. The two largest subcategories are "Elementary and Secondary Expenditures" which account for nearly 86% of total school district expenditure and "Capital Outlay Expenditures" that sum to 7% of total school district expenditures.[10] Our analysis focuses on the largest set of discretionary expenditures of which nearly 60% are accounted for by expenditures related to instruction. Within instructional expenses, the CCD shows budgetary items that range from equipment and textbooks to salaries for instructional staff (i.e. teachers and teacher aides). For the average U.S. school district between 1994 and 2016, salaries for instructional staff amount to nearly 70% of total instructional expenditures and 35% of total annual school district expenditures. The CCD further provides information on quantities of staff hired in various categories. For example, we observe the number of full-time teachers in elementary and secondary schools, the number of teacher aides, administrative staff, support staff, and various other employment designations. The remaining budget line items account for no more than 8.5% of total expenditures with the largest item being operational expenditures related to maintenance and support of facilities.

To arrive at our main estimation sample with school districts as the unit of observation we start with a Common Core of Data extract obtained through the Urban Institute's Education Data Portal (Urban Institute, 2021). Spanning the years 1994 to 2016, this CCD extract provides directory, enrollment, staffing, and finance data for all public school districts that are identifiable through a time-invariant unique identifier issued by the NCES. We identify independent school districts since they have greater revenue enhancing autonomy than districts dependent on a parent government (see Section 2) using the *CENSUSID* variable that includes an identifier for agency type.[11] We merge these data for independent school districts with the plant openings data using year and county FIPS codes to identify school districts located in winner and runner-up counties for each plant opening "case".[12] We create a balanced panel of independent school districts such that all school districts have data available for our outcomes of interest. These variables include district-

[10]Capital outlay expenditures refer to expenditures incurred in the acquisition, lease, or additions to real property assets or equipment held by the school district. These capital outlays include new buildings, parking lots, athletic stadiums, science labs, etc.

[11]The *CENSUSID* is a 14-digit government agency identifier. The third digit in the code takes on the value "5" if the agency is an independent school system.

[12]District information in the CCD is organized by academic year and provides data at the start of the year's Fall semester, whereas MDP years are based on the year the firm announced the final site selected.

level revenue and expenditure, full-time equivalent (FTE) staff counts for all teacher categories, and student enrollment by race and ethnicity. For each school district in either a winning or runner-up county, these variables must exist without gaps for 6 pre-treatment and 7 post-treatment years for each plant opening case. Finally, cases must have at least one district remaining in both the winning and runner-up county that meet these criteria. This cleansing procedure retains 94 cases out of the initial 240.

4 Empirical Specification

In an ideal experiment, researchers would randomly construct new Million Dollar Plant sized facilities in school districts across the U.S. Because construction of these MDPs was through random assignment, the effect of plant openings on school district outcomes would be identified by differences in outcomes of school districts with and without the plant.

Unfortunately, we only observe endogenous sorting of firms to locations on unobserved factors which might include factors that are related to local public goods and correlate with the firm's expected profitability. We overcome this identification challenge by comparing outcomes for school districts in the set of counties that were considered in the late stages of firms's site search to identify the causal impact of exogenous changes in school districts' funding base for the average district in the winning county.

Under the assumption that the final selection between winning and runner-up counties is independent of school district specific factors, we estimate a difference-in-differences specification with time interactions and a fixed effects to force comparisons between winners and runners-up to be within a MDP opening event:

$$
\begin{aligned}
y_{scit} = {} & \alpha_0 + \eta_s + \lambda_c + \mu_i + \gamma_t \\
& + \beta_W \times Win_{sc} + \sum_{k=-5}^{-2} \tau_k \times \mathbf{1}[t=k] + \sum_{k=0}^{7} \tau_k \times \mathbf{1}[t=k] \\
& + \sum_{k=-5}^{-2} \beta_k \times Win_{sc} \times \mathbf{1}[t=k] + \sum_{k=0}^{7} \beta_k \times Win_{sc} \times \mathbf{1}[t=k] + \epsilon_{scit}.
\end{aligned} \tag{1}
$$

In Equation 1, s denotes a school district in case c with a treatment from industry subgroup i in year t. y_{scit} indicates the school district-level dependent variables. Our key coefficients of interest are represented by the set of β_k's. These β_k's represent the effect of the MDP on the winning county relative to the losing county at time k, where time is measured relative to the announcement date of the MDP. Including all time interactions enables us to directly test for any pre-trends and systematic differences in our outcomes of interest. The regressions include a large number of fixed effects to account for time-invariant school district characteristics in η_s and secular trends in school districts through γ_t. We include fixed effects for the industry subgroup at the 3-digit NAICS code of the opening facility in μ_i. These fixed effects capture variation that may be correlated across cases through common industries that appear in the treatment sample. Crucial to identification of the β_k's are the case fixed effects. The λ_c case fixed effects force the β_k's to only be identified by comparing the winning county of a case to only the runner-up county in that particular case without risking attrition of counterfactual counties or comparing counties across different events and time periods.

Table 1: Similarity of Winning and Runners-up Counties

	Winners	Runners-up	Difference	All
Panel A. School District Similarity				
Number of school districts:	844	705		13,556
Per pupil revenue & expenditure:				
Total revenue	$13,259	$12,981	$278	$11,452
State revenue	$6,099	$5,934	$165	$5,466
Federal revenue	$760	$954	-$194*	$733
Local revenue	$6,400	$6,093	$307	$5,252
Property tax revenue	$4,967	$4,876	$91	$4,106
Total expenditure	$13,463	$13,474	-$11	$11,605
Instruction expenditure	$6,811	$6,819	-$8	$6,034
Support services expenditure	$3,861	$3,760	$101	$3,331
Capital outlay	$1,619	$1,718	-$99	$1,119
Other:				
Per pupil teacher FTE	0.058	0.056	0.002	0.057
Enrollment	7,845	8,959	-1,114	2,832
Share white	0.612	0.517	-0.095	0.694
Panel B. County Similarity				
Number of counties:	60	87		3,141
Demographics:				
Total population	652,130	878,383	-226,253	79,152
Total employment	310,247	429,227	-118,981*	27,466
Non-white share	30.97%	34.34%	-3.37%*	24.42%
Immigrant share	8.19%	9.68%	-1.49%	4.34%
Share older than 65	11.87%	11.94%	-0.07%	12.52%
% High school diploma only	32.82%	32.18%	0.63%	38.83%
% at least Bachelor's degree	26.56%	26.85%	-0.29%	18.05%
Economic:				
Prime aged male joblessness	19.68%	20.96%	-1.28%**	22.00%
Self-employment rate	8.38%	8.61%	-0.23%	11.45%
Avg. income	$55,306	$54,749	$557	$41,960
Mfg. share of employment	14.19%	14.46%	0.27%	24.39%
Single family home value (per sq. ft.)	$88.72	$91.71	-$2.99	$67.77
Community bank deposit share	22.17%	20.52%	1.65%	36.94%
Announcement industry:				
Employment	2,665	3,483	-818	12
Employment share of county	1.16%	1.15%	0.01%	0.45%
Establishment size	72	71	0.91	14

Notes: * 10%, ** 5%, *** 1%. All school district information presented in panel A is obtained from the Department of Education's CCD. Total population, non-white share, and share older than 65 are obtained from the National Cancer Institute's SEER population characteristics registry for the year preceding the opening announcement. Immigrant share, % high school diploma only, % at least bachelor's degree, prime aged male joblessness, self-employment rate and average income are obtained from the 5% PUMS sample from Census 1990 or 2000 depending whichever decennial Census immediately preceded the MDP announcement. PUMS files use the PUMA as the smallest geographic definition. Therefore, tabulation use a crosswalk of PUMA definitions in 1990 and 2000 to time-consistent FIPS definitions by using the percentage of a county's total population represented by a PUMA. Education shares reflect the percentage of adult population aged over 25 years having already earned the degree. Prime aged males are individuals between 25 and 55 and identifying as male in the Census and the jobless rate refers the share of these individuals not working or working fewer than 40 hours per week. Self-employment is the numbed of individuals working at least 40 hours as self-employed divided the total number of full-time adult workers. Average income is tabulated at the household-level using the IRS Statistics of Income files for year preceding the opening announcement. Community banks are defined as deposit taking institutions with assets less than $1 billion and either federally chartered and regulated by the Office of Thrift Supervision or state chartered and regulated by the FDIC. Total employment, mfg. share of employment, and all "Case-industry" variables are calculated from County Business Patterns for the year preceding the announcement. The tabulations are calculated at the 4-digit NAICS level. Mfg. share of employment is the percentage of employment between NAICS 3100 and 3399. The announcement industry variables are defined for the industries of firms in the *Site Selection* magazine sample. Establishment size is tabulated as total employment divided by establishment counts in the county-industry pair. Home values per square feet are tabulated using data from Zillow for March 2000.

The key assumption behind our empirical strategy is that the counties in the treated and counterfactual counties do not differ on variables that jointly influence the firm's location decision and conditions of local schools. Greenstone et al. (2010) and Bloom et al. (2019) both run numerous balance tests on the treated and counterfactual counties, but in Table 1 we provide additional balance tests on our matched CCD-MDP sample. The table is divided into two panels each with four columns. Panel A provides descriptive statistics on school district-level variables and Panel B provides descriptive statistics on economic variables at the county-level. In Panel A, we consider all school districts located in winning counties to be "Winners" and all school districts located in runners-up counties to be "Runners-up". The first three columns compare the average values of winners to runners-up and displays the difference in values in the third column. The Difference column further indicates whether the difference between the winners and runners-up is statistically significant. We include a fourth column to show the average value for all school districts regardless of their involvement in the contest for the Million Dollar Plant.

Panel A does not indicate any systematic differences between school districts in winning and runners-up counties. We note that counties considered for Million Dollar Plants are generally better funded on a per pupil basis than districts in the average county. Contest county school districts have higher per pupil revenues that are driven from higher local revenue (property tax collections) and state revenue. In addition, both winner and runner-up school districts have larger per pupil expenditures in instruction than the average school district in the U.S. Furthermore, school districts considered for plant opening decisions are larger and serve a more diverse student body than the average school district. Panel B displays county-level population characteristics that may correlate to both an MDP's location decision as well as factors that lead to differences in our outcomes of interest. The contest counties are similar on all measures aside from total employment and prime aged male joblessness. Winning counties have 118,000 fewer workers relative to runners-up and this difference is significant at the 10% level. Winners also have lower rates of prime aged male joblessness which is significant at the 5% level.

5 Results

This section presents dynamic difference-in-differences estimates of Equation 1 for school district outcomes. First, we present estimates of changes in school district revenue in Section 5.1. Then, Section 5.2 presents estimates of the effect on school district expenditure. All school district outcome variables are transformed to per pupil values using pre-treatment enrollment values and all figures presented in this section plot β_k coefficients and 90% confidence intervals from Equation 1.[13] Tables with the full set of estimates for all outcomes of interest can be found in Appendix A.2.

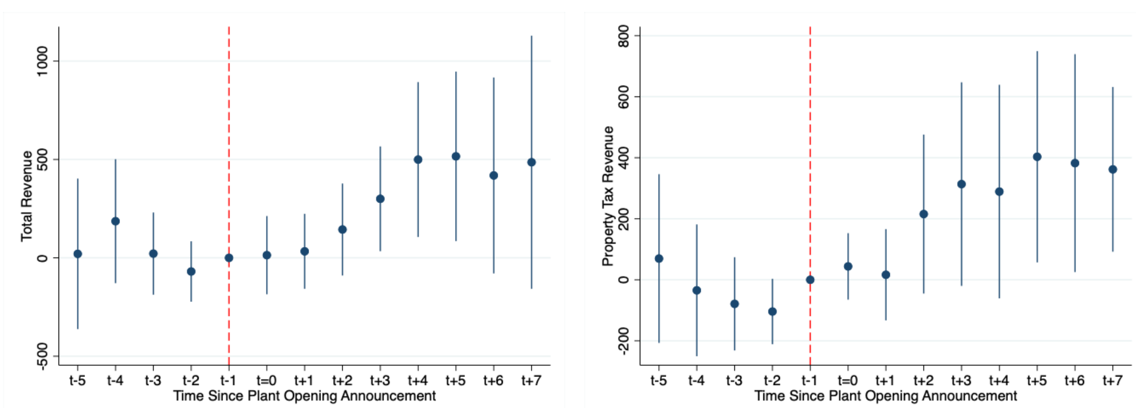
5.1 Revenue

Expansions by large firms into a county may increase property tax collections through one of two channels. The large firm could lead to agglomeration benefits that are capitalized into land and housing values that are taxed by school district or increase the size of the taxable base through migration induced by new employment opportunities. However, because local governments offer companies tax incentives to locate facilities in their jurisdictions, often in the form of property tax abatements, it is unclear whether the arrival of a large firm to a community increases or decreases the resources school districts have available to them.

To identify the effect of the MDP on school district revenue, we use various categories of school district revenue as the outcome of interest in Equation. Figure 1 presents these estimates for models with school district total revenue and property tax revenue (panels (a) and (b), respectively). Panel (a) shows how school districts in counties where a MDP opens see an increase of per pupil revenue three years after the new plant is announced. From $t \in [4, 7]$ relative to the plant opening announcement, school districts in winning counties see increases in per-pupil revenue of approximately \$500 per pupil which amounts to a 4% increase.

Figure 1: School District Revenue Dynamic Difference-in-Differences Estimates

(a) Total Revenue (b) Property Tax Revenue



Notes: This figure plots dynamic difference-in-differences estimates and 90% confidence intervals following Equation 1 for school district total revenue (panel (a)) and revenue from local property tax collection (panel (b)). This figure shows total revenue gains from the new firm begin to accrue commencing in year 3 after the plant opening announcement. These gains are mainly driven by increases in property tax collections. See Table A.1 for full estimates of Equation 1.

Property tax revenue is a critical source of revenue for school districts. It directly reflects local

[13] We divide school district outcomes by pre-treatment enrollment to recover per pupil values. In doing so, we recover causal effects of plant openings on school district finance outcomes alone, rather than enrollment changes.

property values that could be affected by large firm arrivals. Thus, changes in local property tax collections allows us to understand the mechanisms of the revenue gains seen in panel (a) of Figure 1. Panel (b) presents estimates for dynamic difference-in-differences estimated for school district property tax collections. This figure shows that school district revenue gains are primarily driven by property tax gains. Two years after the plant announcement, school district property tax collection increase by \$200 and steadily increase thereafter. Seven years after the plant opening announcement, school districts located in counties with a new firm arrival see property tax revenue gains of \$400 per student which amount to a 9% increase in property tax collections.

Property tax revenue is the main driver of the total school district revenue increase shown in panel (a) of Figure 1. All other sources of revenue (state and federal) do not change after the MDP announcement (see Figure A.1).

5.2 Teacher Staffing and Pay

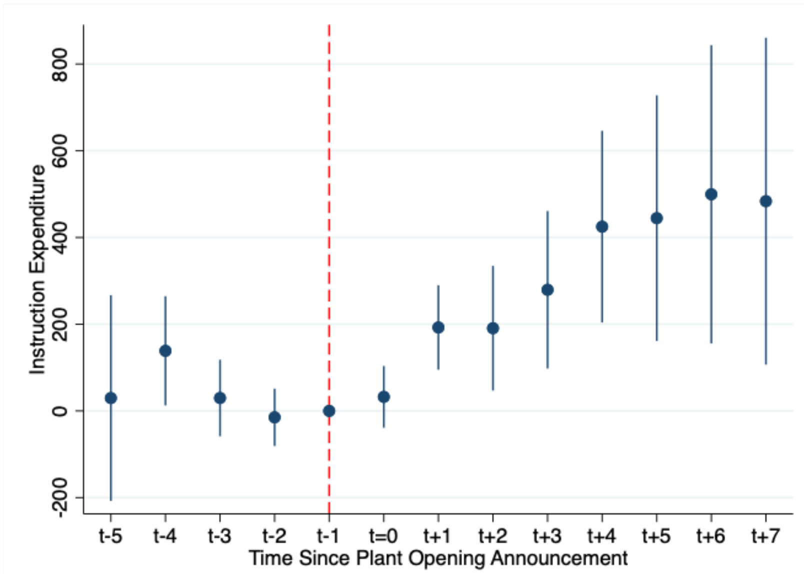
Results presented in Section 5.1 show how MDP openings generated increased local revenue for school districts, mainly driven by increased property tax collection. This section explores how this additional revenue is allocated toward teacher hiring and compensation. Figure 2 presents dynamic difference-in-differences estimates for per pupil expenditures on instruction. School districts in counties where MDPs open spend more each year on instruction from $t \in [1, 7]$ relative to the plant opening announcement. Increases in instruction expenditures correspond to a \$400 per pupil increase ($\uparrow$ %6), which closely tracks increases in revenue.

To understand whether increases in instructional expenditures are driven by teacher hiring or pay, Figure 3 presents estimates for per pupil FTE teacher staffing and average teacher pay in panels (a) and (b). School districts in winning counties systematically hire more teachers per pupil after the new plant opens. While increases in teacher hiring begin after $t = 1$, the bulk of teacher hiring begins from $t \in [3, 7]$. Seven years after the MDP opens, school districts in winning counties hire, on average, 0.004 more teachers per pupil than their counterparts, representing a 7% increase in per pupil teacher FTE.

Panel (b) of Figure 3 presents changes in teacher compensation.[14] While point estimates of changes in teacher compensation after the plant opening are positive, they are not statistically

[14]Data on salary expenditure for teachers is only collected starting in 2003. Therefore, estimates presented in panel (b) of Figure 3 only include a subset of MDP cases than the ones used in all other outcomes presented in this paper. However, given that most instructional expenditures for school districts are allocated towards teacher compensation, there is a high correlation of 0.995 between teacher salary data and instructional expenditure data for the years of overlap.

Figure 2: Expenditure on Instruction Dynamic Difference-in-Differences Estimates

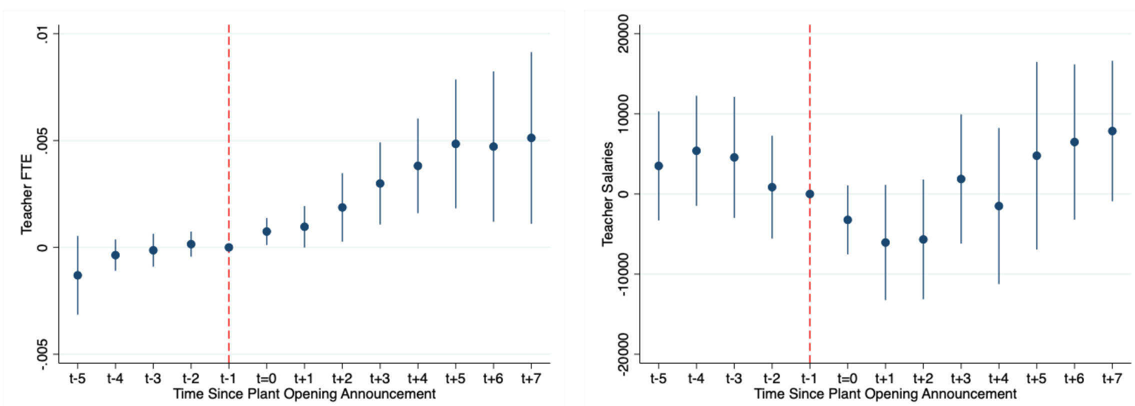


Notes: This figure plots dynamic difference-in-differences estimates and 90% confidence intervals following Equation 1 for school district instructional expenditure. This figure shows increases in school district expenditure on instruction after year 1 of the plant opening. See Table A.1 for full estimates of Equation 1.

Figure 3: School District Teacher Staff Dynamic Difference-in-Differences Estimates

(a) Teacher FTE

(b) Teacher Pay



Notes: This figure plots dynamic difference-in-differences estimates and 90% confidence intervals following Equation 1 for school district per pupil teacher FTE staffing in panel (a) and teacher pay in panel (b). This figure shows increases in teacher hiring after year 2 of the plant opening announcement and noisy increases in teacher pay. See Table A.1 for full estimates of Equation 1.

significant. Thus, taken together, Figure 3 suggests that plant openings lead to increases in school district salary expenditure driven mainly by increased teacher hiring rather than increases in teacher pay.

Increased school spending has been found to improve student achievement, attainment, graduation, wages, adult poverty incidence, among other outcomes (Jackson et al., 2015; Lafortune et al., 2018; Brunner et al., 2020; Lee and Polachek, 2018). A recent and growing literature further indicates that instructional and operational expenditures might be the most effective form of expenditure to boost student learning (Abott et al., 2020; Baron, 2022).

Given the results presented in this section and in Section 5.1, we expect plant openings to lead to better outcomes for students in winning districts. Baron (2022) finds that an increase of \$300 of per pupil operational expenditures leads to an increase in 8% of a standard deviation in student achievement on standardized test scores, 9% reduction in student dropout rates and a 10% increase in student post-secondary enrollment. Thus, using a back-of-the-envelope calculation, we can expect student gains on achievement from plant openings be to around 10% of a standard deviation for students in winning counties.

6 Spatial Heterogeneity

School district revenue gains after a plant opens in a county materialize through greater property tax collections (see Section 5.1). Thus, the increase in property tax collections offsets any tax incentives local governments offer firms. However, the effect of firm arrival on property values varies by distance to the plant (Qian and Tan, 2021). This implies that school districts in winning counties may have heterogeneous effects on property tax revenue that varies by proximity to the new plant.

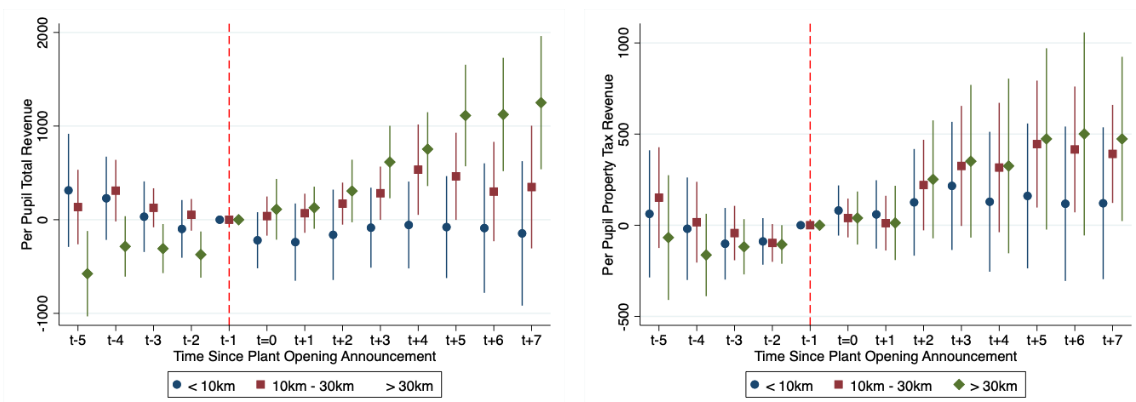
To understand this mechanism, we draw from plant and school district geolocation and explore the relationship between school districts' proximity to the new plant and its capacity to levy property tax revenue. We do so by classifying all school districts located in winning counties into three groups: districts around a 10km radius of the new plant, district between 10km-30km, and districts farther than 30km to the new firm facility. For each of these school district groups (d), we estimating the following equation:

$$\begin{aligned} y^d_{scit} = {} & \alpha^d_0 + \eta^d_s + \lambda^d_c + \mu^d_i + \gamma^d_t \\ & + \beta^d_W \times Win_{sc} + \sum_{k=-5}^{-2} \tau_k \times \mathbf{1}[t=k] + \sum_{k=0}^{7} \tau_k \times \mathbf{1}[t=k] \\ & + \sum_{k=-5}^{-2} \beta^d_k \times Win_{sc} \times \mathbf{1}[t=k] + \sum_{k=0}^{7} \beta^d_k \times Win_{sc} \times \mathbf{1}[t=k] + \epsilon_{scit}, \end{aligned} \tag{2}$$

Equation 2 compares school districts in winning counties and belonging to each distance group d, to *all* school districts in the corresponding runner-up county. Ideally, our spatial comparison would identify school districts in a 10km radius from the new plant opening in winning counties and compare them to counterfactual school districts that would have been located 10km from the plant opening in the runner-up county. Unfortunately, our data does not have counterfactual plant opening geolocation in runner-up counties. Thus, Equation 2 compares school districts at different distances d from the actual plant opening to all school districts in the runner-up county. The assumption behind this comparison is that the average school district in the runner-up county acts as a valid counterfactual to school districts in the winning county across all distances to the new firm.

Figure 4: Dynamic Difference-in-Differences Estimates By Distance

(a) Total Revenue (b) Property Tax Revenue



Notes: This figure plots dynamic difference-in-differences estimates and 90% confidence intervals following Equation 2 for school district total revenue (panel (a)) and property tax revenue (panels b) for school districts at different distance ranges from the new plant location. This figure shows property tax gains (local revenue) from the new firm accrue mostly for school district that are the most distance to the new firm.

Figure 4 presents β_k^d estimates for all winning school district groups (d) for total revenue (panel (a)) property tax collection revenue (panel (b)). These estimates indicate that school districts located father away from the plant opening itself see more revenue gains than districts locates in the close vicinity of the new firm opening. In fact, school districts located with a 10km radius of the new plant opening do not benefit from any revenue gains after the new firm arrival.

Therefore, while most school districts see revenue gains driven by increased property tax collections, school districts that are most proximate to the new plant do not. This spatial heterogeneity is likely driven by property tax abatements offered to these firms that take away revenue gains that come from higher local property values for the most proximate school districts. School districts that are farther away generally do not offer any type of property tax abatement to the incoming firm, and thus do see revenue gains that arise from increased property values.

7 Robustness Checks

Of primary concern to the validity of our research design is possible bias introduced by heterogeneity in treatment timing. Borusyak et al. (2022), Callaway and Sant'Anna (2021), and Goodman-Bacon (2021) discuss disproportionate loading into the two-way fixed effect DiD estimator from certain treatment groups and time periods when treatments are administered at different times.

Our empirical strategy allows us to force the DiD estimator to be identified within plant opening cases and not across cases. Thus, our research design mitigates concerns of bias arising from heterogeneous treatment timing and *forbidden* comparisons (Callaway and Sant'Anna, 2021). Nevertheless, even in the absence of staggered timing *within* plant openings, a potential concern arises from counties being considered in more than one plant opening decision. If previously winner counties become runner-up counties in future plant opening decisions, this might introduce bias to our estimates even if we do force our comparisons to be within plant opening cases.

Of the 94 cases used for the estimates presented in Section 5, we identify 12 plant opening cases in which the runner-up county (or at least one of the runner-up counties) was previously a winner in another plant opening decision. Thus, as a robustness check, we re-run our analyses by excluding these problematic runner-up counties. These estimates are presented in Table 2. Overall, excluding them produce similar estimates to the ones presented in Section 5. Resutls presented in Table 2 indicate that firm arrivals lead to an increase in per pupil revenue that is driven mainly by increases in property tax collections. Furthermore, school districts allocate this additional revenue on increased teacher hiring rather than increased pay.

8 Conclusion

Advocates for place-based policy programs that target large firms to locate major facilities in a particular area focus on potential gains to local tax revenues that finance public services through rising incomes and expansion of the taxable base. This has led state and local officials to use subsidy programs such as property tax abatements to lure large plants. However, there is a dearth of empirical work that measures the impacts of new large plants on local government finance or downstream impacts of these programs on the quality of public services such as public K-12 education. Because most public school districts in the United States rely heavily on local property tax collections for operational revenue, we study the impact the arrival of Million Dollar Plants on public school revenue and expenditure.

Table 2: Dynamic Difference-in-Differences of School District Outcomes

	Revenue			Expenditure		
	(1) Local	(2) Prop. Tax	(3) Total	(4) Instruction	(5) Teacher FTE	(6) Teacher Pay
Win × t-5	-104.398	66.320	31.806	8.882	-0.001	3298.636
	(199.964)	(190.374)	(254.754)	(166.581)	(0.001)	(4260.801)
Win × t-4	-64.673	-37.537	214.421	135.202	-0.000	5351.173
	(156.884)	(146.256)	(208.662)	(86.137)	(0.000)	(4602.890)
Win × t-3	-87.407	-94.451	11.208	17.210	0.000	4590.627
	(114.625)	(102.973)	(131.296)	(57.704)	(0.001)	(5119.197)
Win × t-2	-148.739*	-111.382	-79.374	-29.465	0.000	304.500
	(88.832)	(73.832)	(94.689)	(36.621)	(0.000)	(4194.828)
Win × t-1						
Win × t=0	50.970	50.984	-11.261	27.959	0.001*	-3614.199
	(77.119)	(71.793)	(124.405)	(43.347)	(0.000)	(2759.410)
Win × t+1	74.924	26.603	-13.042	194.405***	0.001	-5860.712
	(112.489)	(97.604)	(110.324)	(62.488)	(0.001)	(4734.442)
Win × t+2	283.320	244.799	145.339	197.626**	0.002**	-5858.952
	(181.932)	(172.646)	(129.935)	(92.351)	(0.001)	(4707.844)
Win × t+3	405.688*	365.364*	289.933*	280.922**	0.003***	-385.905
	(224.985)	(206.408)	(174.833)	(124.511)	(0.001)	(5078.902)
Win × t+4	438.393*	345.057	494.115*	434.539***	0.004***	-3237.786
	(227.351)	(220.771)	(266.964)	(152.930)	(0.001)	(7332.746)
Win × t+5	539.995**	491.937**	521.931*	447.875**	0.005**	3703.345
	(222.122)	(212.866)	(295.633)	(195.937)	(0.002)	(8498.662)
Win × t+6	486.804**	459.273**	384.460	496.208**	0.005**	5408.453
	(233.552)	(221.545)	(347.013)	(241.546)	(0.002)	(7243.191)
Win × t+7	406.574**	387.417**	410.250	478.513*	0.006**	5898.907
	(194.945)	(178.357)	(459.923)	(267.643)	(0.003)	(5792.621)
Main Effects	Y	Y	Y	Y	Y	Y
Case FE	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
NAICS FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	32933	32933	32933	32933	32520	32855
Adjusted R^2	0.942	0.954	0.715	0.775	0.599	0.720

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust t-statistics in parentheses. Standard errors are clustered by county. This table displays coefficients on the interaction terms in a dynamic difference-in-differences model that regresses school district outcomes on time relative to the plant opening announcement dummies, a dummy variable indicating whether the district is in a county that wins a plant, and interaction terms between the time period and winner dummy variables. In this regression, 12 runner-up counties that had been previously winning counties are excluded from the estimation. The regression includes fixed effects for the plant opening event (case fixed effects) to force coefficients to be identified within each contest. The regressions also include school district and year fixed effects. All regressions are weighted by district size.

Our analysis shows that the arrival of MDPs to a county has significant impact on the local revenue sources for the county's school districts. The average school district in a treated county sees an increase of $400 per pupil in property tax revenue per year relative to school districts in the counterfactual county the firm considered in the final stage of its site selection process. This amounts to a 9% increase in school district-level property tax collection. However, counties contain multiple school districts and the location of the MDP within the school district may induce substantial spatial heterogeneity across districts within winning counties. We find that the revenue gains from MDPs accrue not to the school district in which the MDP opens, but in school districts adjacent. This highlights potential adverse distributive impacts from attracting MDPs. There are several plausible explanations for this heterogeneity. One is that MDPs potentially cause pollution, noise, and congestion that erode property values in the district of the MDP, thereby reducing the taxable base. Alternatively, workers at the MDP may commute from other parts of the county and income and property value gains accrue in the districts where employees live rather than in the district of the plant itself. Finally, incentives such as property tax abatements directly limit the extent of the available tax base in the district where the plant locates. This would mean that the district where the MDP was incentivized to locate effectively subsidizes adjacent districts that do see gains in school revenue.

We recognize some limitations to our work that leaves room for future study. While school spending has been found to improve student achievement, attainment, graduation, wages, adult poverty incidence, among other outcomes (Jackson et al., 2015; Lafortune et al., 2018; Brunner et al., 2020; Lee and Polachek, 2018), we cannot measure student performance or outcomes during the period of study. Though we find that the average school district in a treated county increases full-time teacher employment per pupil by 7%, we cannot identify whether this results in improved student learning (Angrist and Lavy, 1999; Finn and Achilles, 1999; Abott et al., 2020; Baron, 2022). Our analysis is policy relevant because we identify that school districts in a county could see revenue and teacher staffing increases as a result of MDPs, but districts where the MDP physically locates may not share in those gains, deepening inequality in the provision of public services. However, we cannot estimate the structure of subsidy deals (Slattery, 2018; Slattery and Zidar, 2020) or property tax abatement offered to firms that would quantify the wealth transfer across districts within winning counties. We believe both understanding the impact of MDPs on student outcomes and measuring the impact of subsidies on the inequality in public services within cities or counties to be essential in understanding the overall welfare implications of Million Dollar Plants and similar place-based policies.

References

Abott, Carolyn, Vladimir Kogan, Stéphane Lavertu, and Zachary Peskowitz. 2020. "School district operational spending and student outcomes: Evidence from tax elections in seven states." *Journal of Public Economics* 183 104142.

Angrist, Joshua D, and Victor Lavy. 1999. "Using Maimonides' rule to estimate the effect of class size on scholastic achievement." *The Quarterly journal of economics* 114 (2): 533–575.

Baron, E Jason. 2022. "School spending and student outcomes: Evidence from revenue limit elections in Wisconsin." *American Economic Journal: Economic Policy* 14 (1): 1–39.

Bartik, Timothy. 2017. "A New Panel Database on Business Incentives for Economic Development Offered by State and Local Governments in the United States."Technical report, W.E. Upjohn Institute, Kalamazoo.

Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen. 2019. "What Drives Differences in Management Practices?" *American Economic Review* 109 (5): 1648–1683.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2022. "Revisiting Event Study Designs: Robust and Efficient Estimation." https://papers.ssrn.com/abstract=2826228.

Brooks, Leah, and Justin H Phillips. 2010. "An institutional explanation for the stickiness of federal grants." *The Journal of Law, Economics, & Organization* 26 (2): 243–264.

Brunner, Eric, Ben Hoen, and Joshua Hyman. 2022. "School district revenue shocks, resource allocations, and student achievement: Evidence from the universe of US wind energy installations." *Journal of Public Economics* 206 104586.

Brunner, Eric, Joshua Hyman, and Andrew Ju. 2020. "School finance reforms, teachers' unions, and the allocation of school resources." *Review of Economics and Statistics* 102 (3): 473–489.

Bryant, Jeff. 2020. "How Corporations Are Forcing Their Way Into America's Public Schools." *Salon*, https://www.salon.com/2020/02/11/how-corporations-are-forcing-their-way-into-americas-public-schools_partner/.

Callaway, Brantly, and Pedro H. C. Sant'Anna. 2021. "Difference-in-Differences with multiple time periods." *Journal of Econometrics* 225 (2): 200–230.

Card, David, Kevin Hallock, and Enrico Moretti. 2010. "The Geography of Giving: The Effect of Corporate Headquarters on Local Charities." *Journal of Public Economics* 94 222–234.

Cascio, Elizabeth U, Nora Gordon, and Sarah Reber. 2013. "Local responses to federal grants: Evidence from the introduction of Title I in the South." *American Economic Journal: Economic Policy* 5 (3): 126–59.

Evans, William N, Robert M Schwab, and Kathryn L Wagner. 2019. "The Great Recession and public education." *Education Finance and Policy* 14 (2): 298–326.

Finn, Jeremy D, and Charles M Achilles. 1999. "Tennessee's class size study: Findings, implications, misconceptions." *Educational evaluation and policy analysis* 21 (2): 97–109.

Glaeser, Edward. 2011. "How Seattle Transformed Itself." March, https://economix.blogs.nytimes.com/2011/03/08/how-seattle-transformed-itself/.

Glass, Ira. 2017. "Our Town." December, https://www.thisamericanlife.org/632/our-town-part-one.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics* 225 (2): 254–277.

Gordon, Nora. 2004. "Do federal grants boost school spending? Evidence from Title I." *Journal of Public Economics* 88 (9-10): 1771–1792.

Greenstone, Michael, Richard Hornbeck, and Enrico Moretti. 2010. "Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings." *Journal of Political Economy* 18 (3): 536–598.

Greenstone, Michael, and Enrico Moretti. 2003. "Bidding for Industrial Plants: Does Winning a 'Million Dollar Plant' Increase Welfare?."

Gupta, Rahul. 2020. "Does Goliath Help David? Anchor Firms and Startup Clusters." *CES Working Papers* 20-17.

Hines, James R, and Richard H Thaler. 1995. "The flypaper effect." *Journal of economic perspectives* 9 (4): 217–226.

Hoxby, Caroline M. 2001. "All school finance equalizations are not created equal." *Quarterly Journal of Economics* 116 (4): 1189–1231.

Jackson, C Kirabo, Rucker C Johnson, and Claudia Persico. 2015. "The Effects of School Spending on Educational and Economic Outcomes: Evidence from School Finance Reforms." *Quarterly Journal of Economics* 131 (1): 157–218.

Jackson, C Kirabo, Cora Wigger, and Heyu Xiong. 2021. "Do school spending cuts matter? Evidence from the Great Recession." *American Economic Journal: Economic Policy* 13 (2): 304–35.

Knight, Brian. 2002. "Endogenous federal grants and crowd-out of state government spending: Theory and evidence from the federal highway aid program." *American Economic Review* 92 (1): 71–92.

Lafortune, Julien, Jesse Rothstein, and Diane Whitmore Schanzenbach. 2018. "School finance reform and the distribution of student achievement." *American Economic Journal: Applied Economics* 10 (2): 1–26.

Lee, Kyung-Gon, and Solomon W Polachek. 2018. "Do school budgets matter? The effect of budget referenda on student dropout rates." *Education Economics* 26 (2): 129–144.

Murray, Sheila E, William N Evans, and Robert M Schwab. 1998. "Education-finance reform and the distribution of education resources." *American Economic Review* 789–812.

NCES, US Department of Education. 2020. "Table 235.10. Revenues for public elementary and secondary schools, by source of funds: Selected years, 1919-20 through 2017-18." https://nces.ed.gov/programs/digest/d20/tables/dt20_235.10.asp?current=yes.

Qian, Franklin, and Rose Tan. 2021. *The Effects of High-skilled Firm Entry on Incumbent Residents.* Stanford Institute for Economic Policy Research (SIEPR).

Slattery, Cailin. 2018. "Bidding for firms: Subsidy competition in the U.S.." *SSRN* 3250256.

Slattery, Cailin, and Owen Zidar. 2020. "Evaluating state and local business incentives." *Journal of Economic Perspectives* 34 (2): 90–118.

Steinberg, Matthew P, Rand Quinn, Daniel Kreisman, and J Cameron Anglum. 2016. "Did Pennsylvania's statewide school finance reform increase education spending or provide tax relief?" *National Tax Journal* 69 (3): 545–582.

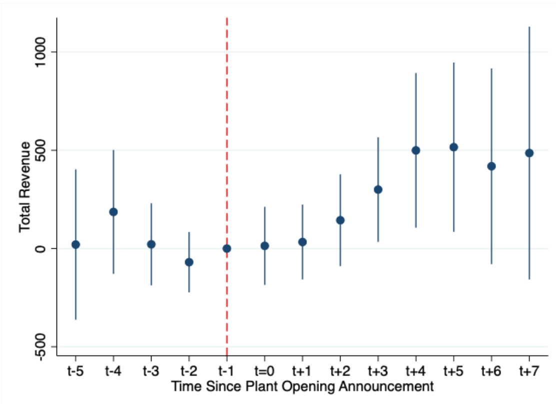
Urban Institute. 2021. "Common Core of Data, Education Data Portal (Version 0.12.0)." accessed February, 04, 2021, https://educationdata.urban.org/documentation/, made available under the ODC Attribution License.

A Appendix

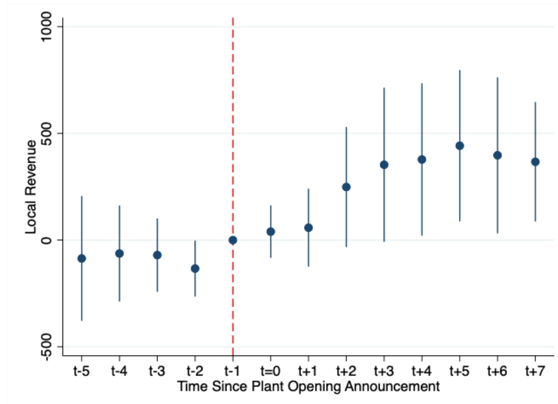
A.1 Revenue by Source

Figure A.1: School District Revenue Dynamic Difference-in-Differences Estimates

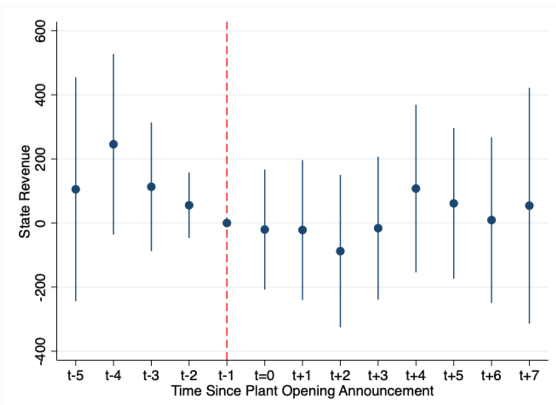
(a) Total



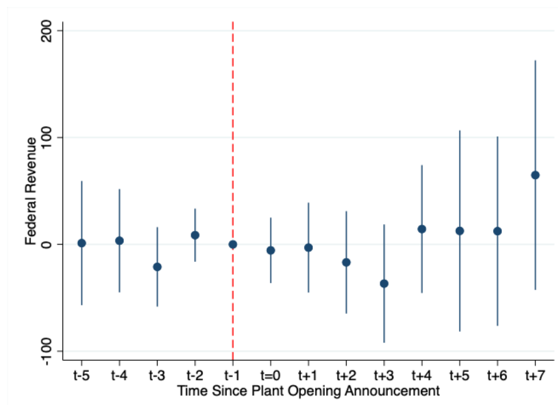
(b) Local



(c) State



(d) Federal



Notes: This figure plots dynamic difference-in-differences estimates and 90% confidence intervals following Equation 1 for school district total revenue (panel (a)) and revenue by source: local, state, and federal in panels (b), (c), and (d), respectively.

A.2 Dynamic Difference-in-Differences Tables

Table A.1: Dynamic Difference-in-Differences for District Revenue and Expenditure

	Revenue					Expenditure		
	(1) Total	(2) Prop. Tax	(3) Local	(4) State	(5) Federal	(6) Instruction	(7) FTE	(8) Pay
Win × t-5	20.312	69.576	-86.132	105.261	1.183	29.679	-0.001	3505.314
	(231.102)	(167.006)	(176.637)	(210.975)	(35.090)	(143.303)	(0.001)	(4111.472)
Win × t-4	186.225	-34.498	-62.865	245.667	3.423	138.597*	-0.000	5389.739
	(190.339)	(130.453)	(135.861)	(170.095)	(29.189)	(76.071)	(0.000)	(4151.859)
Win × t-3	21.514	-78.819	-70.436	113.014	-21.064	29.787	-0.000	4566.579
	(126.200)	(92.251)	(103.887)	(121.285)	(22.446)	(53.350)	(0.000)	(4558.399)
Win × t-2	-69.386	-103.992	-133.401*	55.404	8.611	-14.811	0.000	848.091
	(92.704)	(64.701)	(79.077)	(61.572)	(15.010)	(39.949)	(0.000)	(3877.149)
Win × t=-1								
Win × t=0	13.576	43.910	39.560	-20.378	-5.606	32.376	0.001*	-3231.754
	(120.084)	(65.769)	(74.204)	(113.272)	(18.491)	(42.987)	(0.000)	(2602.844)
Win × t+1	33.159	16.501	57.918	-21.724	-3.035	192.476***	0.001	-6056.622
	(115.076)	(90.333)	(110.286)	(131.672)	(25.412)	(58.859)	(0.001)	(4343.959)
Win × t+2	143.925	215.448	248.610	-87.850	-16.836	190.738**	0.002*	-5673.045
	(141.237)	(157.353)	(169.932)	(143.674)	(28.948)	(86.854)	(0.001)	(4512.708)
Win × t+3	300.012*	313.575	352.909	-16.189	-36.708	279.407**	0.003**	1870.463
	(160.811)	(201.504)	(218.071)	(134.688)	(33.437)	(109.720)	(0.001)	(4871.241)
Win × t+4	499.457**	289.062	377.592*	107.525	14.339	424.939***	0.004***	-1506.925
	(237.755)	(211.374)	(215.496)	(157.965)	(36.156)	(133.564)	(0.001)	(5884.264)
Win × t+5	515.918**	403.216*	442.125**	61.195	12.597	444.547**	0.005***	4774.738
	(260.230)	(209.146)	(214.140)	(141.907)	(56.845)	(171.152)	(0.002)	(7071.729)
Win × t+6	418.733	382.359*	397.197*	9.183	12.353	499.617**	0.005**	6480.061
	(300.756)	(215.724)	(220.857)	(156.207)	(53.532)	(207.835)	(0.002)	(5855.514)
Win × t+7	485.832	361.916**	366.891**	54.127	64.815	483.736**	0.005**	7854.898
	(388.593)	(163.020)	(168.995)	(222.290)	(64.906)	(227.715)	(0.002)	(5296.955)
Main Effects	Y	Y	Y	Y	Y	Y	Y	Y
Case FE	Y	Y	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y	Y	Y
NAICS FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	38210	38210	38210	38210	38210	38210	37708	38132
Adjusted R^2	0.737	0.956	0.944	0.676	0.872	0.796	0.611	0.720

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are clustered by county. This table displays coefficients on the interaction terms in a dynamic difference-in-differences model that regresses school district revenue and expenditure outcomes on time relative to the plant opening announcement dummies, a dummy variable indicating whether the district is in a county that wins a plant, and interaction terms between the time period and winner dummy variables. The regression includes fixed effects for the plant opening event (case fixed effects) to force coefficients to be identified within each contest. The regressions also include school district and year fixed effects. Figures 1, 2, and 3 are plotted using estimates from this table.