When Innovation Outpaces Policy: Hyperscale Data Centers and the Fiscal Costs of Investment Incentives

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Abstract

Governments increasingly use tax incentives to attract capital-intensive projects, but their local economic returns remain uncertain. This paper asks two questions: what are the local effects of capital-intensive projects on public finance, employment, local resources, and political outcomes, and how do these effects change when technological innovation increases the scale and resource intensity of subsidized investment? I study these questions in the context of state-level data center tax incentives in the United States, exploiting staggered state adoption and geographic variation in counties' suitability for data center development based on proximity to major water bodies. I find that data center subsidies are associated with increases in local government revenues, expenditures, and debt issuance, suggesting that these projects expand fiscal activity while also increasing public spending needs. Employment effects reveal an important tradeoff: overall employment declines, while employment rises in sectors more directly exposed to data center activity, consistent with counties shifting toward capital-intensive development that may crowd out more labor-intensive economic activity. I also find evidence of local resource pressures, including increases in developed land prices, declines in farmland prices, and higher electricity rates when data center capacity expands rapidly. Finally, subsidy exposure is associated with greater incumbent electoral losses, suggesting that the local costs of capital-intensive development may have political consequences. Together, the results show that subsidies for capital-intensive projects can generate local fiscal gains, but they also impose employment, infrastructure, resource, and political tradeoffs that become more pronounced as technological change increases project scale.

Keywords: Data Centers; Public Finance; Employment; Local Politics; Energy Demand; Land Price; Regional Economic Activity

JEL Codes: H25; H71; H72; R11; R38; O33; Q41

1 Introduction

Governments increasingly use tax incentives to attract capital-intensive projects, yet the local economic returns to these policies remain uncertain. This paper asks two broad questions about capital-intensive development policy. First, how do capital-intensive projects reshape local economies, public finances, and residents' welfare? Second, how do these consequences change when technological innovation increases the scale and resource intensity of the subsidized investment? These questions are central to evaluating modern place-based incentives. Many subsidy regimes target high-growth industries—such as advanced manufacturing, cloud computing, and other infrastructure-intensive technologies—and are designed when technologies are relatively small, when future growth is uncertain, and when policymakers expect capital investment to translate into broad-based local development. As technologies scale, however, the same policies may attract projects with very different demands on land, infrastructure, and public resources than originally anticipated.

Proponents argue that attracting capital-intensive projects in high-growth industries can generate substantial local benefits. Large investments may create new streams of property, sales, and utility tax revenue, even when subsidies reduce the project's effective tax burden. Construction and ongoing operations can increase local employment through both short-term construction jobs and specialized long-term positions. New projects can also catalyze broader upgrades to local infrastructure and services—such as power, telecommunications, transportation, and land use planning—that reshape how firms and households interact with the region. Finally, landing high-profile investments can signal that the local community is a hub for emerging economic activity, potentially attracting additional firms, workers, and complementary investment.

In contrast, there are concerns that the benefits of such projects are often modest relative to their scale and fiscal cost. Many incentive packages provide tax abatements for a decade or more, limiting the extent to which local governments capture fiscal gains from

new investment. Construction jobs are temporary, and many capital-intensive facilities in high-growth industries create relatively few permanent positions. As these projects scale, they can place substantial strain on local resources, increasing demand for electricity, water, land, and utility infrastructure and driving up input prices for other users. Higher local resource costs can crowd out more labor-intensive or smaller-scale industries that rely on affordable infrastructure and land, shifting the local development path toward capital-intensive production with limited job creation. In this sense, municipalities may be trading more labor-intensive, broadly distributed forms of development for projects that deliver narrow sectoral gains while raising costs and reducing opportunities for other firms and workers. These concerns have led some communities to question whether the economic benefits justify the foregone tax revenue and infrastructure spending used to attract them, and to reconsider zoning, adopt temporary moratoria, or require additional review before approving new projects.

This tradeoff becomes especially important as technological change increases the scale and resource intensity of capital-intensive projects. Subsidy programs originally designed to attract relatively small projects now apply to investments with much larger demands on local resources and infrastructure. As a result, the fiscal and economic consequences of these incentives may differ sharply from what policymakers anticipated ex ante when the programs were adopted and evaluated. Policy structures that were optimal when projects were modest can generate sizable shifts in incidence and distribution once investments scale, creating a gap between expected benefits at the time of enactment and realized outcomes for local economies, public finances, and residents.

This paper examines these questions in the context of data center expansion in the United States, using this setting as a lens on capital-intensive development more broadly. Data centers entail enormous upfront capital expenditures, and policymakers often view them as opportunities to expand the tax base, stimulate construction activity, and position their regions within the digital and AI economy. In response, many states have adopted

targeted tax incentives that reduce the cost of data center investment by exempting equipment, electricity, and other inputs from taxation (Table 1). As of 2025, 40 U.S. states offer such incentives (Figure 3), making data centers among the most heavily subsidized categories of modern infrastructure.

Data centers provide a compelling setting to study these questions for several reasons. First, they are highly capital-intensive and increasingly central to the modern and AI-enabled economy. In the United States, spending on data center construction has risen dramatically over the past decade, making digital infrastructure a key component of aggregate investment. As of January 2026, U.S. spending on data center construction exceeded $2.4 billion per month (Figure 1)—roughly sixteen times the level observed in early 2014—and installed data center capacity has reached approximately 82 gigawatts (Samborska, 2026). Data centers house the servers, storage systems, and networking equipment required to store, process, and transmit the vast quantities of data generated by businesses and consumers. As cloud computing, artificial intelligence, and digital services expand, demand for data center capacity is expected to grow substantially. Some estimates suggest that global data center capacity demand could increase more than 3.5-fold by 2030 (Figure 2) (McKinsey & Company, 2025).

Second, the scale of data center investment has grown dramatically over time. Early-generation facilities were often relatively small operations housed in office buildings or industrial parks (Figure 4). In contrast, modern hyperscale data centers, built to support large-scale cloud and AI workloads, can span hundreds of thousands or even millions of square feet, contain hundreds of thousands of servers, and require hundreds of megawatts of electricity capacity. Major technology firms such as Amazon, Google, Meta, and Microsoft have sharply increased capital expenditures, much of it directed toward new data center infrastructure across the United States. Recent announcements illustrate this shift: Meta's Hyperion data center in Richland Parish, Louisiana, is expected to reach approximately 15 million square feet and consume 5 gigawatts (GW) of power at full capacity. This load

is roughly half of New York City's peak electricity consumption, underscoring how data center development has shifted from individual facilities to massive infrastructure campuses (Goldman, 2026). Novel facility-level data on data center size and electricity usage allow me to document this scaling and to examine whether later-adopting states face different local consequences as subsidies begin to attract larger, more energy-intensive facilities.

Third, data center development is heavily shaped by public policy. Capital-intensive projects are mobile across states, and firms choose locations based on resource prices, permitting conditions, infrastructure, and tax treatment. Data center incentives can therefore meaningfully affect where investment occurs. For example, one study estimates that roughly 90 percent of data center activity in Georgia may be attributable to these tax incentives (Justice and Shepherd, 2025). The staggered adoption of state tax incentives generates variation in when states become more attractive to data center investment, providing a useful source of policy-driven variation in exposure to capital-intensive development.

Fourth, the setting offers rich within-state geographic variation. A concern with using state tax incentives is that their adoption may coincide with other state-level policy changes or shocks. Even when incentives apply statewide, however, their effect on actual data center investment is concentrated in counties that are suitable for development. In this context, waterfront counties are more exposed because large data centers often require access to water resources for cooling. This creates within-state variation: waterfront and non-waterfront counties face the same state-level policy environment, but only waterfront counties are more likely to receive subsidy-induced data center investment.

By combining staggered policy timing with within-state variation in counties' suitability for data center development, the empirical design uses a stacked difference-in-differences framework with a triple-difference structure. Specifically, it compares waterfront and non-waterfront counties within the same state before and after state adoption of data center tax incentives, across treated and not-yet-treated or never-treated states. This approach isolates whether counties are more suitable for data center development experience dif-

ferential changes after the same state-level policy shock. The identifying parallel trends assumption is that, absent data center tax incentives, treated states would not have experienced a differential change in outcomes, specifically in their waterfront counties. In other words, we can assume any post-adoption change in the waterfront–non-waterfront gap in treated states, relative to the same gap in control states, can be attributed to the data center subsidy rather than to pre-existing differential trends.

The empirical specification includes county-by-cohort fixed effects, state-by-year-by-cohort fixed effects, and waterfront-by-time-by-cohort fixed effects. County-by-cohort fixed effects absorb time-invariant differences across counties within each stacked cohort. State-by-year-by-cohort fixed effects absorb shocks or policies that affect all counties within a state in a given year, including other state-level tax changes, macroeconomic shocks, or political changes that coincide with data center incentive adoption. Waterfront-by-time-by-cohort fixed effects absorb shocks common to waterfront counties over time, such as broader changes in waterfront land values, environmental regulation, or infrastructure trends that affect waterfront counties regardless of treatment status. Together, these fixed effects help ensure that identification comes from differential changes in waterfront counties in treated states after subsidy adoption, relative to non-waterfront counties in the same state and to comparable waterfront–non-waterfront differences in control states.

I begin by examining whether the empirical design captures meaningful increases in data center investment. Across stacked event windows, data center exposure is associated with a statistically significant increase in the number of data centers. The estimates are stable across $\pm$5-, $\pm$4-, and $\pm$3-year windows, with treated waterfront counties experiencing increases of 0.76, 0.62, and 0.50 data centers, respectively, after subsidy adoption. Data center exposure also leads to sizable increases in total facility square footage: treated waterfront counties gain roughly 9,800 to 12,300 additional square feet of data center space, depending on the event window. These results indicate that state tax incentives increase data center activity in geographically suitable counties, supporting the paper's identifying

strategy and confirming that the subsidy shocks generate real changes in capital-intensive investment. Event-study estimates show no evidence of differential pre-trends, suggesting that the observed shift coincides with subsidy adoption rather than pre-existing differences between treated waterfront counties and comparison counties. Data center subsidy exposure is associated with meaningful changes in local public finance. Counties more exposed to data center development experience higher local revenues after subsidy adoption: total revenue increases by about 3.7 percent, total taxes by 3.3 percent, general charges by 5.9 percent, and intergovernmental revenue by 2.0 percent. These revenue gains appear to be partly driven by increases in property taxes, sales taxes, and public utility license revenue, consistent with data center development expanding some components of the local fiscal base. However, these fiscal gains are accompanied by higher public spending. Total expenditures rise by 4.3 percent, current operating expenditures by 3.6 percent, and construction spending by 7.8 percent, suggesting that local governments increase spending in response to the infrastructure and service demands associated with data center development. Debt issuance also rises substantially: long-term debt issued for private purposes increases by 37.5 percent, consistent with counties financing upfront infrastructure needs before the full revenue benefits of these projects materialize. Overall, the results suggest that data center subsidies expand local fiscal activity, but they also generate offsetting expenditure and financing pressures.

The labor market results suggest that data center exposure creates an important employment trade-off. Aggregate effects are small and negative: exposed counties experience a 0.9 percent decline in total employment and a 0.7 percent decline in average wages. However, these aggregate declines mask gains in sectors more directly connected to data center development. Nonresidential construction employment rises by 3.9 percent, and nonresidential construction wages increase by 2.2 percent. Employment also rises in power generation and natural gas, with particularly large effects in natural gas employment and wages. At the same time, residential building employment declines by 3.2 percent.

Together, these results are consistent with the view that data center subsidies shift local economic activity toward infrastructure- and energy-related sectors, but do not generate broad-based employment growth. Instead, exposed counties appear to trade off more labor-intensive forms of local development for capital-intensive projects that create sector-specific gains while reducing overall employment and wage growth.

Electricity-price effects appear concentrated in the later period, consistent with the idea that local resource costs rise as data centers become larger and more power-intensive. In the full sample, data center exposure has little effect on residential electricity rates. Before 2016, the estimate is slightly negative and statistically insignificant. After 2016, however, the coefficient becomes positive and significant: exposed counties experience about a 0.8 percent increase in residential electricity rates. The effect grows in more recent periods, rising to about 1.1 percent in the post-2018 and post-2020 samples. These results suggest that data center subsidies do not necessarily raise electricity prices when facilities are smaller, but electricity costs increase as data center development scales up and begins to place greater pressure on local electricity grids.

The land-market results show that data center exposure effects differ across parcel types. In the full sample, the effect on overall price per acre is positive but statistically insignificant. However, developed land prices increase by about 17.4 percent, suggesting that data center subsidies raise demand for land more suitable for commercial, industrial, or infrastructure-related use. These effects are stronger after 2016: developed land prices increase by about 35.5 percent in the post-2016 sample. In contrast, farmland prices decline, with a statistically significant 21.3 percent decrease after 2016. The increase in developed land prices is consistent with higher demand for sites that can support large-scale digital infrastructure, while the decline in farmland prices suggests potential pressure on agricultural land values or a shift away from labor- and land-intensive rural uses. The stronger post-2016 effects are consistent with the view that later data center projects are larger and more resource-intensive, placing greater pressure on local land markets.

The analysis also shows that these local costs have political consequences. In the full sample, data center exposure is associated with a 2.8 percentage point decline in incumbent loss. However, the post-2016 estimates show a different pattern. In the later period, exposed counties experience a 7.6 percentage point increase in incumbent loss, suggesting that political costs become more salient as data centers become larger and more resource-intensive. This is consistent with the view that while early data center projects may have generated limited political backlash, more recent projects create visible local pressures through land use, electricity demand, infrastructure needs, and fiscal costs. Overall, the political results suggest that the consequences of capital-intensive development are not limited to public finances and resource markets, but may also affect local political accountability.

This paper contributes to the literature on fiscal competition and the "winner's curse" in subsidy bidding by emphasizing how subsidy design interacts with uncertainty about future project scale and costs. In many settings, counties observe individual projects and decide whether to enter the bidding and how much to bid, depending on the perceived benefits of the project. Ulbrich (2002), Charlton (2003), and Schragger (2009) argue that communities may overbid for firms and ultimately harm themselves, while empirical work finds mixed evidence on realized fiscal effects, with some studies documenting limited or no fiscal deterioration following subsidy deals (Greenstone and Moretti, 2003) and others showing that incentives can be revenue-negative (Bartik, 1994). More recently, Chava et al. (2024) shows that financial markets price these fiscal costs directly in the municipal bond market: large subsidy deals increase local borrowing costs. This paper builds on this work by studying a setting in which the fiscal incidence of subsidies is especially opaque. Subsidies for capital-intensive investment are often designed and authorized at the state level, while many of the infrastructure and service costs are borne locally. Moreover, because the scale and resource intensity of subsidized projects can change rapidly over time, local governments may not fully anticipate the types of projects, electricity demand,

land use, or infrastructure burdens that follow from a given subsidy regime.

The paper also contributes to the literature on place-based incentives by reframing the evaluation of subsidy policy around fiscal and resource incidence rather than employment creation. Much of the existing work evaluates whether subsidies generate the employment, wage growth, or productivity gains promised by policymakers, often in settings involving manufacturing plants, firm relocations, or other employment-generating investments. Studies such as Ku et al. (2019) and Slattery and Zidar (2020) examine employment and wage effects across subsidized locations and find mixed evidence regarding whether incentives meaningfully improve local labor market conditions, while Greenstone et al. (2010) highlights productivity spillovers from large manufacturing plants, showing that major plant openings can generate sizable gains for incumbent counties and potentially justify aggressive incentive packages. This paper extends this literature by focusing on capital-intensive projects as a broader class of investments in which the primary local impacts may come not through large-scale job creation but through changes in local public finance, resource demand, land markets, electricity infrastructure, and political accountability.

A broader contribution of the paper is to highlight the hidden local costs of the AI economy. Much of the public and academic discussion around artificial intelligence emphasizes productivity gains (Brynjolfsson et al., 2023), labor (Babina et al., 2023), and national-level economic growth (Acemoglu, 2024). Yet the physical infrastructure that powers AI—data centers, high-capacity electricity systems, cooling infrastructure, and land-intensive server campuses—has received far less attention. By examining how state-designed tax incentives for large, capital-intensive digital infrastructure reshape local tax bases, expenditures, debt issuance, land markets, electricity-sector outcomes, and political accountability, this paper shows that the AI boom is not only a technological transformation but also a geographically uneven economic transformation. Contemporaneous work by Alvarez et al. (2026) and Yue and Zeng (2026) also study the local impacts of data centers. I build on this by looking at local finances, land values, and politics in addition to employment and electricity rates.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 outlines the empirical methodology. Section 4 presents the results.

2 Data

The analysis combines multiple data sources, including employment data from the Quarterly Census of Employment and Wages (QCEW), fiscal data from the Census of Governments Annual Survey of State and Local Government Finances, electricity price data from the U.S. Energy Information Administration (EIA), political data from the American Local Government Elections Database, and a hand-collected dataset of U.S. data center locations.

2.1 Quarterly Census of Employment and Wages (QCEW)

The QCEW is based on administrative records from state unemployment insurance programs and covers approximately 95 percent of all U.S. wage and salary employment. Because it is constructed from mandatory employer filings, the dataset provides near-universal coverage of employment across industries and geographic areas.

The QCEW reports quarterly information on employment, wages, and establishment counts at the county and industry level. Establishments are classified using the North American Industry Classification System (NAICS), enabling measurement of employment dynamics within narrowly defined industries. For this study, data centers are identified using NAICS 518210, which includes establishments primarily engaged in data processing, hosting, and related services.

2.2 Census of Governments Annual Survey of State and Local Government Finances.

To examine the fiscal consequences of data center expansion, I also use data from the Census of Governments Annual Survey of State and Local Government Finances. This dataset provides detailed information on government revenues, expenditures, and debt for local governments across the United States. The survey reports annual data on a wide range of fiscal categories, including tax revenues (such as property and sales taxes), public utility revenues, capital expenditures, infrastructure spending, and debt issuance. These data allow the analysis to measure how local government finances evolve in response to large-scale data center investment.

2.3 U.S. Energy Information Administration (EIA) Data

I incorporate electricity price data from the U.S. Energy Information Administration (EIA). Data centers are highly electricity-intensive facilities, often requiring hundreds of megawatts of power capacity to operate large clusters of servers and cooling systems. Electricity prices therefore play an important role in determining the location and operating costs of data center facilities. The EIA provides detailed data on average electricity prices by customer class and geographic region.

2.4 Acres.com

Land price data are obtained from Acres.com, which provides parcel-level information on land transactions, acreage, land use, and sales prices. The parcel-level data are aggregated to the county-year level by summing total acres and total transaction values. The average price per acre is then constructed as the total transaction value divided by the total acres.

The data also allow land prices to be measured separately by land type, including developed land, farmland, forest land, water-related land, and open-water categories. These

measures are used to examine whether data center subsidies create pressure in local land markets, particularly by increasing the value of developed land or changing the relative value of agricultural and undeveloped land. The county-year land price measures are merged to the main panel using county and state identifiers.

2.5 American Local Government Elections Database

To account for the political environment surrounding local policy decisions, I incorporate election data from the American Local Government Elections Database compiled by De Benedictis-Kessner, Lee, Velez, and Warshaw. This dataset provides detailed information on local elections across the United States, including mayoral, city council, and county-level elections. It includes candidate information, vote totals, election outcomes, and measures of political competition and partisan alignment in local governments.

2.6 Data Center Data

Information on the location and characteristics of data centers is hand-collected from Baxtel.com, a commercial database that tracks data center facilities worldwide. Baxtel provides detailed information on the geographic location, operator, and operational status of data centers, including whether facilities are active, planned, or under construction. The database is widely used by industry practitioners to track the development of digital infrastructure and provides one of the most comprehensive publicly available sources on data center locations.

Using Baxtel, I construct a dataset of data center facilities located in the United States. For each facility, the database provides information on the operator, facility location, and in many cases the type of data center (such as enterprise, colocation, or hyperscale facilities). These data allow the identification of counties that host data center investments and the timing of facility entry or expansion.

2.7 Waterfront Counties

Waterfront status is constructed using county boundary shapefiles from the U.S. Census Bureau and spatial data on major water bodies. County polygons are matched to water features using geographic information system (GIS) methods. A county is classified as a waterfront county if its boundary intersects a major coastline, lake, river, or other large water body. The resulting indicator captures counties with greater geographic suitability for data center development, since large facilities may benefit from access to water resources for cooling, utility infrastructure, and large-scale industrial siting.

3 Empirical Strategy

3.1 Identification Strategy

The goal of the empirical analysis is to estimate the economic and fiscal effects of data center expansion while addressing potential endogeneity in the location of both data centers and state subsidy policies. States that adopt data center incentives may differ systematically from those that do not, and counties that attract data center investment may differ from those that do not along unobservable dimensions such as economic growth potential or infrastructure capacity. To address these concerns, the identification strategy exploits geographic variation within states combined with differences in exposure to water resources.

Data centers require substantial cooling capacity. Proximity to large water bodies—such as rivers, lakes, or coastal areas—can reduce the cost of cooling systems and facilitate facility operation. As a result, counties located near large water bodies are more likely to attract data center investment than otherwise similar inland counties. Importantly, the presence of a water body is largely predetermined and unlikely to be directly affected by contemporary economic development policies. This geographic feature therefore provides a source of variation in the attractiveness of locations for data center development.

The empirical strategy uses a triple-difference (difference-in-difference-in-differences) design that compares outcomes across counties with and without access to large water bodies, before and after the introduction of state-level data center incentives. The specification compares counties that are geographically suited for data center development (near water) to counties that are not, within the same state and time period. This approach allows the analysis to isolate the incremental effect of subsidy policies on counties that are most likely to attract data center investment.

The baseline estimating equation is:

$$Y_{isct} = \beta_1 \left(Treat_{sc} \times Post_{sct} \times NearWater_i \right) + \alpha_{ic} + \lambda_{stc} + \mu_{NearWater_i \times t \times c} + \varepsilon_{isct}. \quad (1)$$

where Y_{isct} is the outcome of interest for county i, in state s, cohort c, and year t. The variable $Treat_{sc}$ is equal to one for states treated in cohort c, $Post_{sct}$ is equal to one after the data center subsidy is adopted, and $NearWater_i$ is an indicator for counties located near a major water body, such as a river, lake, or coastline.

The coefficient of interest is β_1. It captures the differential change in outcomes for waterfront counties in states that adopt data center tax incentives after the policy takes effect, relative to non-waterfront counties in the same state and relative to the corresponding waterfront–non-waterfront difference in not-yet-treated or never-treated states. This coefficient identifies whether subsidy adoption has larger effects in counties that are more geographically suitable for data center development.

The specification includes county-by-cohort fixed effects, α_{ic}, which absorb time-invariant county characteristics within each stacked cohort, such as geography, baseline economic conditions, industrial composition, and persistent fiscal capacity. State-by-year-by-cohort fixed effects, λ_{stc}, absorb shocks or policies affecting all counties within a state in a given year, including other state-level policy changes, macroeconomic shocks, or political changes that coincide with subsidy adoption. Waterfront-by-year-by-cohort fixed effects, $\mu_{NearWater_i \times t \times c}$, absorb time-varying shocks common to waterfront counties, such as

changes in waterfront land values, environmental regulation, or broader trends affecting counties near water bodies. Standard errors are clustered at the state level to account for serial correlation in policy exposure across counties within a state.

3.2 Event Study Specification

To examine the dynamic effects of subsidy adoption and assess the validity of the parallel trends assumption, the analysis estimates an event-study specification that replaces the single post-treatment indicator with a series of leads and lags relative to the adoption of data center incentives:

$$Y_{isct} = \sum_{k \neq -1} \beta_k \left(Treat_{sc} \times NearWater_i \times \mathbf{1}[t - T_{sc} = k] \right) + \alpha_{ic} + \lambda_{stc} + \mu_{NearWater_i \times t \times c} + \varepsilon_{isct}. \tag{2}$$

Here, Y_{isct} is the outcome for county i, in state s, cohort c, and year t. T_{sc} denotes the year in which the treated state in cohort c adopts a data center tax incentive. The indicator $\mathbf{1}[t - T_{sc} = k]$ equals one when county i is k years away from subsidy adoption. The period immediately before adoption, $k = -1$, is omitted as the reference period.

The coefficients β_k trace the evolution of outcomes in waterfront counties in treated states relative to non-waterfront counties, before and after subsidy adoption, compared with the corresponding waterfront–non-waterfront difference in not-yet-treated or never-treated states. The pre-treatment coefficients provide a test of the parallel trends assumption: if the identifying assumption is plausible, the coefficients for $k < 0$ should be close to zero and statistically insignificant. The post-treatment coefficients show how the effects of subsidy-induced data center development evolve after adoption.

The specification includes county-by-cohort fixed effects, state-by-year-by-cohort fixed effects, and waterfront-by-year-by-cohort fixed effects, ensuring that identification comes from differential changes in treated waterfront counties around subsidy adoption rather

than from permanent county differences, state-level shocks, or time-varying shocks common to waterfront counties.

3.3 Identification Assumptions

The identification strategy relies on the assumption that, absent the introduction of data center subsidies, counties near large water bodies and inland counties within the same state would have followed similar trends in the outcomes of interest relative to those counties in non-subsidy states. By comparing counties within the same state, the design mitigates concerns that states adopting subsidies differ systematically from those that do not. The additional geographic variation based on proximity to water bodies isolates differences in exposure to data center investment while holding constant broader state-level policy environments.

Together, the triple-difference design and event study framework allow the analysis to estimate the causal effects of data center incentives on local economic and fiscal outcomes while accounting for both policy selection and geographic determinants of data center location.

3.4 Descriptive Statistics

3.4.1 Data Centers

Figure 5 and Table 2 describe the growth of data center activity over time. The number of operational data centers increases steadily from 402 in 2000 to 1,402 in 2020, before rising sharply to 3,342 by 2024. This acceleration is even more pronounced when examining facility scale and power capacity. Total data center space grows from approximately 24.9 million square feet in 2000 to 173.1 million square feet in 2020, and then more than triples to 564.7 million square feet by 2024. Estimated power capacity follows a similar pattern, increasing from 2,742 MW in 2000 to 25,347 MW in 2020, before rising to 117,889 MW in 2024. The change between 2015 and 2016 suggests that data center expansion was not

simply driven by an increase in the number of facilities, but also by a shift toward larger and more power-intensive projects. The number of new data centers increased from 62 in 2015 to 89 in 2016, a 44 percent increase. However, added data center space rose much more sharply, from 8.0 million square feet to 14.2 million square feet, an increase of 78 percent. Estimated added power capacity increased even more dramatically, more than doubling from 1,087 MW in 2015 to 2,269 MW in 2016.

This divergence is also visible on a per-facility basis. The average new data center added in 2015 was associated with roughly 129,000 square feet of space and 17.5 MW of power capacity. In 2016, the corresponding averages rose to about 159,500 square feet and 25.5 MW per new facility. Thus, the 2016 increase reflects both more data center entries and a meaningful increase in the scale and power intensity of the facilities being added. This pattern supports the paper's framing that data centers became increasingly capital- and resource-intensive during this period.

4 Results

4.1 Datacenters

Subsidy exposure is associated with a statistically significant increase in data center investment in treated waterfront counties. Across the ±5-, ±4-, and ±3-year stacked event windows, treated waterfront counties experience increases of 0.76, 0.62, and 0.50 data centers, respectively, after subsidy adoption. Relative to the sample mean of 0.26 data centers, these estimates correspond to increases of approximately 294 percent, 240 percent, and 194 percent. These magnitudes indicate that subsidy exposure generates economically meaningful increases in data center activity, not just statistically detectable changes.

Data center exposure also leads to sizable increases in total facility square footage. Treated waterfront counties gain roughly 9,800 to 12,300 additional square feet of data center space, depending on the event window. Relative to the sample mean of approxi-

mately 29,744 square feet, these effects correspond to increases of about 33 to 41 percent. Taken together, these results indicate that state tax incentives increase data center activity in geographically suitable counties. This supports the paper's identifying strategy by confirming that the subsidy shocks generate real changes in capital-intensive investment. Event-study estimates show no evidence of differential pre-trends, suggesting that the observed shift coincides with subsidy adoption rather than pre-existing differences between treated waterfront counties and comparison counties.

4.2 Local Government Finances

Data center subsidy exposure is also associated with meaningful changes in local public finance. Total revenue increases by about 3.7 percent, which corresponds to approximately $15.4 million relative to the sample mean. Total taxes increase by 3.3 percent, or about $5.6 million, while general charges increase by 5.9 percent, or about $4.1 million. Intergovernmental revenue increases by 2.0 percent, corresponding to roughly $3.5 million. These revenue gains appear to be partly driven by increases in property taxes, sales taxes, and public utility license revenue, consistent with data center development expanding some components of the local fiscal base.

However, these fiscal gains are accompanied by higher public spending. Total expenditures rise by 4.3 percent, which corresponds to approximately $22.2 million. Current operating expenditures increase by 3.6 percent, or about $13.6 million, while construction spending rises by 7.8 percent, or roughly $4.0 million. These magnitudes suggest that local governments increase spending in response to the infrastructure and service demands associated with data center development. Debt issuance also rises substantially: debt issued increases by 37.5 percent, corresponding to approximately $37.3 million relative to the sample mean. This effect is large relative to other fiscal responses and is consistent with counties financing upfront infrastructure needs before the full revenue benefits of these projects materialize.

Overall, the results suggest that data center subsidies expand local fiscal activity, but they do not generate a simple fiscal windfall. Treated counties experience higher revenues, but these gains are accompanied by even larger increases in expenditures, construction spending, and debt issuance. The economic magnitudes are consistent with the paper's central mechanism: subsidies attract capital-intensive data center investment, but the local fiscal benefits arrive alongside meaningful infrastructure and financing pressures.

4.3 Employment

Data center exposure is associated with an important labor-market trade-off. Aggregate labor-market effects are small but negative: exposed counties experience a 0.9 percent decline in total employment and a 0.7 percent decline in average wages. These aggregate effects, however, mask sectoral gains in industries more directly connected to data center development. Nonresidential construction employment rises by 3.9 percent, and nonresidential construction wages increase by 2.2 percent. Employment also increases in power generation and natural gas, with particularly large effects in natural gas employment and wages. At the same time, residential building employment declines by 3.2 percent.

These patterns suggest that data center subsidies shift local economic activity toward infrastructure- and energy-related sectors, rather than generating broad-based employment growth. The results are consistent with the paper's proposed opportunity-cost channel: capital-intensive projects create some direct and multiplier jobs, particularly in construction and energy, but may crowd out more labor-intensive forms of local development. As a result, exposed counties experience sector-specific gains alongside weaker aggregate employment and wage growth.

4.4 Electricity Rates

Electricity-price effects are concentrated in the later period, consistent with rising resource costs as data centers become larger and more power-intensive. In the full sample, data

center exposure has little effect on residential electricity rates. Before 2016, the estimate is slightly negative and statistically insignificant. After 2016, however, exposed counties experience a statistically significant 0.8 percent increase in residential electricity rates. The effect becomes larger in more recent periods, rising to approximately 1.1 percent in both the post-2018 and post-2020 samples. These results suggest that data center subsidies do not necessarily raise electricity prices when facilities are smaller, but electricity costs increase as data center development scales up and places greater pressure on local electricity grids.

4.5 Land Prices

The land-market results also point to resource reallocation. In the full sample, the effect on overall price per acre is positive but statistically insignificant. However, developed land prices increase by about 17.4 percent, suggesting that data center subsidies increase demand for land suitable for commercial, industrial, or infrastructure-intensive use. These effects become much stronger after 2016: developed land prices increase by approximately 35.5 percent in the post-2016 sample. In contrast, farmland prices decline, with a statistically significant 21.3 percent decrease after 2016. The increase in developed land prices is consistent with higher demand for sites that can support large-scale digital infrastructure, while the decline in farmland prices suggests a shift away from agricultural or other land-intensive rural uses. The stronger post-2016 effects are consistent with the view that later data center projects are larger and more resource-intensive, placing greater pressure on local land markets.

4.6 Local Politics

The final results examine whether these local costs translate into political consequences. In the full sample, data center exposure is associated with a 2.8 percentage point decline in incumbent loss, suggesting that earlier data center development may have been viewed favorably or generated limited political backlash. However, the post-2016 estimates show

the opposite pattern. In the later period, exposed counties experience a 7.6 percentage point increase in incumbent loss. This reversal suggests that political costs become more salient as data centers become larger and more resource-intensive. The pattern is consistent with voters responding not only to potential economic benefits, but also to visible local pressures from land use, electricity demand, infrastructure needs, and fiscal costs.

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5 Figures

Figure 1: Data Center Construction Spending

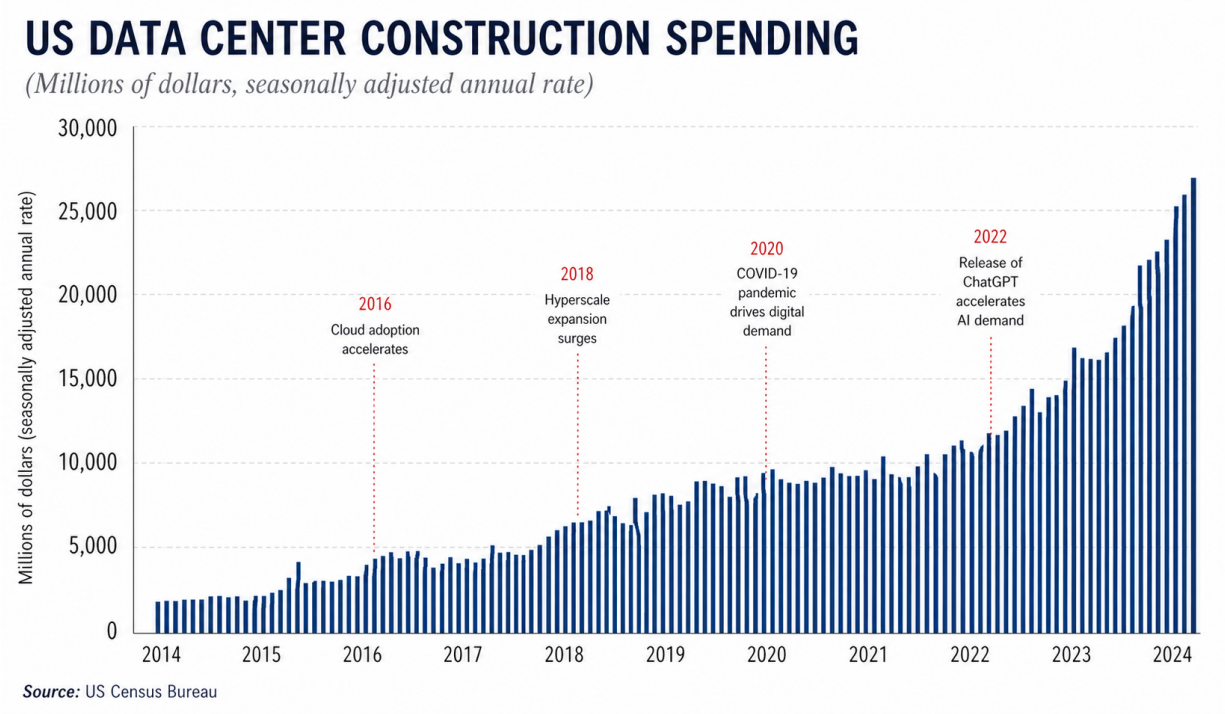


Figure 2: Data Center Projected Growth

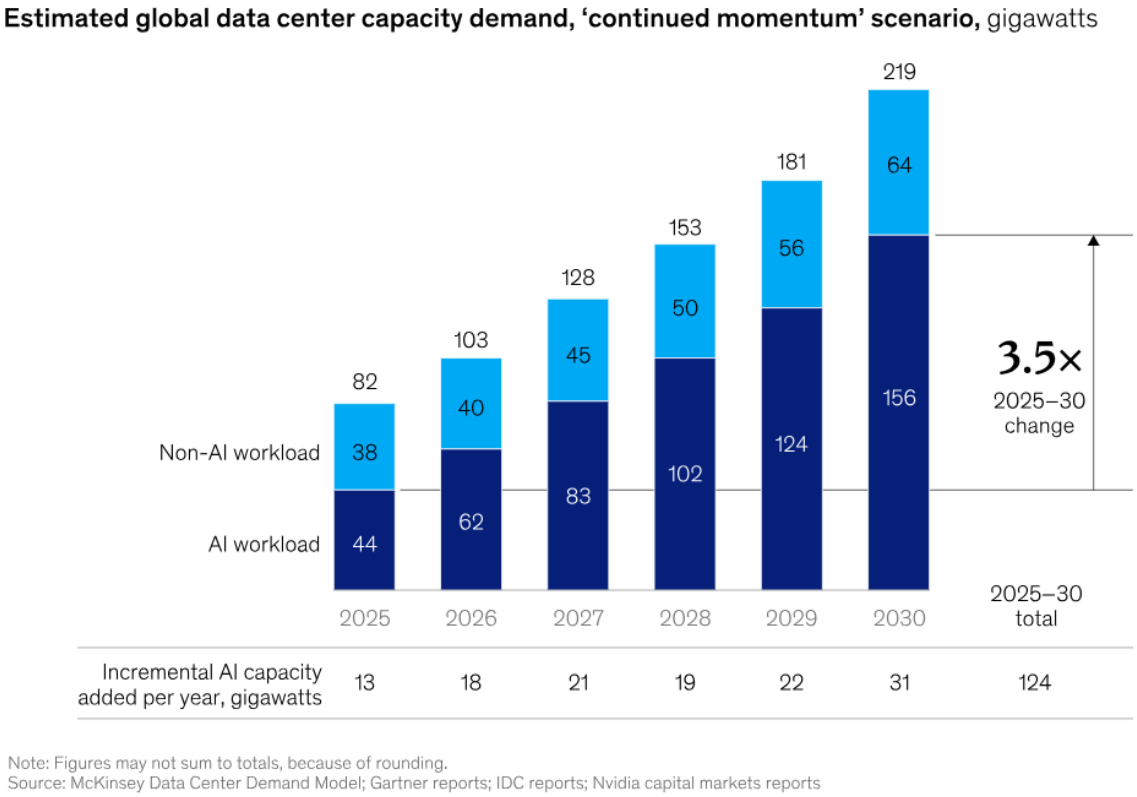


Figure 3: States with Tax Incentives

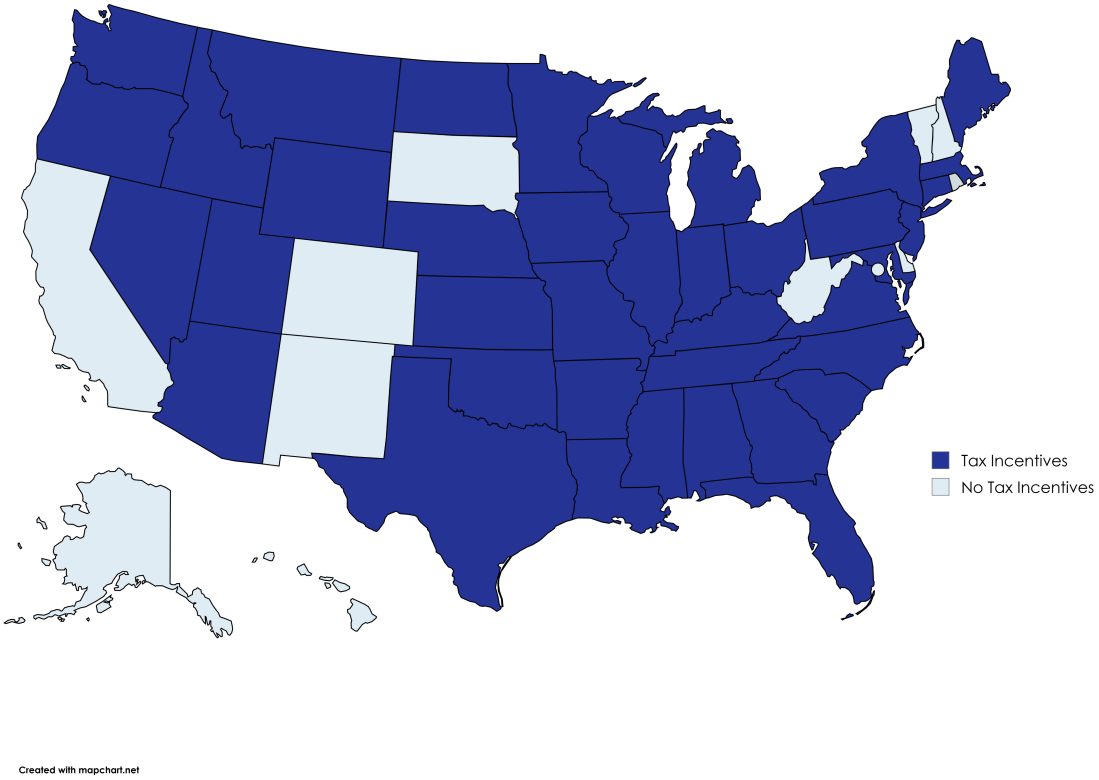


Figure 4: Data Centers Over Time

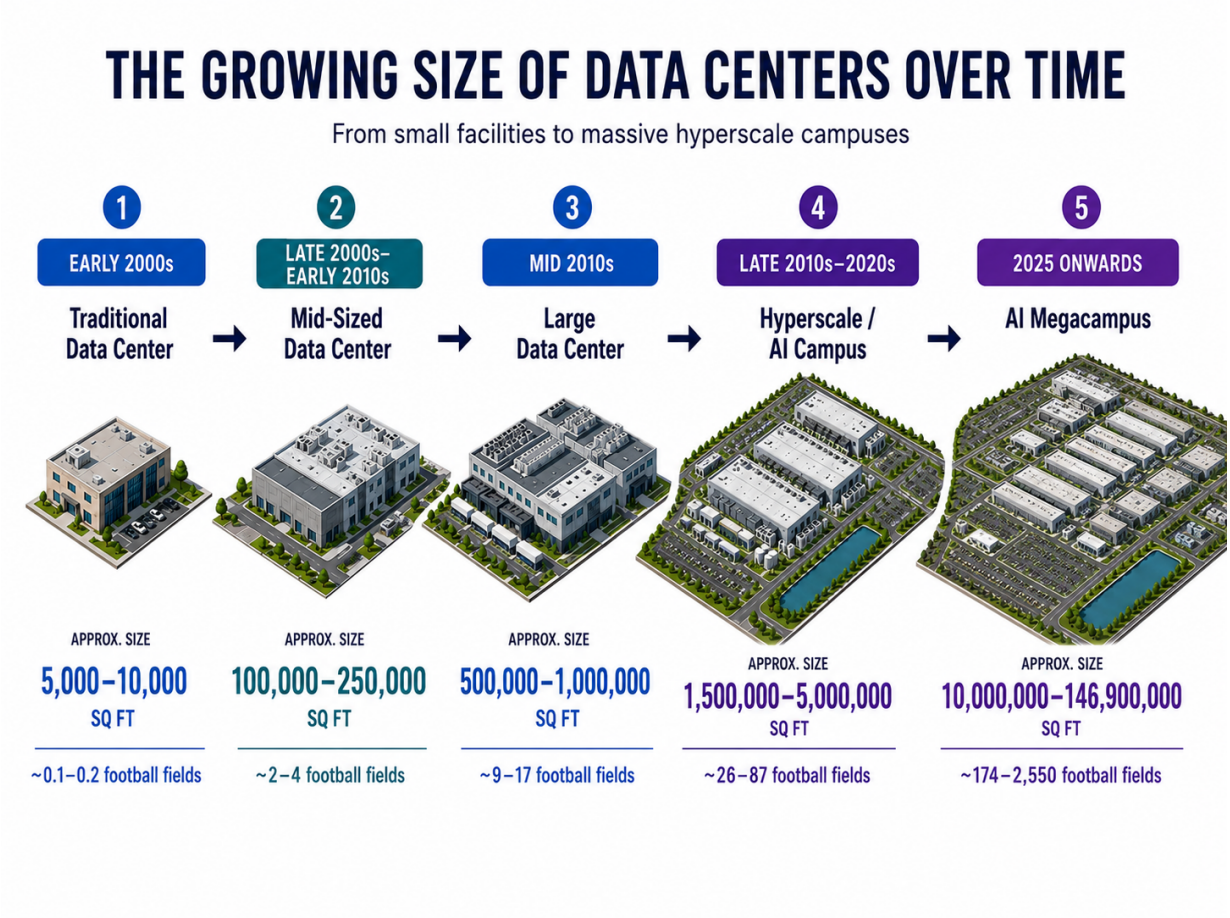
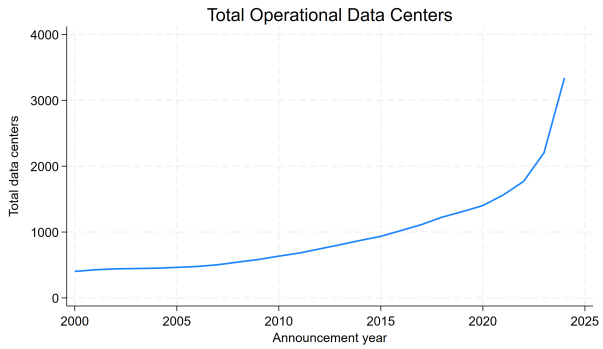
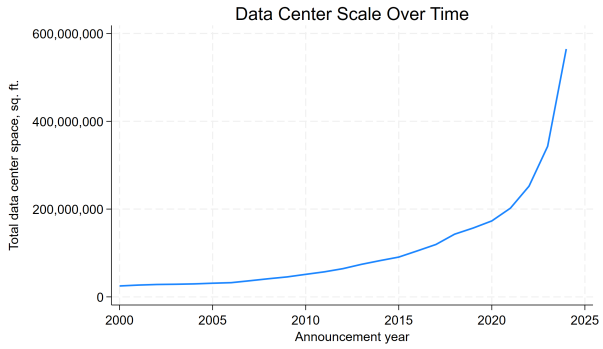


Figure 5: Growth in Data Center Scale Over Time

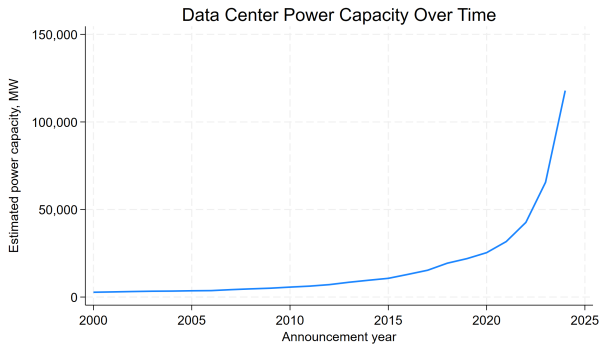
(a) Total Operational Data Centers



(b) Total Data Center Space

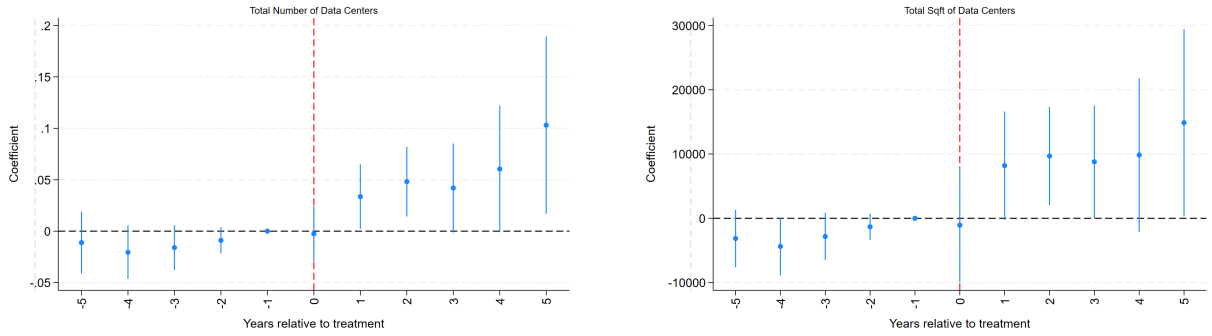


(c) Estimated Power Capacity



Notes: This figure plots the growth of data center activity from 2000 to 2024. Panel A reports the cumulative number of operational data centers, Panel B reports cumulative data center space in square feet, and Panel C reports estimated cumulative power capacity in megawatts. The figures show that recent data center growth reflects not only an increase in the number of facilities, but also a sharp increase in facility scale and power intensity.

Figure 6: Dynamic Effects of Data Center Subsidies on Data Center Investment

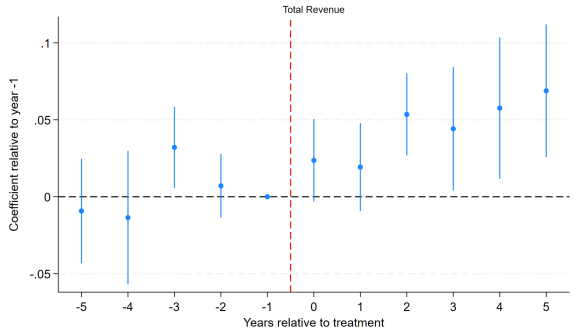


(a) Number of Data Centers

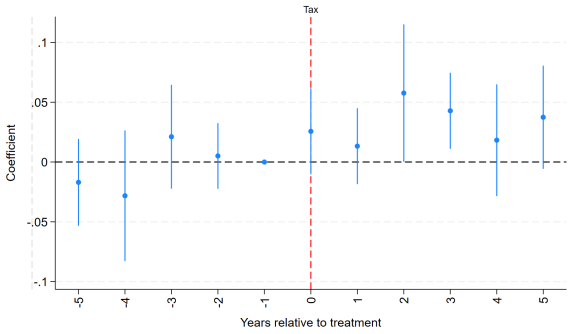
(b) Total Data Center Square Footage

Notes: This figure plots event-study estimates of the effect of data center tax incentives on data center investment. Panel (a) shows the effect on the number of data centers, and Panel (b) shows the effect on total data center square footage. Coefficients are estimated relative to the omitted year before treatment. Vertical bars report 95 percent confidence intervals. The red dashed line indicates the timing of subsidy adoption. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors are clustered at the state level.

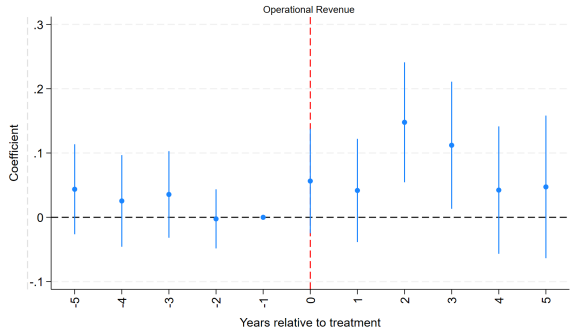
Figure 7: Dynamic Effects of Data Center Exposure on Local Revenues



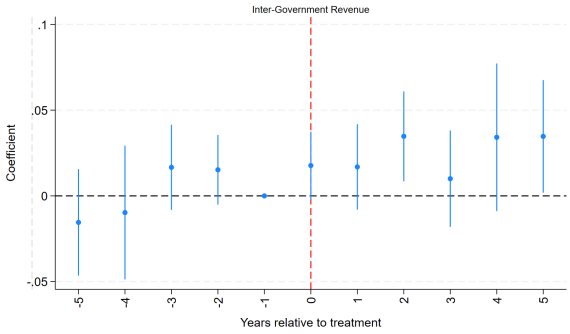
(a) Total Revenue



(b) Total Taxes



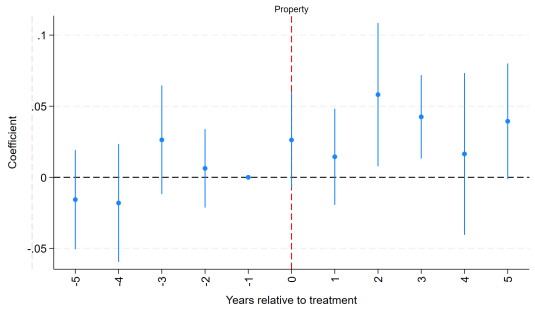
(c) General Charges



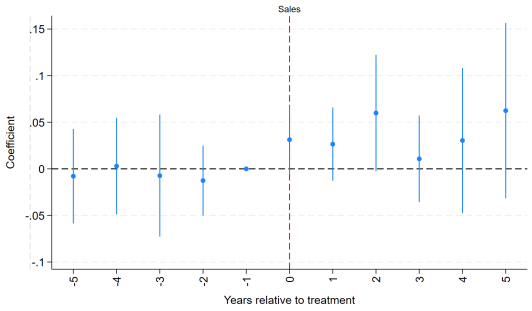
(d) Intergovernmental Revenue

Notes: This figure presents event-study estimates of the dynamic effects of data center exposure on local fiscal outcomes. Each panel reports coefficients from regressions that interact treatment status with event-time indicators relative to the adoption of data center incentives. The omitted period corresponds to the year prior to policy adoption. All specifications include county-by-cohort, year-by-cohort, and state-by-year-by-cohort fixed effects. Standard errors are clustered at the state level.

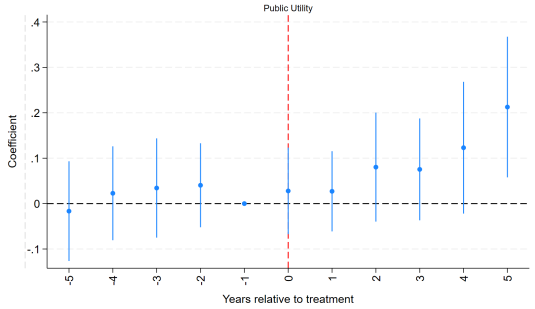
Figure 8: Dynamic Effects of Data Center Exposure on Local Tax Components



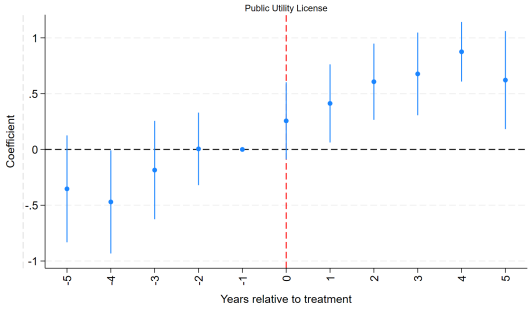
(a) Property



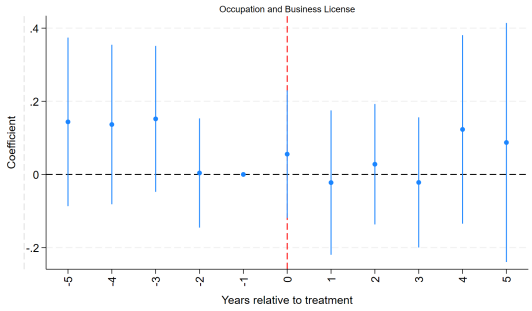
(b) Sales



(c) Public Utility



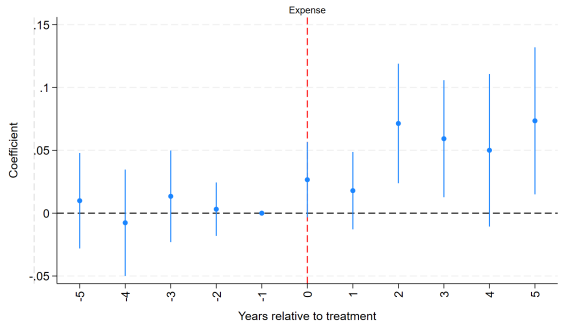
(d) Public Utility License



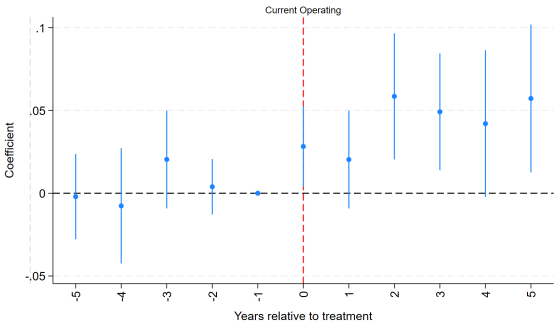
(e) Occupation & Business License

Notes: This figure presents event-study estimates of the dynamic effects of data center exposure on local tax components. Each panel reports coefficients on event-time indicators relative to the adoption of data center incentives. The omitted period corresponds to the year prior to policy adoption. All specifications include county-by-cohort, year-by-cohort, and state-by-year-by-cohort fixed effects. Standard errors are clustered at the state level.

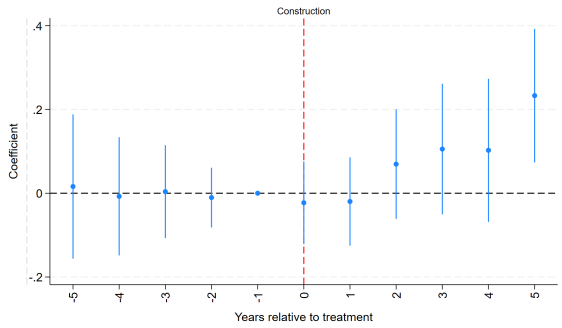
Figure 9: Dynamic Effects of Data Center Exposure on Local Expenditure and Debt



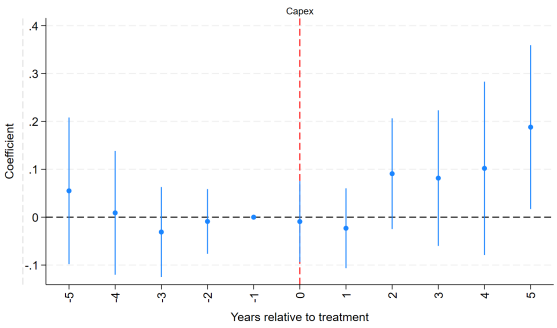
(a) Expense



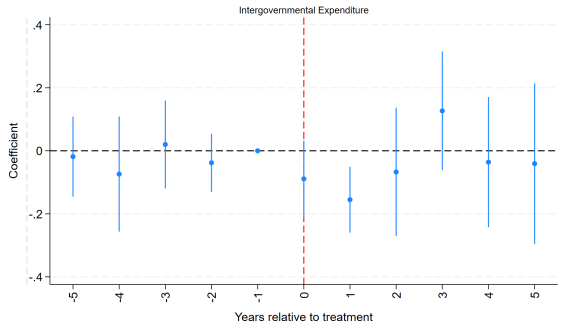
(b) Current Operating



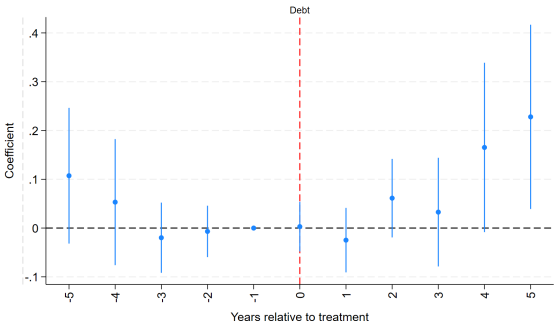
(c) Construction



(d) Capex



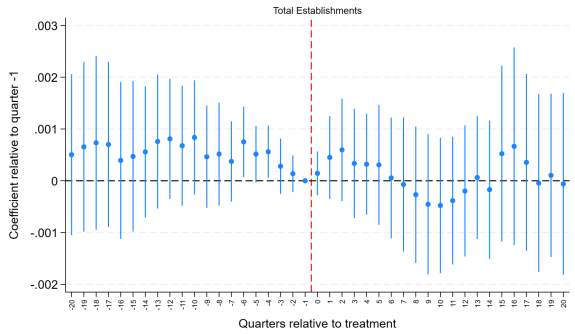
(e) Intergovernmental Expenditure



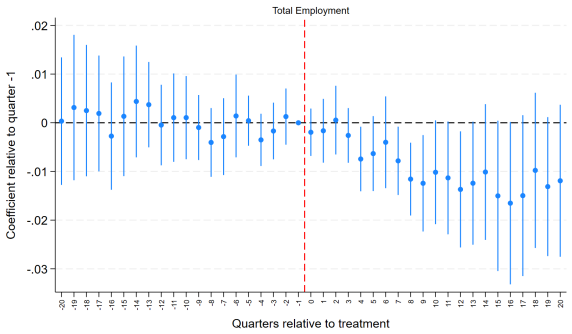
(f) Debt

Notes: This figure presents event-study estimates of the dynamic effects of data center exposure on local expenditure and debt outcomes. Each panel reports coefficients on event-time indicators relative to the adoption of data center incentives. The omitted period corresponds to the year prior to policy adoption. All specifications include county-by-cohort, year-by-cohort, and state-by-year-by-cohort fixed effects. Standard errors are clustered at the state level.

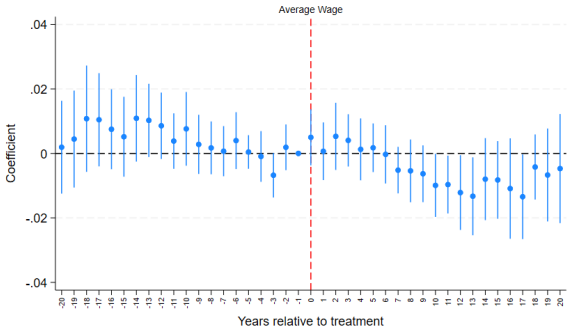
Figure 10: Event Study Estimates for Log Employment Outcomes



(a) Log Total Establishments



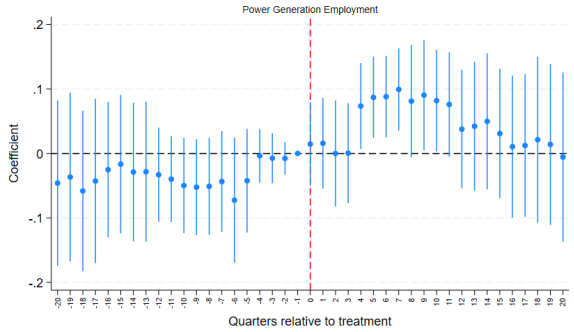
(b) Log Total Employment



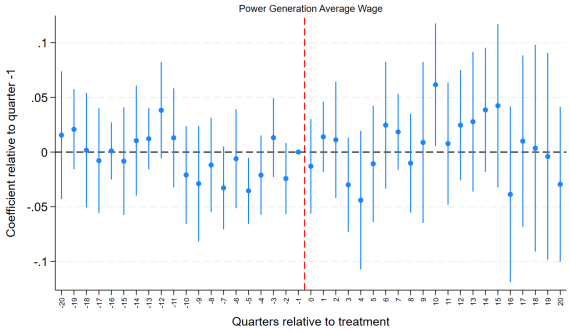
(c) Log Total Wage

Notes: This figure plots event-study estimates for log total establishments, log total employment, and log total wages around the timing of data center incentive adoption. The coefficients correspond to event-time indicators relative to the treatment period and can be interpreted approximately as percentage changes. All specifications include county-by-cohort, quarter-by-cohort, and state-by-quarter-by-cohort fixed effects. Standard errors are clustered at the state level.

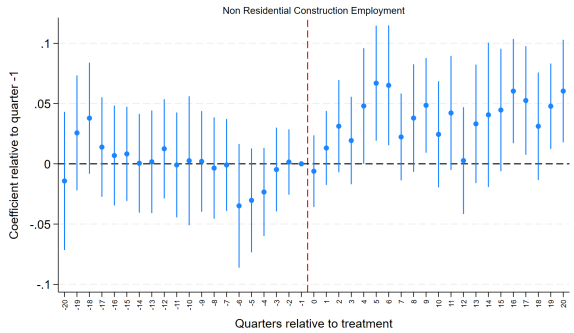
Figure 11: Event Study Estimates for Related Industry Outcomes



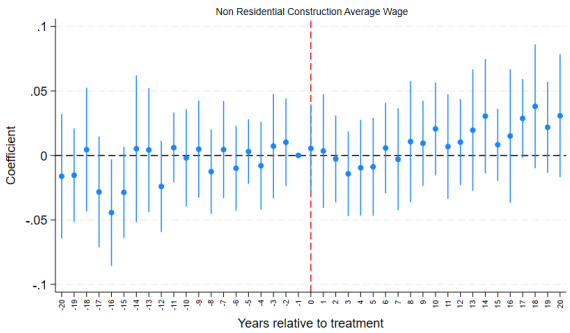
(a) Log Power Generation Employment



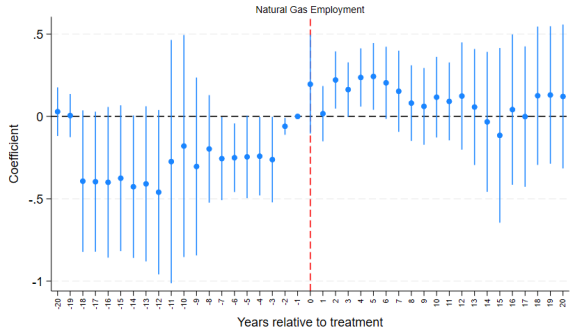
(b) Log Power Generation Wage



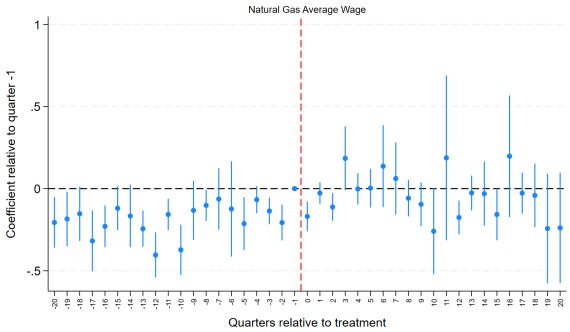
(c) Log Nonresidential Construction Employment



(d) Log Nonresidential Construction Wage



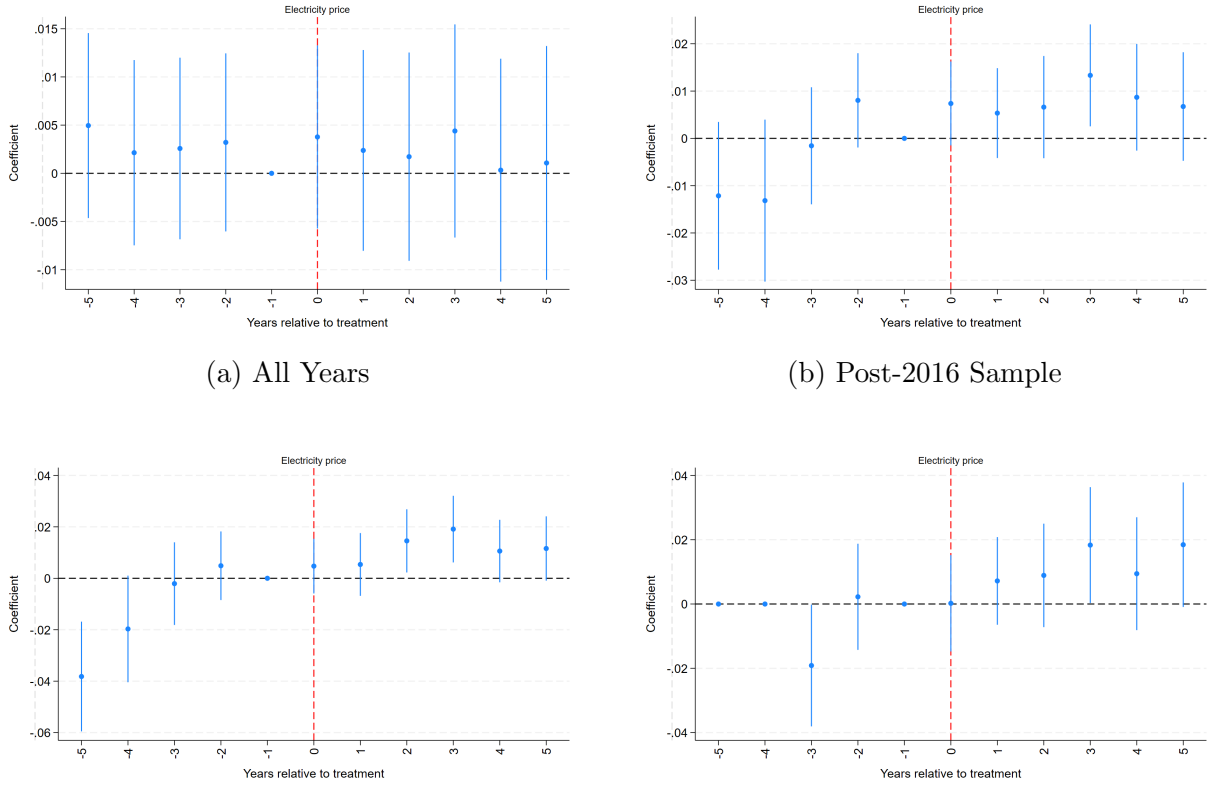
(e) Log Natural Gas Employment



(f) Log Natural Gas Wage

Notes: This figure plots event-study estimates for log employment and log wage outcomes in related industries around the timing of data center incentive adoption. The outcomes shown are power generation, nonresidential construction, and natural gas. The coefficients correspond to event-time indicators relative to the treatment period and can be interpreted approximately as percentage changes. All specifications include county-by-cohort, quarter-by-cohort, and state-by-quarter-by-cohort fixed effects. Standard errors are clustered at the state level.

Figure 12: Event Study Estimates for Residential Electricity Rates



(a) All Years

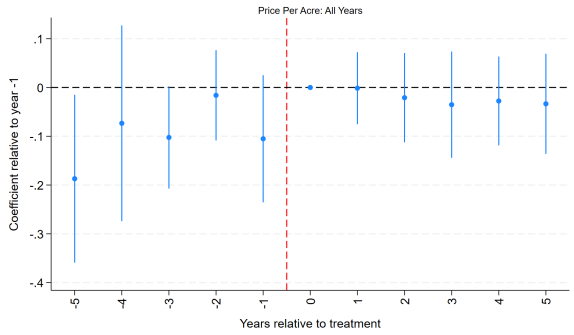
(b) Post-2016 Sample

(c) Post-2018 Sample

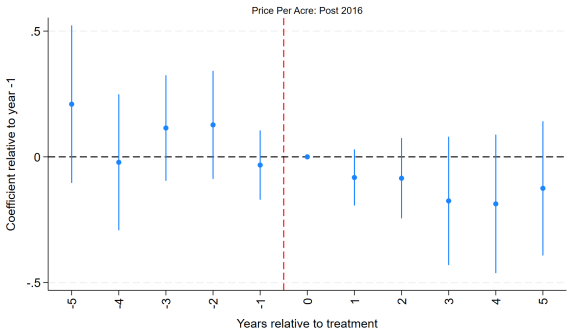
(d) Post-2020 Sample

Notes: This figure plots event-study estimates for log residential electricity rates around the timing of data center incentive adoption. The coefficients correspond to event-time indicators relative to the treatment period and can be interpreted approximately as percentage changes. Panels differ by sample restriction as indicated in the panel captions. All specifications include county-by-cohort, time-by-cohort, and state-by-time-by-cohort fixed effects. Standard errors are clustered at the state level.

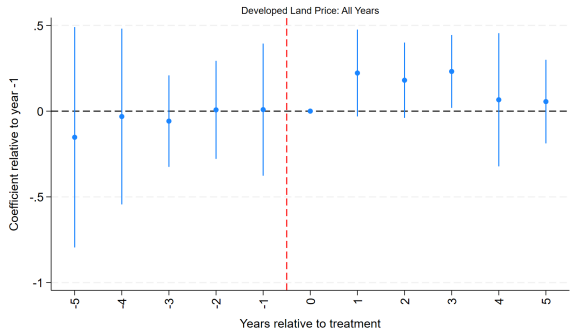
Figure 13: Dynamic Effects of Data Center Exposure on Land Prices



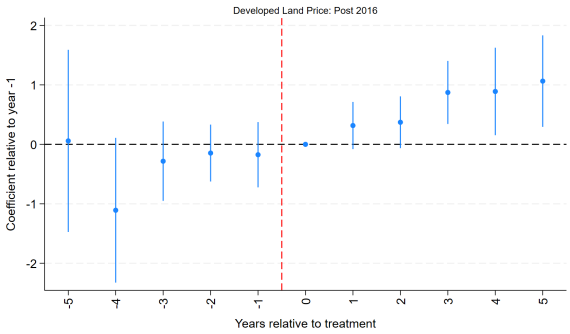
(a) Price per Acre: All Years



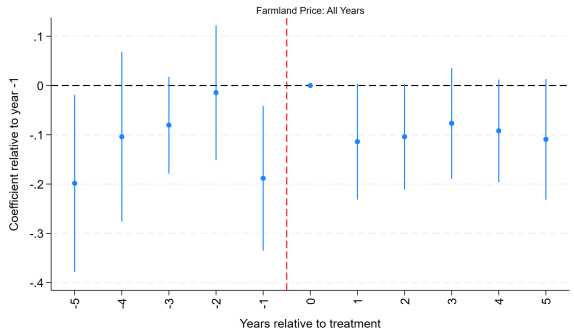
(b) Price per Acre: Post-2016



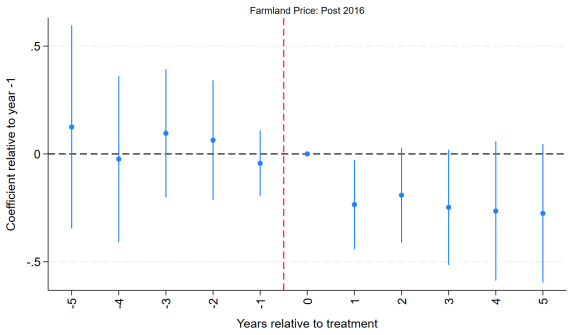
(c) Developed Land Price: All Years



(d) Developed Land Price: Post-2016



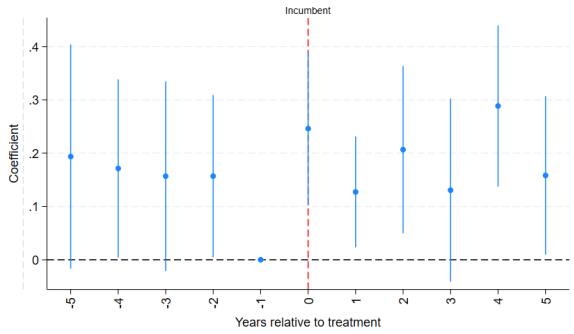
(e) Farmland Price: All Years



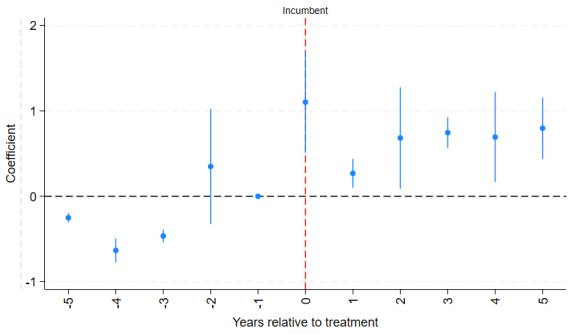
(f) Farmland Price: Post-2016

Notes: This figure plots event-study estimates of the effect of data center exposure on land prices. The left column reports estimates using the full sample, while the right column reports estimates for the post-2016 sample. Coefficients are estimated relative to the omitted year before treatment. Vertical bars report 95 percent confidence intervals. The red dashed line indicates the timing of subsidy adoption.

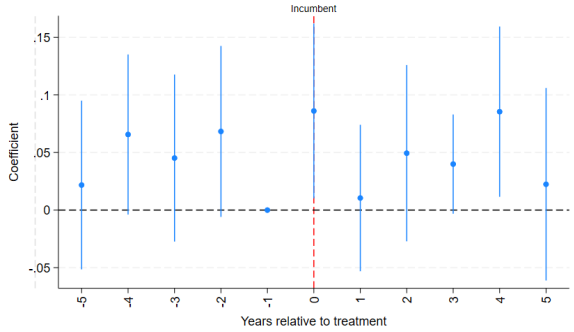
Figure 14: Event Study Estimates for Incumbency Outcomes



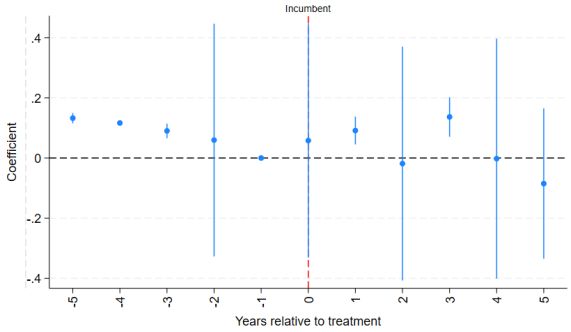
(a) Incumbent



(b) Incumbent, Post-2016 Sample



(c) Incumbent Lost



(d) Incumbent Lost, Post-2016 Sample

Notes: This figure plots event-study estimates for local election incumbency outcomes around the timing of data center incentive adoption. Panels (a) and (b) examine whether the incumbent runs or remains in office, while Panels (c) and (d) examine whether the incumbent loses. The coefficients correspond to event-time indicators relative to the treatment period. All specifications include county-by-cohort, quarter-by-cohort, and state-by-quarter-by-cohort fixed effects. Standard errors are clustered at the state level.

6 Tables

Table 1: State Data Center Tax Incentives

State	Year	State Sales	Local Sales	Local Property Taxes	Investment Threshold	Jobs	Wage Requirement
AL	2012	Yes	Yes	Yes	$200M; $400M	20	$40K+
AZ	2013	Yes	Yes	No	$25M; $50M		
AR	2023	Yes	Yes	No	$500M	25	
CT	2021	Yes	No local sales tax	No	$200M	30	
FL	2017	Yes	Yes	No	$150M	20	
GA	2018	Yes	Yes	No	$250M	25	
ID	2020	Yes	No local sales tax	No	$250M	30	
IL	2019	Yes	Yes	No	$250M	20	120% of median wage
IN	2019	Yes	No local sales tax	No	$25M; $150M	None	
IA	2009	Yes	Yes	No	$200M; $1B	10; 50	
KS	2025	Yes	Yes	No	$250M	20	
KY	2023	Yes	No local sales tax	No	$100M; $450M	None	
LA	2024	Yes	Yes	Yes	$200M	50	
ME	2021	Yes	No local sales tax	No	None	20	
MD	2020	Yes	No local sales tax	No	$2M	5	
MA	2024	Yes	No local sales tax	No	$50M	100	
MI	2016	Yes	No local sales tax	No	$250M	30	150% of median wage
MN	2012	Yes	No local sales tax	Yes	$30M		
MS	2010	Yes	No	No	$20M	20	150% of mean wage
MO	2015	Yes	Yes	No	$25M	10	
MT	2017	No sales tax	No local sales tax	Yes	$50M		
NE	2012						
NV	2015	Yes	Yes	Yes	$25M; $100M	10; 50	
NJ	2024						
NY	2000	Yes	Yes	No	None		
NC	2016	Yes	Yes	No	$75M		
ND	2021	Yes	Yes	No	$150M		
OH	2011	Yes	Yes	No	$100M; $500M	10; 50	
OK	2010	Yes	Yes	No	$5M	5	125% of mean wage
OR	2015	No sales tax		Yes	$50M	10–35	

Continued on next page

Table 1 continued

State	Year	State Sales	Local Sales	Local Property Taxes	Investment Threshold	Jobs	Wage Requirement
PA	2022	Yes	Yes	No	$75M	25	
SC	2012	Yes	Yes	No	$50M		
TN	2016	Yes	Yes	No	$100M	15	
TX	2013	Yes	Yes	No	$200M	20	120% of mean wage
UT	2016	Yes	Yes	No	$150M	15	110% of mean wage
VA	2009	Yes	Yes	No	$150M; $1B	50; 25	
WA	2010	Yes	Yes	No	$25M	20	
WI	2023	Yes	Yes	No	$150M	30	150% of mean wage
WV	2016	Yes	None	Yes	$50M	50	
WY	2010	Yes	Yes	No	$50M	20	

Notes: This table summarizes state-level data center incentive provisions, including the year of adoption, whether the incentive applies to state sales taxes, local sales taxes, and local property taxes, and the associated investment, employment, and wage requirements. Dollar values are reported in millions unless otherwise indicated.

Table 2: Data Center Growth Over Time

Year	Total DCs	New DCs	Total Space (sq. ft.)	New Space (sq. ft.)	Total Power (MW)	New Power (MW)
2000	402	.	24,893,481	.	2,742	.
2001	427	25	26,920,055	2,026,574	2,936	194
2002	441	14	28,242,290	1,322,235	3,160	224
2003	446	5	28,770,400	528,110	3,329	169
2004	451	5	29,615,075	844,675	3,411	82
2005	463	12	31,122,318	1,507,243	3,585	174
2006	477	14	32,422,518	1,300,200	3,682	96
2007	503	26	36,769,571	4,347,053	4,229	547
2008	544	41	41,351,873	4,582,302	4,680	452
2009	583	39	45,472,539	4,120,666	5,062	381
2010	634	51	51,359,258	5,886,719	5,682	620
2011	681	47	57,048,295	5,689,037	6,243	561
2012	744	63	64,285,392	7,237,097	7,094	850
2013	807	63	74,179,874	9,894,482	8,452	1,358
2014	873	66	82,667,581	8,487,707	9,604	1,152
2015	935	62	90,664,913	7,997,332	10,691	1,087
2016	1,024	89	104,859,884	14,194,971	12,960	2,269
2017	1,114	90	119,442,695	14,582,811	15,314	2,353
2018	1,226	112	142,853,617	23,410,922	19,340	4,027
2019	1,310	84	156,892,765	14,039,148	21,937	2,596
2020	1,402	92	173,052,196	16,159,431	25,347	3,410
2021	1,563	161	202,097,193	29,044,997	31,694	6,347
2022	1,770	207	252,267,817	50,170,624	42,650	10,956
2023	2,206	436	343,024,585	90,756,768	65,544	22,894
2024	3,342	1,136	564,723,473	221,698,888	117,889	52,345

Notes: This table reports annual cumulative data center counts, total data center space, and estimated power capacity. New data centers, new space, and new power capacity are calculated as year-over-year changes in cumulative totals.

Table 3: Summary Statistics

Variable	N	Mean	SD
Panel A: Data Center Variables			
Total data centers	94,320	0.258	2.726
Total data center space	94,320	29,743.570	465,080.200
Total data center power	94,320	4.636	92.046
Panel B: Local Public Finance Variables			
Total revenue	85,226	415,261.31	2,325,632.37
Total taxes	84,926	168,839.00	1,049,898.29
Total general charges	84,972	70,298.04	393,206.94
Total intergovernmental revenue	85,103	177,183.82	971,841.66
Property tax	84,767	122,042.31	591,404.11
Total sales tax	57,051	35,979.74	221,751.42
Public utility tax	48,946	6,266.90	38,581.36
Public utility license revenue	5,934	1,343.51	5,632.24
Other license taxes	41,146	3,789.21	19,289.47
Occupation and business license revenue	28,442	4,124.52	29,646.17
Total expenditures	85,352	516,662.58	2,902,703.06
Total current operations	85,341	376,666.20	2,016,000.80
Total construction	82,512	51,710.15	333,272.85
Total capital outlays	78,596	38,728.31	259,280.04
Total intergovernmental expenditures	76,802	14,091.23	142,852.62
Long-term debt issued for private purposes	29,822	99,553.94	579,291.15

Notes: This table reports summary statistics for data center and local public finance variables. Panel A reports data center outcomes, including the number of data centers, total data center space, and estimated power capacity. Panel B reports county-year local public finance variables. Total data center space is measured in square feet, total data center power is measured in megawatts, and fiscal variables are measured at the county-year level in thousands of dollars.

Table 4: Effect of Data Center Exposure on Number of Data Centers

	(1)	(2)	(3)
	±5-Year Window	±4-Year Window	±3-Year Window
Post × Waterfront × Treated	0.076***	0.062***	0.053***
	(0.022)	(0.018)	(0.014)
County × Cohort FE	Y	Y	Y
Year × Cohort FE	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y
Waterfront × Year × Cohort FE	Y	Y	Y
Observations	292,460	241,115	188,881
R^2	0.920	0.940	0.955
F-statistic	11.345	12.029	13.142

Notes: This table reports estimates from high-dimensional fixed effects regressions examining the effect of data center exposure on the number of data centers. Columns (1)–(3) use stacked difference-in-differences windows of five, four, and three years around subsidy adoption, respectively. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Effect of Data Center Exposure on Total Data Center Square Footage

	(1)	(2)	(3)
	±5-Year Window	±4-Year Window	±3-Year Window
Post × Waterfront × Treated	12,269.813***	10,823.583***	9,812.966***
	(4,501.511)	(3,840.517)	(3,450.170)
County × Cohort FE	Y	Y	Y
Year × Cohort FE	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y
Waterfront × Year × Cohort FE	Y	Y	Y
Observations	292,460	241,115	188,881
R^2	0.852	0.885	0.911
F-statistic	7.429	7.943	8.089

Notes: This table reports estimates from high-dimensional fixed effects regressions examining the effect of data center exposure on total data center square footage. Columns (1)–(3) use stacked difference-in-differences windows of five, four, and three years around subsidy adoption, respectively. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Effect of Data Center Exposure on Local Revenue

	(1)	(2)	(3)	(4)
	Total Revenue	Total Taxes	General Charges	Intergov. Revenue
Post × Waterfront × Treated	0.037***	0.033**	0.059*	0.020**
	(0.010)	(0.014)	(0.034)	(0.010)
County × Cohort FE	Y	Y	Y	Y
Year × Cohort FE	Y	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y	Y
Waterfront × Year × Cohort FE	Y	Y	Y	Y
Observations	232,277	231,653	231,829	232,076
Pseudo R^2	0.992	0.991	0.976	0.991

Notes: This table reports estimates from Poisson pseudo–maximum likelihood regressions examining the effect of data center exposure on local revenue outcomes. The sample period is 1995–2023. The stacked difference-in-differences design uses a five-year window around each subsidy adoption event. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. Counties near large water bodies are more likely to host data center facilities due to access to cooling water and related infrastructure. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Effect of Data Center Exposure on Local Tax Revenue Components

	(1)	(2)	(3)	(4)	(5)
	Property Tax	Sales Tax	Public Utility Tax	Public Utility License	Occup. & Bus. License
Post × Waterfront × Treated	0.031**	0.036*	0.063	0.738***	-0.048
	(0.015)	(0.022)	(0.050)	(0.182)	(0.062)
County × Cohort FE	Y	Y	Y	Y	Y
Year × Cohort FE	Y	Y	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y	Y	Y
Waterfront × Year × Cohort FE	Y	Y	Y	Y	Y
Observations	231,232	154,726	129,494	18,656	94,063
Pseudo R^2	0.992	0.985	0.982	0.950	0.964

Notes: This table reports estimates from Poisson pseudo–maximum likelihood regressions examining the effect of data center exposure on local tax revenue components. The sample period is 1995–2023. The stacked difference-in-differences design uses a five-year window around each subsidy adoption event. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. Counties near large water bodies are more likely to host data center facilities due to access to cooling water and related infrastructure. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: Effect of Data Center Exposure on Local Expenditures and Debt Issuance

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Expenditure	Current Operations	Construction	Capital Outlays	Intergov. Expenditure	Debt Issued
Post × Waterfront × Treated	0.043***	0.036***	0.078**	0.065	-0.013	0.375**
	(0.015)	(0.012)	(0.039)	(0.055)	(0.050)	(0.157)
County × Cohort FE	Y	Y	Y	Y	Y	Y
Year × Cohort FE	Y	Y	Y	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y	Y	Y	Y
Waterfront × Year × Cohort FE	Y	Y	Y	Y	Y	Y
Observations	232,716	232,684	225,375	231,486	211,572	90,037
Pseudo R^2	0.991	0.992	0.953	0.952	0.962	0.898

Notes: This table reports estimates from Poisson pseudo–maximum likelihood regressions examining the effect of data center exposure on local expenditure and debt issuance outcomes. The sample period is 1995–2023. The stacked difference-in-differences design uses a five-year window around each subsidy adoption event. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. Counties near large water bodies are more likely to host data center facilities due to access to cooling water and related infrastructure. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: Effect of Data Center Exposure on Employment and Wages

	(1)	(2)	(3)
	Total Establishments	Total Employment	Average Wage
Post × Waterfront × Treated	-0.004	-0.009*	-0.007*
	(0.004)	(0.005)	(0.004)
County × Cohort FE	Y	Y	Y
Quarter × Cohort FE	Y	Y	Y
State × Quarter × Cohort FE	Y	Y	Y
Waterfront × Quarter × Cohort FE	Y	Y	Y
Observations	1,568,136	1,562,325	1,562,325
R^2	0.999	0.998	0.948

Notes: This table reports estimates from fixed effects regressions examining the effect of data center exposure on local employment and wage outcomes. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. Counties near large water bodies are more likely to host data center facilities due to access to cooling water and related infrastructure. All specifications include county-by-cohort, quarter-by-cohort, state-by-year-by-cohort, and waterfront-by-quarter-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10: Effect of Data Center Exposure on Sectoral Employment and Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Nonres. Const. Emp.	Nonres. Const. Wage	Power Emp.	Power Wage	Natural Gas Emp.	Natural Gas Wage	Res. Build Emp.	Res. Build Wage
Post × Waterfront × Treated	0.039***	0.022*	0.077*	0.012	0.581*	0.153**	-0.032*	0.002
	(0.013)	(0.011)	(0.040)	(0.016)	(0.335)	(0.070)	(0.019)	(0.010)
County × Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter × Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Waterfront × Quarter × Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	651,600	747,344	138,739	138,739	25,242	25,242	901,476	832,772
R^2	0.987	0.801	0.983	0.868	0.970	0.846	0.976	0.838

Notes: This table reports estimates from fixed effects regressions examining the effect of data center exposure on sectoral employment and wage outcomes. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. Counties near large water bodies are more likely to host data center facilities due to access to cooling water and related infrastructure. All specifications include county-by-cohort, quarter-by-cohort, state-by-year-by-cohort, and waterfront-by-quarter-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 11: Effect of Data Center Exposure on Residential Electricity Rates

	(1)	(2)	(3)	(4)	(5)
	All Years	Pre-2016	Post-2016	Post-2018	Post-2020
Post × Waterfront × Treated	0.002	-0.002	0.008*	0.011**	0.011*
	(0.004)	(0.006)	(0.004)	(0.005)	(0.006)
County × Cohort FE	Y	Y	Y	Y	Y
Year × Cohort FE	Y	Y	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y	Y	Y
Waterfront × Year × Cohort FE	Y	Y	Y	Y	Y
Observations	245,883	175,921	68,419	44,194	23,274
R^2	0.920	0.901	0.942	0.949	0.963

Notes: This table reports estimates from fixed effects regressions examining the effect of data center exposure on residential electricity rates. The dependent variable is the log of the residential electricity rate. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. Column (1) uses the full sample, while Columns (2)–(5) restrict the sample to the pre-2016, post-2016, post-2018, and post-2020 periods, respectively. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: Effect of Data Center Exposure on Land Prices

	(1)	(2)	(3)	(4)	(5)	(6)
	All Years: Acres	Post-2016: Acres	All Years: Developed Land	Post-2016: Developed Land	All Years: Farmland	Post-2016: Farmland
Post × Waterfront × Treated	0.028	-0.080	0.174*	0.355**	-0.034	-0.213**
	(0.031)	(0.056)	(0.097)	(0.175)	(0.037)	(0.100)
County × Cohort FE	Y	Y	Y	Y	Y	Y
Year × Cohort FE	Y	Y	Y	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y	Y	Y	Y
Waterfront × Year × Cohort FE	Y	Y	Y	Y	Y	Y
Observations	71,386	32,339	50,285	20,863	70,277	31,716
R^2	0.856	0.881	0.669	0.767	0.773	0.801

Notes: This table reports estimates from fixed effects regressions examining the effect of data center exposure on land prices. The dependent variables are log price per acre, log developed land price, and log farmland price. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. Columns (1), (3), and (5) use the full sample, while Columns (2), (4), and (6) restrict the sample to the post-2016 period. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13: Effect of Data Center Exposure on Local Political Outcomes

	(1)	(2)	(3)	(4)
	Incumbent All Years	Incumbent Post-2016	Incumbent Lost All Years	Incumbent Lost Post 2016
Post × Waterfront × Treated	0.032	0.236**	-0.028**	0.076**
	(0.027)	(0.100)	(0.013)	(0.028)
County × Cohort FE	Y	Y	Y	Y
Year × Cohort FE	Y	Y	Y	Y
State × Year × Cohort FE	Y	Y	Y	Y
Waterfront × Year × Cohort FE	Y	Y	Y	Y
Observations	111,211	24,740	111,211	24,740
R^2	0.244	0.304	0.149	0.220

Notes: This table reports estimates from fixed effects regressions examining the effect of data center exposure on local political outcomes. The key coefficient of interest, Post × Waterfront × Treated, captures the triple-difference interaction between treated states, the post-policy period, and counties located near large water bodies. Columns (1) and (3) use the full sample, while Columns (2) and (4) restrict the sample to the post-2016 period. All specifications include county-by-cohort, year-by-cohort, state-by-year-by-cohort, and waterfront-by-year-by-cohort fixed effects. Standard errors clustered at the state level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.