Capital Without Labor: Data Centers and the Local Economy*

Liu Ee Chia† Jess Cornaggia‡ David Haushalter§ Qiang Wang¶

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Abstract

Can capital-intensive firm entry generate local economic development when it brings limited labor demand, local interaction, and production linkages? We study this question using U.S. data center development, comparing counties receiving data centers with near-miss counties that attracted proposals but did not host operational facilities. We find that data center entry alone does not significantly change local government borrowing costs; borrowing costs rise only with larger, more infrastructure-intensive exposure. These increases are concentrated in water-related debt, are larger in water-scarce counties, and appear primarily in water revenue bonds rather than water general obligation bonds, consistent with infrastructure-specific repayment risk rather than broad tax-base effects. We find limited evidence of gains in fiscal balance, employment, or business formation. Overall, the results in this paper suggest that when local economic ties are weak, capital-intensive investment generates limited economic benefits while straining local resources and public infrastructure.

Keywords: Data centers, Artificial Intelligence, Agglomeration, Municipal finance, Labor market
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†NUS Business School, National University of Singapore. Email: liueechia@nus.edu.sg.
‡Smeal College of Business, Pennsylvania State University. Email: jnc29@psu.edu.
§Smeal College of Business, Pennsylvania State University. Email: gdh12@psu.edu.
¶Haskayne School of Business, University of Calgary. Email: qiang.wang3@ucalgary.ca.

1 Introduction

A central rationale for local economic development policy is that firm entry can generate gains beyond the entering firm (Greenstone et al., 2010; Giroud et al., 2024). The agglomeration literature shows that spatial proximity among firms can raise productivity through labor-market pooling, knowledge spillovers, and input-output linkages (e.g., Marshall, 1890; Krugman, 1991, 1992; Lucas Jr, 1988; Jovanovic and Rob, 1989; Grossman and Helpman, 1993; Glaeser, 1999; Moretti, 2004a,b). These spillovers provide an economic rationale for place-based investment incentives.

Whether firm entry generates such gains, however, may depend on how it combines labor, capital, and local infrastructure. The settings studied in prior work, from large industrial plants to high-tech clusters, typically involve thick labor markets, specialized human capital, and production or knowledge linkages across firms (Moretti, 2021; Glaeser and Saiz, 2004; Buera and Kaboski, 2012). As the economy becomes increasingly digital and AI-intensive, a new class of fixed, capital-intensive establishment has become increasingly salient: the data center.

Data centers provide core physical infrastructure for cloud computing, data storage, and artificial intelligence, but their local economic footprint differs substantially from traditional industries. They are large and durable facilities whose operations rely more heavily on computing equipment, electricity, water, land, and supporting infrastructure than on local labor or nearby production networks.[1] Projections suggest that global spending on data centers could reach $7 trillion by 2030.[2] This distinction raises our central question: what are the local consequences of firm entry when investment arrives primarily as capital, infrastructure needs, and resource demand rather than employment and production linkages?

[1] For a 100-megawatt facility, upfront investment in land, buildings, and power and cooling infrastructure typically ranges from $900 million to $1.5 billion, but operate with as few as 20 to 30 permanent employees. In contrast, between 2019 and 2025, U.S. manufacturing investment generated more than one million jobs from $1.1 trillion in capital investment, implying roughly 1,000 direct jobs per $1 billion of investment. See, for example, Deconstructing the Data Center: A Look at the Cost Structure Igniting the AI Boom! and Advanced Manufacturing in America: Driving Innovation, Investment, and Workforce Transformation

[2] See, for example, The cost of compute: A $7 trillion race to scale data centers.

This paper investigates whether data center entry translates private investment into local economic and fiscal gains, or instead creates fiscal and economic exposure for local public systems and residents. We examine this question using evidence from government borrowing costs, local fiscal conditions, labor-market outcomes, and housing prices. Specifically, we measure borrowing costs using primary-market municipal bond yields, which provide a direct setting to assess how data center entry affects the current and expected future economic conditions, tax-base growth, infrastructure costs, and hence repayment risk of public debt. Ex ante, the effect is ambiguous. Broad tax-base or economic gains should leave municipal credit conditions stable or improved, whereas risks arising from infrastructure and resource demands should increase yields of bonds tied to the affected public systems.

Identification is challenging because data centers are not randomly located: developers select sites based on power and land availability, network connectivity, water access, and local regulatory conditions (Du et al., 2026; Gargano and Giacoletti, 2025). To construct a credible counterfactual, we compare counties that host data centers with 'near-miss' counties that attracted data center proposals but did not host an operational facility. Because near-miss counties received data center proposals, they are likely to share some of the characteristics that make treated counties plausible hosts for data center development. This design avoids comparing treated counties either with places that were unlikely to attract data centers in the first place or with later-treated counties whose outcomes may be affected by announcements, anticipations, or pre-construction activity that is hardly observed in the data. We then implement a stacked difference-in-differences design around the year in which a county first hosts a data center (Cengiz et al., 2019).

We find that local government borrowing costs are more sensitive to the scale of data center exposure than to entry alone. On the extensive margin, the arrival of a data center is not associated with a statistically significant change in borrowing costs. In contrast, greater exposure to facility scale—measured by footprint, power capacity, and server infrastructure—leads to higher borrowing costs; evaluated at the average county-level data center scale, the estimates imply an increase of

approximately 6.4 basis points in adjusted yields.[3] The increase is not broad-based across municipal debt. It appears primarily in water bonds and primary and secondary education bonds, while bonds financing general-purpose projects, higher education, utility, housing, healthcare, and transportation show little comparable response.[4]

The water-bond effect is strongest where local water constraints are more binding.[5] Using U.S. Geological Survey measures of local water constraints, we find that data center entry raises adjusted water-bond yields by 25.5 basis points more in water-scarce counties than in water-abundant counties, where the baseline effect is small and statistically insignificant. The effect is also larger for water revenue bonds, which are repaid from water-system revenues, rather than in water general obligation bonds backed by broad taxing authority. This distinction provides suggestive evidence that data center entry is not viewed primarily as changing the municipality's broad economic base, but as affecting the cash flows of the specific infrastructure system exposed to data center demand. Taken together, these results provide evidence against a broad establishment-entry channel in which data centers strengthen local fiscal capacity through the canonical mechanisms of agglomeration. Instead, they point to a different local effect of capital-intensive digital investment: when entry brings capital and resource demand rather than labor and production linkages, its consequences appear in the public infrastructure systems required to support production.

The education-bond results point to a different channel. Primary and secondary education bonds are often supported by local property-tax revenues, making their yields sensitive to changes in housing values and expectations about the future tax base. First, We show that the education-bond response is concentrated in major data center hubs: after excluding the most heavily exposed counties, the yield effects become smaller and statistically insignificant.[6] Second, to further

[3]The mean county-level data center footprint in our sample is 1.5 million square feet as of 2025.

[4]Water bonds finance long-term capital projects for water infrastructure and are commonly repaid from water-system revenues.

[5]Corpus Christi, Texas, illustrates how water scarcity can enter municipal credit risk. In 2025, Moody's downgraded the city, citing accelerated water-depletion risk, while Fitch and S&P revised the outlook on the city's utility-system revenue bonds to negative over concerns about water-supply security. See Moody's downgrades Corpus Christi's ratings over water woes.

[6]We define major data center hubs as counties that rank among the top five in 2025 by at least one measure of data center scale. Specifically, major data center hubs are Maricopa County, Arizona; Santa Clara County, California; Cook

investigate the channel, we examine housing prices in the same high-exposure counties. We find that housing price growth declines with data center development scale in these counties, while there is little evidence of comparable effects outside the major data center hubs. The parallel concentration of education-bond and housing-market responses suggests that investors price education debt where large-scale data center development coincides with weaker housing-market conditions, rather than through the direct infrastructure-capacity channel documented for water bonds. More broadly, the housing-price evidence shows that the local effects of data center development extends beyond public borrowing costs: instead of generating broad residential capitalization consistent with local economic gains, large-scale data center exposure appears to weaken housing-market conditions in the places most exposed to the buildout.

We next turn to real-side outcomes that map directly to the channels emphasized in the agglomeration literature. If data centers convert large private investment into a stronger local economy, the effects should appear not only in municipal credit conditions but also in fiscal capacity, employment, and business formation. If, instead, data centers represent capital-intensive entry with limited labor and production linkages, the evidence should show weaker broad gains and greater pressure on the public systems and residents exposed to the facilities.

We find limited evidence that data center entry improves the overall fiscal position of local governments. Revenues do not rise systematically relative to expenditures, and property and sales tax revenues show limited responses. We also find little evidence of increases in local employment or business establishments, consistent with the labor-light nature of data center operations. Taken together, the fiscal and labor-market results reinforce the central interpretation: when firm entry arrives mainly as capital and resource demand rather than labor and production networks, its local effects are less visible in broad agglomeration gains and more visible in public systems and residents exposed to the infrastructure demands of digital production.

County, Illinois; Sarpy County, Nebraska; Licking County, Ohio; Morrow County, Oregon; Loudoun County, Virginia; and Prince William County, Virginia.

Our paper is related to several strands of literature. First, it contributes to the literature on place-based policy and agglomeration economies by separating capital investment from agglomeration-generating local activity. Prior studies show that targeted development policies, spatial concentration, large establishment entry can raise local employment (Busso et al., 2013; Kline and Moretti, 2014; Austin et al., 2018), productivity (Greenstone et al., 2010; Giroud et al., 2024), innovation (Jaffe et al., 1993; Moretti, 2021; Giroud et al., 2026) when they deepen labor markets, create production linkages, or facilitate localized knowledge flows (Marshall, 1890; Duranton and Puga, 2004; Rosenthal and Strange, 2001; Ellison et al., 2010; Rosenthal and Strange, 2004; Giroud and Mueller, 2019). We use large data center development as a setting that cleanly separates capital investment from the local economic activity that gives rise to agglomeration gains. This enables us to show directly that capital-intensive entry is not a substitute for agglomeration: when the economic linkages surrounding the investment are thin, local effects shift away from broad employment, business-formation, and fiscal-capacity gains toward costs borne by public infrastructure systems and exposed residents.

Second, our paper contributes to the literature on local public finance. Prior work shows that municipal bond issuance yields respond to localized risk exposures, including climate change and sea-level rise (Painter, 2020; Goldsmith-Pinkham et al., 2023), credit fundamentals and rating signals (Schwert, 2017; Cornaggia et al., 2018), and major local shocks or fiscal pressures related to public health, demographics, information, and policy environments (Novy-Marx and Rauh, 2012; Gao et al., 2019, 2020; Butler and Yi, 2022; Cornaggia et al., 2022; Dagostino, 2025). We extend this literature by exploiting the institutional structure of municipal debt, that is, the distinction between general obligation bonds and revenue bonds, to disentangle broad tax-base exposure from risks tied to specific infrastructure cash flows. This gives us a clean way to identify where the local consequences of capital- and resource-intensive development, such as data center development, are borne.

Finally, our paper contributes to the growing literature on the economic effects of the digital economy. While a large literature studies the economic consequences of AI, telecommunication,

and cryptocurrency, less is known about the local effects of the physical infrastructure that supports the digital economy.[7] Recent work on data centers examine their geography, market structure, subsidies, financing, and energy use (e.g., Greenstein and Fang, 2022; Halaburda and Yermack, 2023; Gargano and Giacoletti, 2025; Van Nieuwerburgh, 2026; Gete and Mercader, 2026; Du et al., 2026), as well as their effects on local labor-market outcomes, economic activity, and housing markets (Alvarez et al., 2026; Yue and Zeng, 2026; Bahar and Wright, 2025; Chia et al., 2026).

Our study is closest to Alvarez et al. (2026) and Yue and Zeng (2026), who document positive effects of data center development on local economic activity and housing-market outcomes. By contrast, we find more muted labor-market responses and negative effects on housing prices. We view these findings as complementary, with the differences plausibly reflecting a more targeted empirical design and a focus on modern, infrastructure-intensive facilities. Specifically, we compare treated counties to near-miss counties that were plausible host locations; we concentrate on post-2015 facilities most closely tied to cloud and AI demand, which are driving the contemporary data center buildout and the attendant concerns over scale, siting, and infrastructure requirements; we distinguish facility scale and power capacity from entry alone; and we examine local public finance alongside standard real-side outcomes. Together, these design features allow us to ask not merely whether data centers raise local economic activity, but whether modern, capital- and resource-intensive digital infrastructure generates broad local gains or instead shifts costs toward public systems and exposed residents.

[7] See the following papers on the economic impacts of artificial intelligence, including firm growth (Babina et al., 2024; Chen et al., 2019; Hirvonen et al., 2022; Rock, 2019), labor-market disruption (Babina et al., 2023; Grennan and Michaely, 2020; Abis and Veldkamp, 2024; Cao et al., 2024; Acemoglu et al., 2022; Cockburn et al., 2018; Hirvonen et al., 2022), trading behavior (D'Acunto et al., 2019), and credit underwriting and inequality (Jansen et al., 2020; Fuster et al., 2022).

2 Data and Sample Construction

2.1 Data Centers in the United States

Our analysis begins with the facility-level information on data centers from the S&P Global 451 Research Knowledge Base. The database provides detailed information on each facility's geographic location, construction and operational timing, power capacity, utilization, facility type, and ownership. For facilities operated by publicly traded firms, we obtain Standard Industrial Classification (SIC) codes from the Center for Research in Security Prices (CRSP) and link them to facility operators. We restrict the sample to operational facilities with geographic coordinates and nonmissing opening years, as these variables are required to assign facilities to local markets and measure the timing of data center entry. The resulting facility-level panel forms the basis for measuring county-level exposure to data center development.

[Insert Figure 1 here.]

Figure 1 shows the concentration of U.S. data center ownership across major operators from 2000 to 2025. Recent expansion is concentrated among large technology firms. By 2025, Amazon, Microsoft, Google, and Meta account for roughly one-quarter of all U.S. data centers, with Amazon the largest operator, followed by Microsoft and Google. Publicly traded real estate investment trusts (REITs), including Equinix, Digital Realty, and QTS Realty Trust, represent the second-largest ownership group and account for about one-fifth of facilities in 2025. The remaining facilities are owned by a broader set of technology, telecommunications, energy, and privately held firms. This ownership structure underscores the institutional and capital-intensive nature of modern data center development, linking the sector to large corporate investment, cloud computing, artificial intelligence demand, and specialized real estate capital.

[Insert Figure 2 here.]

Figure 2 documents a pronounced increase in the scale of newly constructed data centers beginning around 2015. Facilities built before 2015 were relatively modest in size, and average facility characteristics changed only gradually during the early part of the sample. In contrast,

post-2015 facilities are substantially larger across three dimensions: physical footprint, measured by floor area; power capacity, measured by utility power, and uninterruptible power supply (UPS) capacity; and server infrastructure, measured by rack counts. Relative to the pre-2015 period, the average facility roughly doubled in scale by 2020, increasing from about 100,000 to 200,000 square feet, with comparable growth in power capacity and rack infrastructure. Facility scale increased further after 2020, coinciding with the rapid growth of AI-related computing demand. By 2025, the average newly constructed facility exceeded 300,000 square feet, with around 60 megawatts of utility power, 40 megawatts of UPS capacity, and 6,000 server racks.

In our analysis, we therefore focus on data center entry after 2015. This period captures the modern wave of data center development, in which facilities are more capital- and infrastructure-intensive than earlier generations. These features make modern data center entry relevant for studying local fiscal and economic outcomes: large facilities may broaden the local tax base and generate investment-related activity, but their power, water, and land requirements can increase pressure on local infrastructure and utilities, while creating relatively few permanent jobs.

[Insert Table 1 here.]

Table 1 reports county-level data center capacity in 2025. By the end of the sample, 174 U.S. counties host at least one data center facility built after 2015. Among host counties, average data center capacity is 1.5 million square feet and 253 megawatts of utility power, while the corresponding medians are 0.32 million square feet and 36.7 megawatts. The distribution of data center capacity is highly right-skewed, indicating that a small number of counties account for a disproportionate share of data center development.[8]

[Insert Figure 3 here.]

Data center development is geographically concentrated across U.S. counties over time (Figure 3). Loudoun County, Virginia, is the largest data center hub, hosting approximately 157 facilities in

[8] In robustness tests, we verify that our results are not driven by the largest data center hubs by excluding the five counties with the greatest data center scale.

2025. Other major hubs include Maricopa County, Arizona; Prince William County, Virginia; Santa Clara County, California; and Cook County, Illinois, each with 30 to 70 facilities.

2.2 Municipal Bond Data

We obtain municipal bond data from Mergent for 2010–2024. Mergent provides bond-level information on primary market issuances, including offering amounts, maturities, coupon rates, insurance status, use of proceeds, and source of repayment. We assign bonds to counties using the first six digits of the bond CUSIP, which identify the issuing entity, together with issuer geographic information. Following Cornaggia et al. (2022), we merge bond-level observations with county-level characteristics using Federal Information Processing Standard (FIPS) codes.

Our primary outcome variable is the adjusted yield, defined as the tax-adjusted municipal bond yield net of the yield on a maturity-matched U.S. Treasury security. Following Gustafson et al. (2025), we adjust municipal yields to account for the tax exemption feature of municipal bond interest income based on Garrett et al. (2023). Adjusted municipal bond yields measure local governments' primary-market borrowing costs and investors' pricing of municipal credit risk.

2.3 Local Public Finance and Labor Market Outcomes

We construct county-level local public finance measures from the U.S. Census Bureau's Annual Survey of State and Local Government Finances and the quinquennial Census of Governments Finance component. The data provide standardized information on revenues, expenditures, debt, and assets for U.S. state and local governments using uniform Census definitions, concepts, and classification procedures. Our sample covers fiscal years 2010–2023. In Census of Governments years, which occur in years ending in 2 and 7, the Census Bureau canvasses the universe of government units; in intervening years, it surveys a sample of governments and produces comparable

survey-based estimates.[9] We aggregate local government records to the county-year level and use the resulting panel to measure local revenues, total expenditures, and spending by major function.

We obtain local labor-market outcomes from the Quarterly Census of Employment and Wages (QCEW) for 2010–2024. The QCEW is an administrative dataset compiled by the U.S. Bureau of Labor Statistics from employer filings to state unemployment insurance programs. It provides near-universal coverage of U.S. wage-and-salary employment and reports employment and establishment counts by county and industry.

2.4 Near-Miss Counties and Estimation Sample

A central challenge in estimating the local effects of data center entry is that facilities are not randomly located across counties. Developers select locations based on factors such as power availability, network connectivity, land, water access, and local regulatory conditions (Du et al., 2026; Gargano and Giacoletti, 2025). To construct a credible control sample, we identify near-miss counties as counties that received data center proposals but did not host an operational facility by 2025, the end of our sample. Because near-miss counties attracted data center proposals, they likely share key site-selection characteristics with treated counties. Using these counties as controls therefore compares treated counties with places that were plausible hosts, rather than with locations that had little apparent likelihood of receiving data center investment.

[Insert Figure 4 here.]

We identify proposed data center projects from Tracking American AI Data Center Buildout.[10] Figure 4 maps the resulting near-miss counties. These counties attracted data center proposals but did not host an operational facility, making them plausible counterfactual locations for treated

[9] Census edits individual government-unit records to reduce reporting and processing errors and imputes missing or unusable responses for nonresponse units before producing the survey estimates.

[10] See Tracking American AI Data Center Buildout. The database records community responses, policy actions, and regulatory or legal developments related to data center development. Its entries include actions such as zoning restrictions, moratoria, public comments, lawsuits, project withdrawals, utility regulation, executive orders, and legislation. To construct our near-miss sample, we retain entries that explicitly refer to a proposed data center project or facility and identify a sponsoring company. We exclude entries without an identifiable company, which primarily correspond to broader legislative, regulatory, or policy actions rather than specific development proposals.

counties. Many entries in the tracker involve local opposition, zoning or land-use decisions, moratoria, litigation, utility regulation, project withdrawals, or resource-related concerns. Our sample includes 462 data center proposals submitted to 303 near-miss counties between July 1, 2023, and May 24, 2026. Appendix Figure A1 reports the distribution of concerns raised in these data center proposals. Among the 462 proposals, community impacts are the most frequently cited concern, appearing in 58.9% of cases, followed by zoning (53.7%), water resources (44.8%), environmental impacts (34.4%), and grid energy capacity (34.0%).

We define treated counties as counties that receive their first operational data center after 2015. For each treated county, the treatment year is the year in which its first post-2015 data center begins operation. We construct county-year measures of data center exposure using facility counts, floor area, utility power, UPS capacity, and rack counts. The estimation sample combines treated counties with near-miss counties defined above as counties with proposed data center activity but no operational facility by the end of the sample. We organize the sample by treatment cohort, based on the year of first data center entry, and retain observations within a five-year window around entry. We then merge this county-year structure with municipal bond issuances, local public finance outcomes, labor-market outcomes, housing prices, and county characteristics.

[Insert Table 2 here.]

Table 2 reports summary statistics for the main variables used in our analysis. Panel A summarizes primary-market municipal bond characteristics. Our main outcome variable is the adjusted yield, which has a mean of 1.77% and a standard deviation of 1.14%. The average bond has a coupon rate of 3.55% and 9.57 years to maturity. In the sample, 17% of bonds are insured, 53% are general obligation bonds, 46% are refunding issues, 47% of bonds are callable, and 35% are bank-qualified bonds. Offering types are broadly balanced, with 45% of bonds sold through negotiated offerings and 54% through competitive offerings.

Panel B reports summary statistics for county-level outcomes and characteristics. Fiscal revenues and expenditures average $979 thousand and $966 thousand, respectively, with substantial cross-county variation. Labor-market outcomes are similarly dispersed: average employment is 79,940

workers, and the average number of establishments is 5,060. We measure county-level housing price growth using the Federal Housing Finance Agency (FHFA) house price index from 2010 to 2024. The average annual change in the index is 5.06%, with a standard deviation of 5.42%.

3 Empirical Strategy and Results

3.1 The Effects of Data Centers on Local Government Borrowing Costs

We study data center development to examine how local economies respond when large private investment arrives with limited labor demand, local interaction, and production linkages. We begin with local government borrowing costs in the primary municipal bond market because issuance yields provide a market-based lens on these local economic consequences of data center entry: to the extent that data center entry affects expected fiscal capacity, infrastructure costs, or local economy in general, those effects should be should be capitalized into the borrowing costs faced by local governments.

We estimate the effects of data center entry on municipal borrowing costs using a stacked difference-in-differences design following Cengiz et al. (2019). We assign each treated county to a treatment cohort based on the year of its first new data center entry after 2015. Within each cohort, the design compares treated counties with near-miss counties over a five-year window around the entry year. Identification requires that, in the absence of data center entry, changes in municipal borrowing costs for treated counties would have been comparable to those for near-miss counties in the same cohort. We begin with primary-market municipal bond yields, estimated using the following specification:

$$\text{Adjusted Yield}_{i(c),t,g} = \beta \text{DC Exposure}_{c,t,g} + \boldsymbol{\theta}' \mathbf{B}_{i,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g}, \quad (1)$$

where i, c, t, and g index bonds, counties, years, and treatment cohorts, respectively. $\text{DC Exposure}_{c,t,g}$ denotes data center exposure, measured alternatively by an entry indicator (*After Entry*$_{c,t,g}$), facility

footprint ($Space_{c,t,g}$), utility power capacity ($Utility\ Power_{c,t,g}$), UPS capacity ($UPS\ Power_{c,t,g}$), or rack counts ($Racks_{c,t,g}$). $After\ Entry_{c,t,g}$ equals one if county c hosts at least one data center in year t.[11] $Space_{c,t,g}$ is the total data center floor area in county c in year t, measured in millions of square feet. $Utility\ Power_{c,t,g}$ and $UPS\ Power_{c,t,g}$ measure the total utility power capacity and uninterruptible power supply capacity, respectively, in county c and year t, expressed in gigawatts. $Racks_{c,t,g}$ is the total number of data center racks in county c and year t, measured in millions.

Bond-level controls include coupon rate, maturity, insurance status, general obligation status, refunding status, offering type, callability, and bank qualification; county-level controls include racial composition, educational attainment, population, households, median household income, and housing units.[12] County–cohort fixed effects, $\alpha_{c,g}$, absorb time-invariant county characteristics within each stacked cohort, and State-Year–Cohort fixed effects, $\delta_{s(c),t,g}$, absorb state-level shocks within each cohort. The coefficient of interest, β, estimates the effect of data center exposure on adjusted municipal bond yields. Standard errors are clustered at the county level to account for serial correlation within counties over time.

[Insert Table 3 here.]

Table 3 reports the baseline estimates for municipal yields. Column (1) measures data center exposure on the extensive margin, using an indicator for whether a county hosts a data center. The coefficient is positive but statistically insignificant, suggesting that the entry of a facility alone does not affect municipal borrowing costs. Columns (2) through (5) instead use intensive-margin measures of data center scale. The estimates indicate that borrowing costs increase with the size and exposure intensity of local data center development. Specifically, a one-million-square-foot increase in data center space is associated with a 4.4-basis-point increase in adjusted yields. Similar patterns hold for power and server capacity: a one-gigawatt increase in utility power capacity is associated with a 30.7-basis-point increase, a one-gigawatt increase in UPS capacity with a 47.1-basis-point increase, and an additional one million server racks with a 308.2-basis-point increase.

[11] In our baseline specification, data center entry is defined as one year before construction is completed. The results are robust when we define entry as one year before the facility begins operations.

[12] We use logarithms of population, households, housing units, and median household income.

To assess economic magnitudes, we evaluate the estimates at the average county-level data center scale reported in Table 1. At this scale, data center exposure is associated with an increase of approximately 6.4 basis points in adjusted municipal bond yields relative to counties without data centers. Overall, the results suggest that municipal markets respond more to the scale of data center exposure than to the presence of a facility per se.

We next examine whether the bond-market response varies by the use of proceeds. This heterogeneity is informative because data center entry may have uneven implications across municipal projects. If data centers expand the tax base or generate local spillovers through investment, workers, firms, or complementary activity, yields should decline broadly across municipal debt. If instead local gains are limited and costs arise through resource or infrastructure demands, yield increases should be concentrated among bonds tied to the affected public systems. We therefore classify bonds into eight use-of-proceeds categories: general purpose, education, utility, water, transportation, housing, health, and other. Table A1 reports the use-of-proceeds codes corresponding to each bond category and the share of bonds issued in each category in our sample. General-purpose bonds, primary and secondary education bonds, and water bonds are the three largest categories, accounting for 33.62%, 31.20%, and 11.20% of observations, respectively. Higher education, utility, housing, healthcare, and transportation bonds each account for less than 10% of observations. Bonds outside these categories account for the remaining 8.06% of the sample.

Appendix Table A4 reports estimates of Equation 1 separately by use-of-proceeds category. Across both extensive- and intensive-margin measures of data center exposure, yield increases are concentrated among bonds financing water infrastructure and primary and secondary education, while other bond categories show no comparable response. These results suggest that municipal bond markets do not reprice local debt uniformly following data center entry. Instead, the increase in borrowing costs is concentrated in sectors most directly tied to water infrastructure and primary and secondary education.

We estimate dynamic effects separately for bonds in each category using the following specification:

$$\text{Adjusted Yield}_{i(c),t,g} = \sum_{k=-5,k\neq-1}^{5} \beta_k \text{Treated}_{c,g} \times \mathbf{1}[\text{Event Time}_{t,g}\text{= k}] + \boldsymbol{\theta}'\mathbf{B}_{i,t} + \boldsymbol{\lambda}'\mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g}, \tag{2}$$

where Event Time$_{t,g}$ denotes calendar year t relative to treatment cohort g, with $k = 0$ corresponding to the year of the first data center entry in county c and $k = -1$ omitted as the reference period. All other variables are defined as in Equation 1. The coefficients β_k measure the dynamic treatment effects of data center entry on municipal bond yields, comparing treated counties with near-miss control counties within the same cohort stack in each event year k, relative to the omitted pre-entry year.

[Insert Figure 5 here.]

Figure 5 plots the dynamic effects of data center entry by bond use of proceeds. The increase in borrowing costs is concentrated among water bonds and primary and secondary education bonds. Adjusted yields for these bonds exhibit no pre-trends but rise following data center entry. In contrast, we find little evidence of comparable yield responses for bonds financing general-purpose, higher education, utility, housing, healthcare, or transportation projects.These patterns raise a natural question: why are yield effects concentrated in water and education bonds, rather than across municipal debt more broadly? The following sections examine the mechanisms linking data center development to these two public systems.

3.1.1 Data Center Development and Water Bonds

We first examine the water-system channel. Because data center capacity is highly right-skewed, we begin by assessing whether the water-bond response is concentrated among the most heavily exposed counties. Table **??** excludes counties that rank among the top five in 2025 by any measure

of data center scale, including facility count, floor area, utility power capacity, UPS capacity, or rack count.[13] The water-bond estimates remain close to the baseline, indicating that the response is not driven solely by the largest data center clusters.

We then examine whether the water-bond response varies with local water constraints. If data center development affects borrowing costs through demands on specific public systems, the response of water bonds should be stronger where local water capacity is more constrained. This setting is particularly relevant because data centers can increase water demand directly through cooling needs and indirectly through the water requirements of electricity generation.[14] In water-constrained areas, additional demand from data center entry may affect water-system cash flows through channels such as higher expected system costs, greater uncertainty about future water availability, and more complicated cost recovery.[15] We therefore test whether water-bond yields respond more strongly to data center entry in counties with more limited water resources.

We measure local water scarcity using water resource data from the U.S. Geological Survey (USGS) National Water Availability Assessment data, which are reported at the HUC12 watershed level and aggregated to counties for our analysis. Our main measure is *Water Scarcity Index*, defined as the first principal component of water availability, water consumption, and the Surface Water Supply and Use Index (SUI), with higher values indicating greater water scarcity.[16] We classify a county as water scarce if its 2010 *Water Scarcity Index* is above the national median.

[Insert Table 4 here.]

We estimate Equation 1 for water bonds after interacting each measure of data center exposure with an indicator for water-scarce counties. Table 4 reports the results. Across both extensive- and intensive-margin measures of exposure, the interaction terms are positive and statistically

[13] This exercise addresses the right-skewed distribution of data center capacity documented in Table 1.

[14] Thermoelectric power generation relies heavily on water for cooling.

[15] Consistent with the salience of this channel, Appendix Figure A1 shows that water-related concerns are the third most frequently cited issue among communities opposing data center development.

[16] Table A2 defines the underlying measures and reports pairwise correlations. We exclude *Streamflow* from the index because it is nearly collinear with *Water Availability*, with a correlation coefficient of 0.99. Table A3 reports the principle-component loadings. The index loads negatively on *Water Availability* and positively on *Water Consumption* and *SUI*, so higher values indicate greater water scarcity.

significant, indicating that the yield response to data center development is larger in counties with more constrained water resources. Focusing first on the extensive margin, Column (1) shows that data center entry is associated with a 25.5-basis-point larger increase in adjusted yields for water bonds in water-scarce counties relative to water-abundant counties. The baseline effect in water-abundant counties is small and statistically insignificant, suggesting that data center entry does not lead to a broad repricing of water bonds across all host counties. Instead, the response appears where the local resource constraint is most salient.

Columns (2) through (5) show similar heterogeneity when data center exposure is measured on the intensive margin. A one-million-square-foot increase in data center space is associated with a 29.6-basis-point larger increase in water-bond yields in water-scarce counties than in water-abundant counties. The estimates using utility power, UPS capacity, and rack counts show the same pattern. Evaluated at the average county-level data center scale reported in Table 1, the estimates imply an increase of approximately 42 basis points in water-bond yields for water-scarce counties. These estimates suggest that constrained water resources make local government borrowing costs more sensitive not only to the arrival of data centers, but also to the scale of data center development.

[Insert Figure 6 here.]

Figure 6 plots the dynamic effects of data center entry on adjusted yields for water bonds separately for water-scarce and water-abundant counties, estimated using Equation 2. Panel A classifies counties using the constructed Water Scarcity Index. Water bond yields exhibit no clear differential pre-trend before data center entry. After entry, adjusted yields increase significantly in counties with above-median water scarcity, while yields in below-median counties show little change.

Panels B through D report consistent results when we classify water-scarce counties using each underlying measure of local water conditions. Water-bond yields increase significantly following data center entry in counties with low *Water Availability*, high *Water Consumption*, and high *SUI*. In contrast, we find little evidence of significant changes in water-bond yields in counties with more abundant water resources.

We next provide a second test of the water-system channel by distinguishing between water general obligation bonds and water revenue bonds. This bond-security structure allows us to assess whether the increase in water-bond yields reflects general fiscal risks or risks tied more directly to water-system repayment capacity. Water GO bonds are backed by the issuer's general taxing authority, whereas water revenue bonds are repaid from revenues generated by the underlying water system or project. If data center entry weakens broad municipal fiscal capacity, yields should rise for water GO bonds as well. If instead the response reflects exposure of the water system itself, the effect should be concentrated in water revenue bonds.

We re-estimate the specifications in Table 4 separately for water GO bonds and water revenue bonds. Table A6 reports the results for water GO bonds, and Table A7 reports the results for water revenue bonds. We find little evidence that data center development affects yields on water GO bonds. In contrast, yields on water revenue bonds increase significantly, particularly in water-scarce counties. The contrast between GO and revenue bonds sharpens the interpretation: the pricing response is tied to the repayment structure and operating exposure of the affected water system, rather than to a deterioration in general municipal credit quality.

3.1.2 Data Center Development and Primary and Secondary Education Bonds

We next turn to primary and secondary education bonds. As in the water-bond analysis, we first examine whether the education-bond response is concentrated among counties with the largest data center exposure. Table A8 reports estimates after excluding counties that rank among the top five in 2025 by any measure of data center scale. The results weaken substantially after these counties are removed: the intensive-margin estimates become smaller and lose statistical significance. This pattern indicates that the scale-related increase in education-bond yields is driven primarily by the upper tail of data center exposure, rather than by a continuous response to facility scale across all treated counties. The contrast with the water-bond results is informative. Whereas water-bond yields respond more broadly to resource and infrastructure demands, education-bond yields appear to be less directly tied to routine infrastructure exposure and may instead reflect concerns that

become salient only when data center development is sufficiently large and concentrated, such as changes in the local tax base, housing market, or public-service financing.

This scale dependence motivates a housing-market test. Primary and secondary education bonds are typically backed by local property tax revenues, so their yields may reflect investor concerns about whether large-scale data center development affects housing values, and in turn, the future property-tax base.[17] We therefore test whether housing price growth weakens in the high-exposure counties where the education-bond response is most pronounced.

[Insert Table 5 here.]

Table 5 reports the effects of data center development on housing prices in the most heavily exposed data center counties. Column (1) shows a negative but statistically insignificant effect of data center entry. Columns (2) through (5) show that housing price growth decliens with data center exposure when exposure is measured on the intensive margin. For example, a one-million-square-foot increase in data center space is associated with a 28.6-basis-point decline in annual housing price growth. Similar patterns emerge when data center exposure is measured using utility power capacity, UPS capacity, and rack capacity.

[Insert Table 6 here.]

Table 6 repeats the analysis after excluding the most heavily exposed counties. In this subsample, the estimated effects on housing price growth are smaller and statistically insignificant. This pattern mirrors the education-bond-yield results: both responses are concentrated in counties at the upper tail of data center exposure. Taken together, the evidence indicates that the education-bond response is concentrated where data center development is large enough to coincide with weaker housing-market conditions, pointing to a property-tax-base channel distinct from the water-system channel documented above.

[17] Consistent with this channel, Chia et al. (2026) find that hyperscale data centers reduce nearby house prices by 6.8%.

4 The Effects of Data Centers on Fiscal Conditions and Labor Market Outcomes

The results in the previous section show that data center development leads to higher municipal bond yields. We next examine whether these yield responses are accompanied by changes in observed local government finances. Specifically, using the county-year fiscal panel, we examine data-center-entry effects on fiscal revenues and expenditures by estimating Equation 1, excluding bond-level controls and replacing the dependent variable with the logarithm of total revenues relative to total expenditures, *Log(Total Revenue/Total Expenditure)*. This outcome allows us to assess whether data center entry is associated with changes in revenues relative to spending, which is central to evaluating whether these projects improve or strain local fiscal capacity.

[Insert Table 7 here.]

Table 7 reports the effects of data center exposure on county fiscal conditions. We find little evidence that fiscal revenues increase relative to expenditures following data center entry. The estimates are also small and statistically insignificant when data center exposure is measured using the facility scale. These results suggest that data center development does not generate a clear improvement in overall local fiscal balance. This helps reconcile the bond-market evidence: the repricing appears concentrated in infrastructure-specific debt rather than in broad claims on local fiscal capacity.

We further examine labor-market outcomes. This analysis assesses whether data center development generates broader local economic gains beyond the bond-market and fiscal effects documented above. We estimate Equation 1, excluding bond-level controls and replacing the dependent variable with local employment and establishment counts.

[Insert Table 8 here.]

Table 8 provides little evidence that data center development increases local employment or the number of business establishments. The estimates are small and statistically insignificant across measures of data center exposure. These results are consistent with the capital-intensive and

labor-light nature of data centers, and suggest that the local agglomeration channels associated with traditional industrial plants are limited in this setting.

5 Conclusion

This paper studies what happens to local economies when firm entry brings substantial private capital and resource demand but limited labor demand and production linkages. Data centers are central to cloud computing and artificial intelligence, and local governments often view them as sources of investment, tax-base growth, and economic development. Yet their operating model differs from the establishments emphasized in the agglomeration literature: they are large, fixed, capital-intensive, and dependent on local infrastructure. This distinction makes data centers a useful setting for examining whether large private investment generates broad local gains when it is weakly connected to local labor and production networks.

Using facility-level data on U.S. data centers and primary-market municipal bond issuances, we compare counties receiving post-2015 data centers with near-miss counties that attracted proposed projects but did not host an operational facility by the end of the sample. We find that local borrowing costs respond more to facility scale than to entry alone. The increase is not broad-based across municipal debt, but appears primarily in water-related bonds, is stronger in water-scarce counties, and is larger for water revenue bonds than for water general obligation bonds. These patterns indicate that data center development is not primarily reflected as a broad change in municipal fiscal capacity. Instead, its fiscal consequences appear in the infrastructure systems most exposed to data center demand. Consistent with this interpretation, we find limited evidence of broad improvements in fiscal balance, employment, or business formation, and we find declines in housing price growth after entry.

The findings have implications for how local governments evaluate capital-intensive digital infrastructure. Headline investment and projected tax revenues may overstate local fiscal value when private facilities rely on constrained public infrastructure. Approval decisions, incentive packages,

and financing arrangements should incorporate the capacity, financing, and repayment risks borne by local utilities, taxpayers, and residents. More broadly, the results show that capital-intensive entry is not a substitute for agglomeration: when private investment arrives without strong local economic linkages, its consequences may appear less in broad local development than in the public systems and residents exposed to the demands of production.

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Figure 1. Number of data centers in the United States

This figure plots the number of data centers in the United States by company or industry from 2000 to 2025.

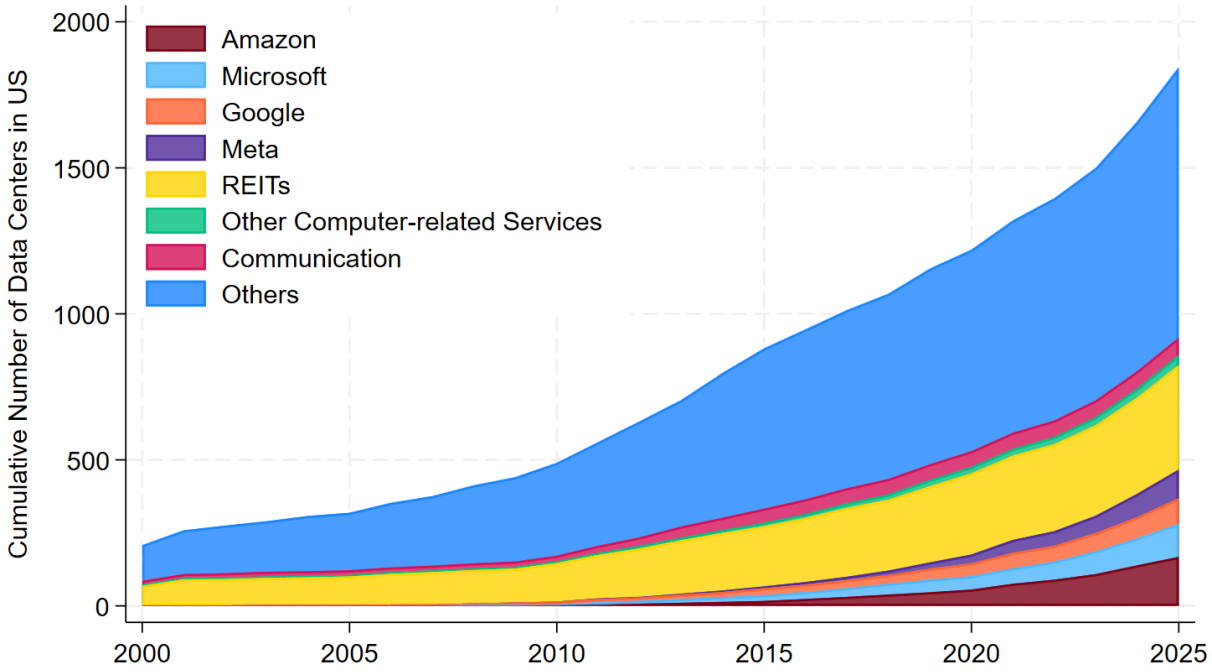


Figure 2. Data center scale by year of construction

This figure reports the scale of newly built data centers by year. Panel A shows the average space of newly built data centers by year of construction, measured in thousands of square feet. Panel B shows the average utility power capacity, measured in megawatts. Panel C shows the average uninterruptible power supply (UPS) capacity, measured in megawatts. Panel D shows the average number of racks, measured in thousands.

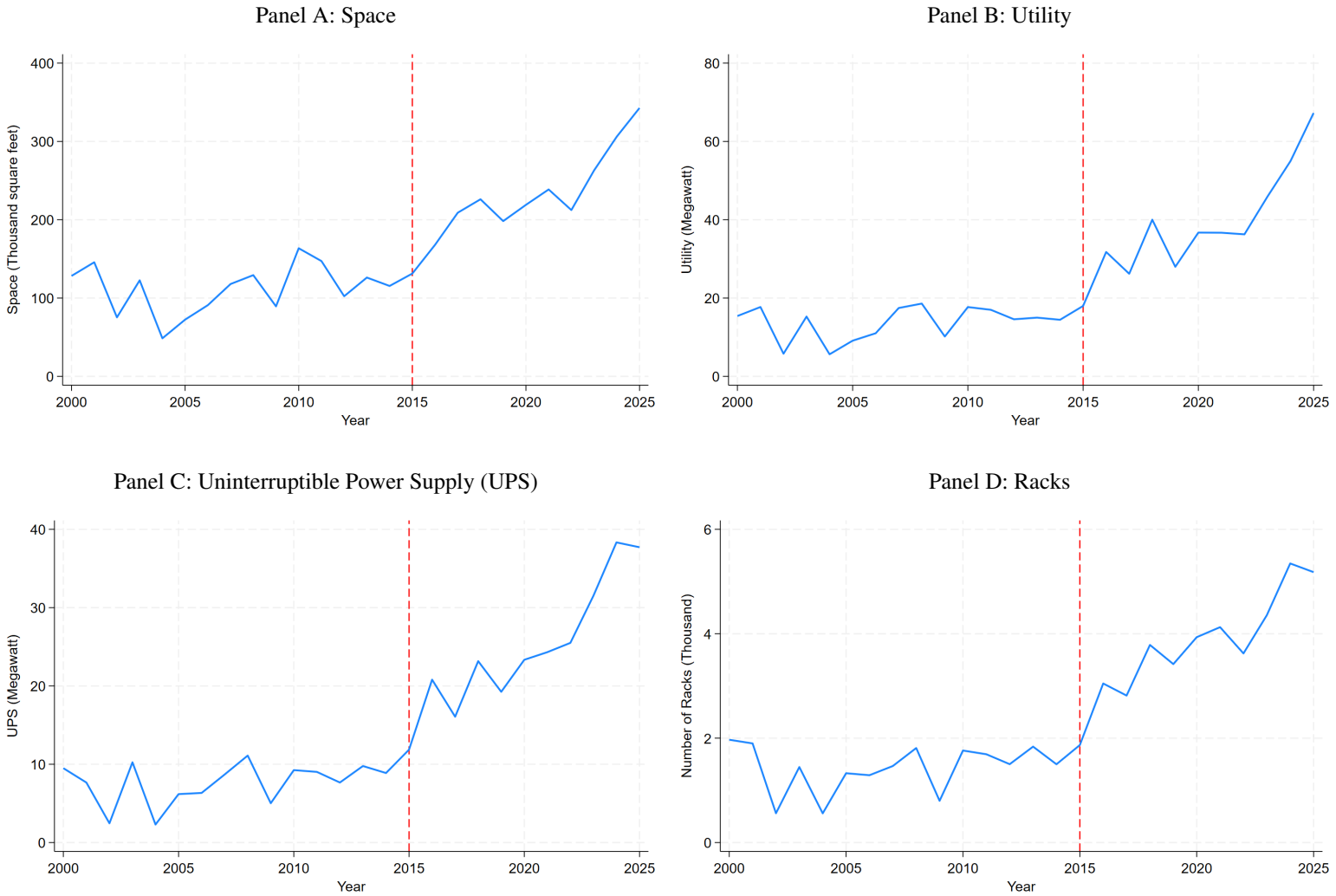


Figure 3. Map of data centers built from 2015 to 2025

This figure maps the county-level distribution of data centers in 2015, 2018, 2021, and 2025. The sample includes data centers constructed after 2015. Data centers without geographic location information, construction-year information, or operational status are excluded from the sample.

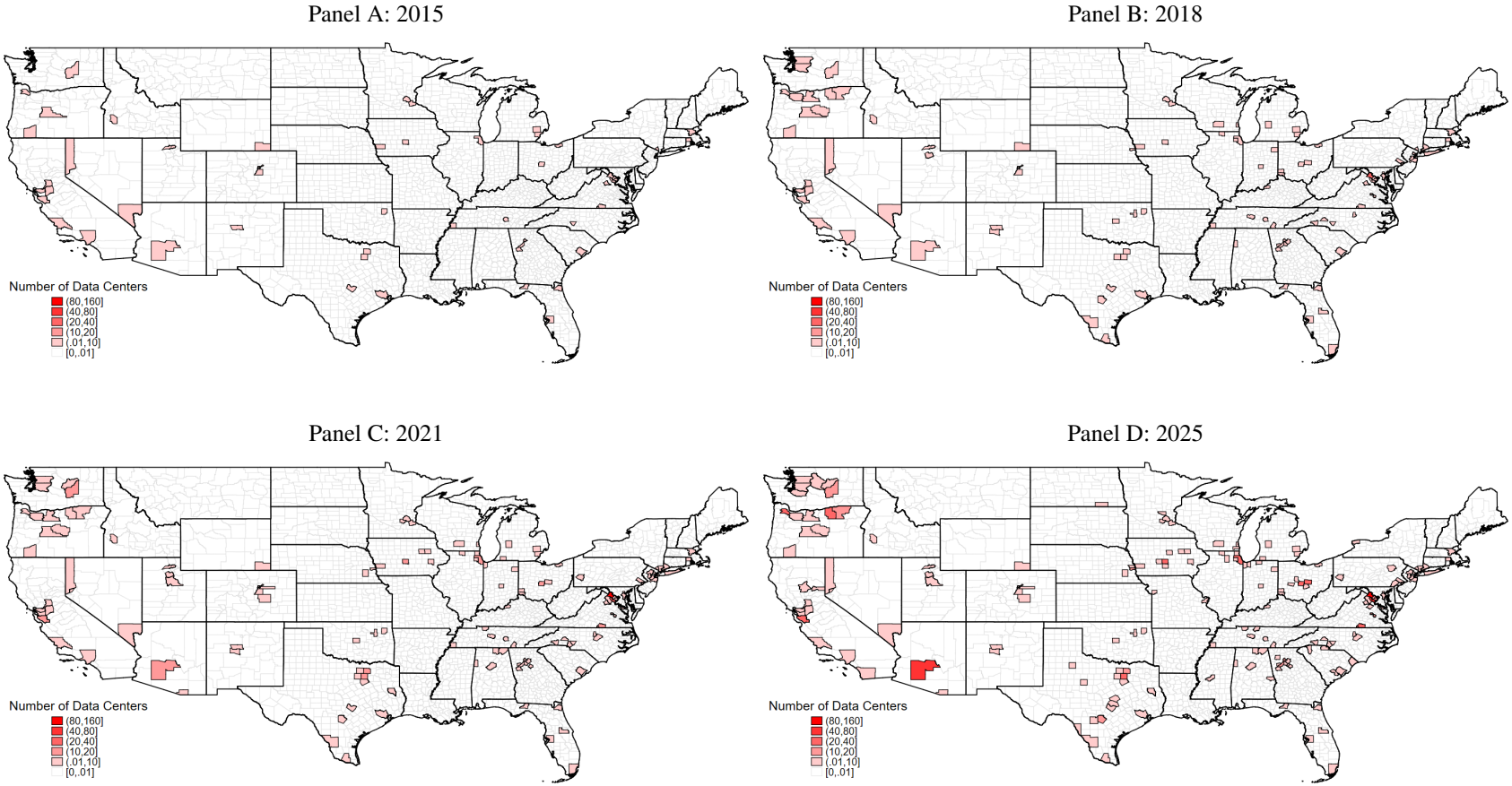


Figure 4. Map of control groups

This figure maps the distribution of control counties that received data center proposals but did not host an operational data center by 2025.

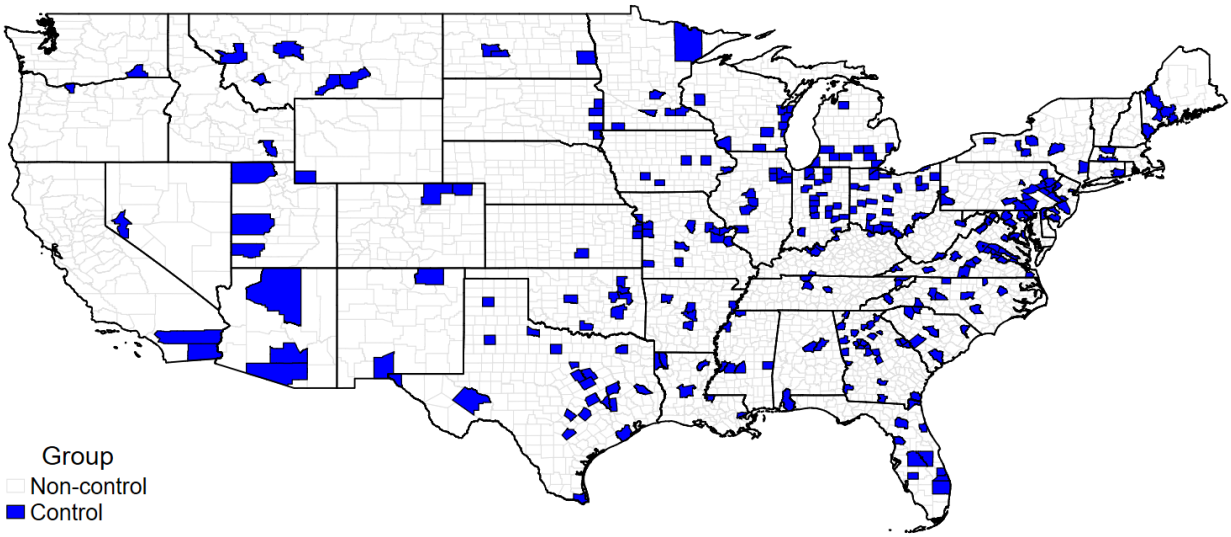


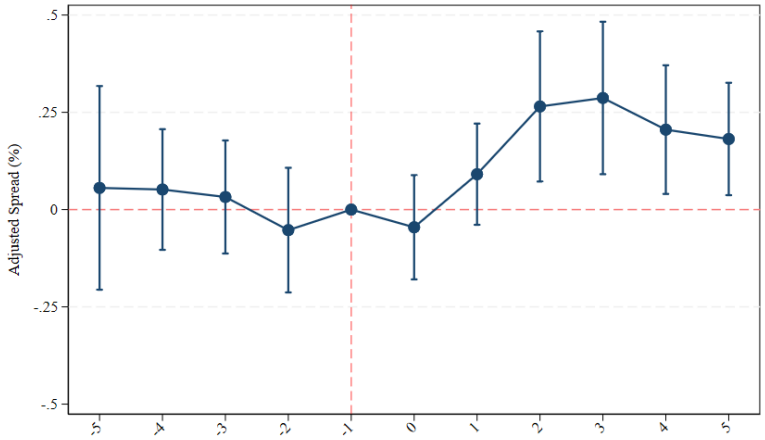
Figure 5. The effects of data centers on municipal bond yields by use of proceeds

This figure plots the estimated β_s coefficients from the following OLS regression:

$$\text{Adjusted Yield}_{i(c),t,g} = \sum_{k=-5,k\neq-1}^{5} \beta_k \text{Treated}_{c,g} \times \mathbf{1}[\text{Event Time}_{t,g}\text{= k}] + \boldsymbol{\theta}'\mathbf{B}_{i,t} + \boldsymbol{\lambda}'\mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g},$$

where i indexes bonds, c indexes counties, t indexes years. and g indexes treatment cohort. *Event Time*$_{t,g}$ denotes event-time indicators. Standard errors are clustered at the county level. The vertical bars represent 95% confidence intervals.

Panel A: Water



Panel B: Primary and Secondary Education

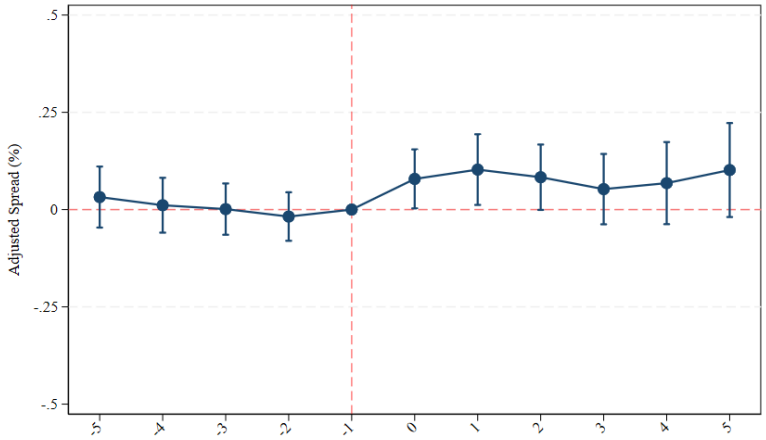


Figure 6. The effects of data center on water bond yields

This figure plots the estimated β_s coefficients from Equation 2 separately for counties with high and low water scarcity. Water scarcity is measured using the Water Scarcity Index, water availability, water consumption, and the Surface Water Supply and Use (SUI) Index. The sample is restricted to water bonds. Vertical bars represent 95% confidence intervals.

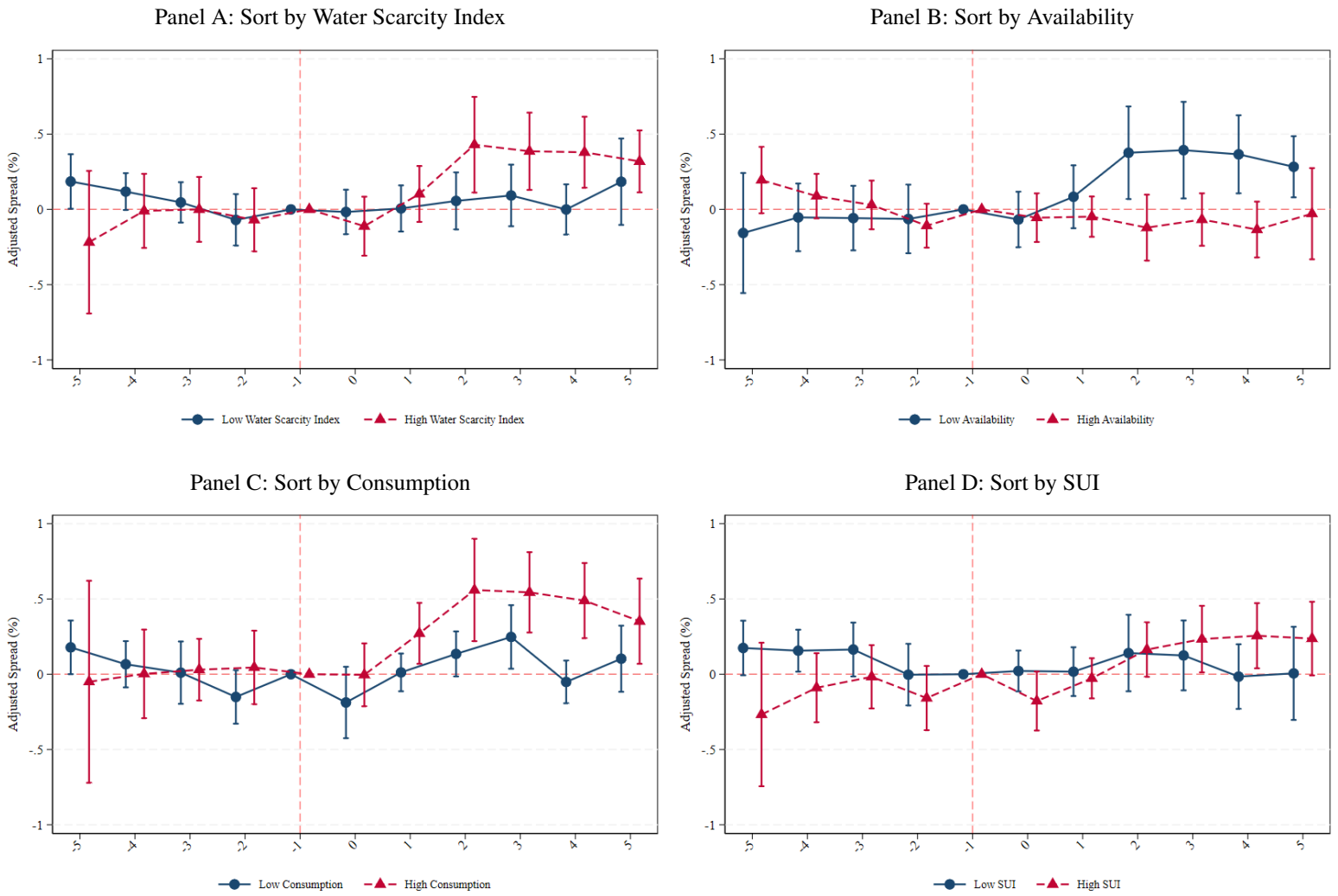


Table 1. Data center scale

This table provides variable summary statistics on county-level data center scale in 2025. *Space* is the total space of the data center in million square feet. *Utility* is the total utility capacity of the data center in megawatts. *UPS Power* is the total uninterruptible power supply in megawatts. *Racks* is the total number of racks in the data center in thousands.

Variable	Obs	Mean	Std. dev.	P25	P50	P75
Space (Million Square Feet)	174	1.46	3.92	0.05	0.32	1.20
Utility Power (Megawatt)	174	253.02	660.68	5.00	36.66	200.00
UPS Power (Megawatt)	174	141.23	389.45	1.33	10.67	130.00
Racks (Thousand)	174	21.21	61.39	0.30	2.11	17.14

Table 2. Summary statistics

This table provides variable definitions and summary statistics. Panel A reports summary statistics on municipal bond primary market variables and Panel B reports summary statistics on labor market variables for all industries as well as the information industry at the county level. *Adjusted Yield (%)* is the tax-adjusted bond yield minus maturity-matched treasury bond yield (Mergent). *Log(Offering Amount)* is the natural logarithm of the bond offering amounts (Mergent). *Coupon Rate* is the coupon rate of the bond in percentage (Mergent). *Years to Maturity* is the years left until the bond matures (Mergent). *I(Insured)* is an indicator equal to one if the bond is insured (Mergent). *I(GO)* is an indicator equal to one if the bond is a general obligation bond (Mergent). *I(Refund)* is an indicator equal to one if the bond's capital purpose is refunding (Mergent). *I(Callable)* is an indicator equal to one if the bond has a call option (Mergent). *I(Bank Qualify)* is an indicator equal to one if the bond enjoys a tax-advantaged status when purchased by commercial banks (Mergent). *I(Negotiated)* is an indicator equal to one if the bond's offering type is negotiated (Mergent). *I(Competitive)* is an indicator equal to one if the bond's offering type is competitive (Mergent). *Total Revenue ($'000)* and *Total Expenditure ($'000)* are the total amounts of revenue and expenditure for local government in a given year (U.S. Census Bureau). *Employ ('000)* is the annual average of monthly employment levels for a given year (QCEW). *Establishment ('000)* is the annual average of quarterly establishment counts for a given year in thousands (QCEW). *Change in Housing Price Index (%)* measures the annual change in single-family home values (Federal Housing Finance Agency). *% White*, *% Asian*, and *% Hispanic* measure the percentage of the county population that are White, Asian, and Hispanic, respectively (U.S. Census Bureau). *% Less than 9th Grade* and *% College Degree* measure the percentage of the population with less than a ninth-grade education and with a college degree, respectively (U.S. Census Bureau). *Poverty Rate* is the percentage of households whose total pre-tax annual income falls below the poverty threshold. *Total Population ('000)*, *Total Households ('000)*, and *Total Housing Units ('000)* measure the total population, number of households, and number of housing units in a county, respectively (U.S. Census Bureau). *Median Household Income ($'000)* is the median household income in a given year (U.S. Census Bureau). All variables are winsorized at the 1st and 99th percentiles.

Panel A. Municipal bond primary market variables

Variable	Obs	Mean	Std. dev.	P25	P50	P75
Adjusted Yield (%)	2,181,018	1.77	1.14	0.89	1.57	2.45
Coupon Rate	2,183,472	3.55	1.20	2.70	3.75	5.00
Year to Maturity	2,183,470	9.57	6.50	4.32	8.45	13.78
I(Insured)	2,183,472	0.17	0.38	0.00	0.00	0.00
I(GO)	2,183,472	0.53	0.50	0.00	1.00	1.00
I(Refinance)	2,183,472	0.46	0.50	0.00	0.00	1.00
I(Call Option)	2,183,472	0.47	0.50	0.00	0.00	1.00
I(Bank Qualified)	2,183,472	0.35	0.48	0.00	0.00	1.00
I(Negotiated)	2,183,472	0.45	0.50	0.00	0.00	1.00
I(Competitive)	2,183,472	0.54	0.50	0.00	1.00	1.00

Panel B. Fiscal conditions, labor market outcomes, housing price, and other county-level variables

Variable	Obs	Mean	Std. dev.	P25	P50	P75
Total Revenue ($'000)	31,119	978.96	1984.13	131.90	397.48	1019.69
Total Expenditure ($'000)	31,119	965.57	1976.16	129.05	384.73	996.15
Employ ('000)	33,508	79.94	140.31	11.54	35.54	90.71
Establishment ('000)	33,508	5.06	9.33	0.84	2.30	5.54
Change in Housing Price Index (%)	34,314	5.25	5.42	2.10	4.45	7.72
% of White	35,044	0.79	0.16	0.71	0.83	0.92
% of Asian	35,044	0.05	0.05	0.02	0.03	0.06
% of Hispanic	35,044	0.10	0.13	0.03	0.05	0.11
% of Less than 9th Grade	35,044	0.03	0.02	0.02	0.02	0.04
% College Degree	35,044	0.47	0.08	0.43	0.48	0.53
Poverty Rate	35,044	0.14	0.05	0.10	0.13	0.17
Total Population ('000)	35,044	186.41	291.93	35.35	99.64	208.16
Total Household ('000)	35,044	69.75	104.67	13.56	36.86	82.23
Median Household Income ($'000)	35,044	60.75	17.48	48.50	57.13	69.99
Total Housing Units ('000)	35,044	77.99	116.76	16.36	40.75	90.46

Table 3. The effects of data centers on municipal bond yields

This table reports the estimates of β coefficients from OLS regression:

$$\text{Adjusted Yield}_{i(c),t,g} = \beta \text{DC Exposure}_{c,t} + \boldsymbol{\theta}' \mathbf{B}_{i,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g},$$

where i indexes bonds, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is one of the following variables: *After Entry*$_{c,t}$, *Space*$_{c,t}$, *Utility Power*$_{c,t}$, *UPS Power*$_{c,t}$, and *Racks*$_{c,t}$. *After Entry*$_{c,t}$ is an indicator equal to one if county c hosts data centers in year t. *Space*$_{c,t}$ is a continuous variable measuring the total space of all data centers for county c in year t in million square feet. *Utility Power*$_{c,t}$ and *UPS Power*$_{c,t}$ are continuous variables measuring the total utility capacity and uninterruptible power supply of all data centers for county c in year t in gigawatt. *Racks*$_{c,t}$ is a continuous vairbale measuring the total number of racks in all data centers for county c in year t in million. The sample includes counties hosting data centers and counties that received data center proposals but don't host data centers before 2025. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Variable	Adjusted Spread (%)				
	(1)	(2)	(3)	(4)	(5)
After Entry	0.029				
	(0.028)				
Space		0.044**			
		(0.019)			
Utility Power			0.307***		
			(0.109)		
UPS Power				0.471***	
				(0.178)	
Racks					3.082***
					(1.180)
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	2,180,980	2,180,980	2,180,980	2,180,980	2,180,980
R-squared	0.655	0.655	0.655	0.655	0.655

Table 4. The effects of data centers on water bond yields

This table reports the estimates of β coefficients from OLS regression:

$$\text{Adjusted Yield}_{i(c),t,g} = \beta \text{DC Exposure}_{c,t} \times \text{Water Scarce}_c + \boldsymbol{\theta}'\mathbf{B}_{i,t} + \boldsymbol{\lambda}'\mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g},$$

where i indexes bonds, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is defined in Table 3. *Water Scarce*$_c$ is an indicator variable equal to one if county c's Water Scarcity Index in 2010 is above the sample median. The sample is restricted to water bonds. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	Adjusted Spread (%)				
	(1)	(2)	(3)	(4)	(5)
After Entry	-0.016				
	(0.056)				
Space		-0.010			
		(0.025)			
Utility Power			0.088		
			(0.193)		
UPS Power				-0.060	
				(0.246)	
Racks					-0.772
					(1.356)
Water Scarce×After Entry	0.255***				
	(0.096)				
Water Scarce×Space		0.296***			
		(0.071)			
Water Scarce×Utility Power			1.958***		
			(0.458)		
Water Scarce×UPS Power				3.565***	
				(0.747)	
Water Scarce×Racks					19.774***
					(3.919)
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	244,043	244,043	244,043	244,043	244,043
R-squared	0.733	0.733	0.733	0.733	0.733

Table 5. The effects of data centers on housing price growth for large data center counties

This table reports the estimates of β coefficients from OLS regression:

$$Y_{c,t,g} = \beta \text{DC Exposure}_{c,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{c,t,g},$$

where $Y_{c,t,g}$ denotes the change in the House Price Index, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is defined in Table 3. The treatment group only includes counties that rank among the top five in 2025 by any measure of data center scale, including the number of facilities, total data center space, total utility power capacity, total UPS capacity, or total number of racks. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. respectively.

Dep. Var.	Change in House Price Index (%)				
	(1)	(2)	(3)	(4)	(5)
After Entry	-1.029				
	(1.055)				
Space		-0.286***			
		(0.091)			
Utility Power			-1.657***		
			(0.480)		
UPS Power				-2.573***	
				(0.745)	
Racks					-15.666***
					(4.664)
ind_top5					
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	28,301	28,301	28,301	28,301	28,301
Pseudo R-squared	0.840	0.840	0.840	0.840	0.840

Table 6. The effects of data centers on housing price growth excluding large data center counties

This table reports the estimates of β coefficients from OLS regression:

$$Y_{c,t,g} = \beta \text{DC Exposure}_{c,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{c,t,g},$$

where $Y_{c,t,g}$ denotes the change in the House Price Index, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is defined in Table 3. Counties that rank among the top five in 2025 by any measure of data center scale, including the number of facilities, total data center space, total utility power capacity, total UPS capacity, or total number of racks, are excluded. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. respectively.

Dep. Var.	Change in House Price Index (%)				
	(1)	(2)	(3)	(4)	(5)
After Entry	-0.277				
	(0.217)				
Space		-0.127			
		(0.273)			
Utility Power			-0.058		
			(1.409)		
UPS Power				0.360	
				(2.097)	
Racks					7.873
					(10.436)
ind_top5					
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	29,825	29,825	29,825	29,825	29,825
Pseudo R-squared	0.843	0.843	0.843	0.843	0.843

Table 7. The effects of data centers on fiscal revenues and expenditures

This table reports the estimates of β coefficients from OLS regression:

$$Y_{c,t,g} = \beta \text{DC Exposure}_{c,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{c,t,g},$$

where $Y_{c,t,g}$ denotes the logarithm of total fiscal revenues divided by total fiscal expenditures, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is defined in Table 3. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. respectively.

Dep. Var.	Log(Total Revenue/Total Expenditure)				
	(1)	(2)	(3)	(4)	(5)
After Entry	0.000				
	(0.006)				
Space		-0.000			
		(0.004)			
Utility Power			-0.004		
			(0.023)		
UPS Power				0.005	
				(0.039)	
Racks					0.022
					(0.228)
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	30,467	30,467	30,467	30,467	30,467
R-squared	0.514	0.514	0.514	0.514	0.514

Table 8. The effects of data centers on labor market outcomes

This table reports the estimates of β coefficients from OLS regression:

$$Y_{c,t} = \beta \text{DC Exposure}_{c,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{c,t,g},$$

where $Y_{c,t,g}$ denotes the logarithm of number of employment or establishment, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is defined in Table 3. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. respectively.

Dep. Var.	Log(Employ)					Log(Establishment)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
After Entry	0.008					0.011***				
	(0.007)					(0.004)				
Space		0.007					0.005			
		(0.007)					(0.006)			
Utility Power			0.049					0.029		
			(0.042)					(0.033)		
UPS Power				0.074					0.040	
				(0.064)					(0.048)	
Racks					0.396					0.301
					(0.373)					(0.351)
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,467	30,467	30,467	30,467	30,467	30,467	30,467	30,467	30,467	30,467
R-squared	0.999	0.999	0.999	0.999	0.999	1.000	1.000	1.000	1.000	1.000

Online Appendix for

Capital Without Labor: Data Centers and the Local Economy

Appendix A Additional Tables and Figures

Figure A1. Distribution of issues raised in data center proposals

This figure presents the distribution of issues raised in data center proposals. Bars represent the percentage of proposals citing each issue category.

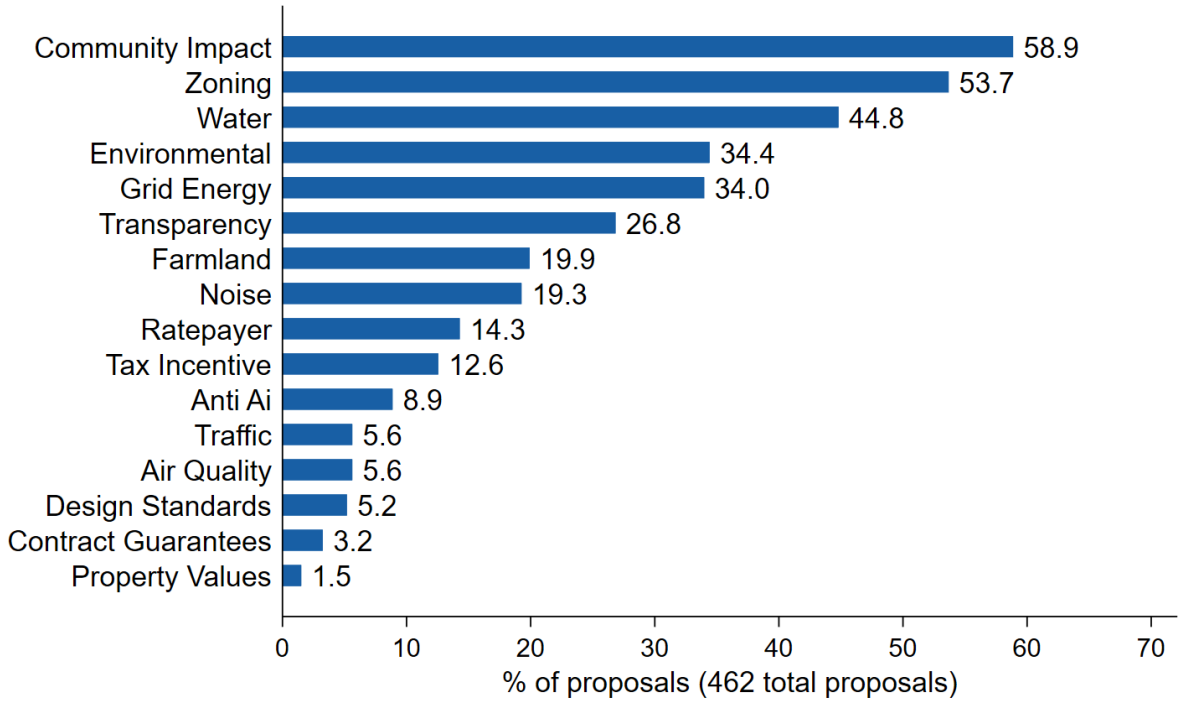


Table A1. Use of proceeds

This table reports the use-of-proceeds categories, their corresponding codes, and the percentage of observations in each category.

Category	Code	Percent of Sample (%)
Water	WTR	11.20%
Primary and Secondary Education	PSED	31.20%
General Purpose	GPPI	33.62%
Higher Education	HIED	5.67%
Utility	CUTI, ELEC, GAS, OUTI	2.69%
Housing	CMOH, MFHG, NPHG, OTHS, SFHG, SMHG	3.05%
Healthcare	HOEQ, HOSP, NURS, OHCA	2.58%
Transportation	AIL, AIR, BRDG, MASS, OTRN, PKG, SEAP, TOLL, TUNN	1.93%

Table A2. Correlation among water availability measures

This table presents correlations among measures of water availability. Availability measures the total volume of water delivered from one 12-digit hydrologic unit (HUC12) to the next downstream HUC12. Streamflow is the total water supply available within an HUC12, including both upstream inflows and locally generated water. Consumption measures the total amount of water consumed for public supply, thermoelectric power generation, and crop irrigation. Water consumption refers to the permanent removal of water from the local environment through evaporation, incorporation into products, or transfer outside the local hydrologic cycle. SUI (Surface Water Supply and Use Index) measures the fraction of long-term water supply that is unavailable due to either climatic variability or consumptive water use.

	Availability	Streamflow	Consumption	SUI
Availability	1.00			
Streamflow	0.99	1.00		
Consumption	-0.33	-0.21	1.00	
SUI	-0.40	-0.35	0.53	1.00

Table A3. PCA Loadings

This table reports the loadings of the first principal component constructed from *Availability*, *Consumption*, and *SUI*.

	Weight
Availability	-0.523
Consumption	0.588
SUI	0.617

Table A4. Data center and municipal bond spread by use of proceeds

This table reports the estimates of β coefficients from OLS regression:

$$\text{Adjusted Yield}_{i(c),t,g} = \beta \text{DC Exposure}_{c,t} + \boldsymbol{\theta}' \mathbf{B}_{i,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g},$$

where i indexes bonds, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is one of the following variables: *After Entry*$_{c,t}$, *Space*$_{c,t}$, *Utility Power*$_{c,t}$, *UPS Power*$_{c,t}$, and *Racks*$_{c,t}$. *After Entry*$_{c,t}$ is an indicator equal to one if county c hosts data centers in year t. *Space*$_{c,t}$ is a continuous variable measuring the total space of all data centers for county c in year t in million square feet. *Utility Power*$_{c,t}$ and *UPS Power*$_{c,t}$ are continuous variables measuring the total utility capacity and uninterruptible power supply of all data centers for county c in year t in gigawatt. *Racks*$_{c,t}$ is a continuous vairbale measuring the total number of racks in all data centers for county c in year t in million. The sample includes bonds issued for different uses of proceeds. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Use of Proceeds	Water					Primary and Secondary Education				
Dep. Var.	Adjusted Spread (%)									
After Entry	0.134***					0.079**				
	(0.051)					(0.031)				
Space		0.112**					0.082***			
		(0.049)					(0.028)			
Utility Power			0.711**					0.613***		
			(0.308)					(0.178)		
UPS Power				1.196**					0.809***	
				(0.589)					(0.291)	
Racks					7.623**					5.101**
					(3.628)					(2.036)
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,187	244,187	244,187	244,187	244,187	680,544	680,544	680,544	680,544	680,544
R-squared	0.733	0.733	0.733	0.733	0.733	0.736	0.736	0.736	0.736	0.736

Table A4. Data center and municipal bond spread by use of proceeds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Use of Proceeds	General Purpose					Higher Education				
Dep. Var.	Adjusted Spread (%)									
After Entry	-0.033					0.063				
	(0.024)					(0.083)				
Space		-0.000					-0.006			
		(0.013)					(0.059)			
Utility Power			0.009					0.234		
			(0.072)					(0.286)		
UPS Power				0.035					0.372	
				(0.113)					(0.609)	
Racks					0.201					1.650
					(0.690)					(3.551)
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	732,901	732,901	732,901	732,901	732,901	123,387	123,387	123,387	123,387	123,387
R-squared	0.728	0.728	0.728	0.728	0.728	0.752	0.752	0.752	0.752	0.752

Table A4. Data center and municipal bond spread by use of proceeds

Use of Proceeds	(1)	(2)	(3) Utility	(4)	(5)	(6)	(7)	(8) Housing	(9)	(10)
Dep. Var.	Adjusted Spread (%)									
After Entry	-0.073					0.382***				
	(0.091)					(0.139)				
Space		-0.057					0.111			
		(0.093)					(0.177)			
Utility Power			0.216					0.272		
			(0.777)					(1.281)		
UPS Power				1.473					-2.129	
				(1.389)					(3.588)	
Racks					9.492					-11.929
					(6.968)					(21.027)
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,614	58,614	58,614	58,614	58,614	66,196	66,196	66,196	66,196	66,196
R-squared	0.793	0.793	0.793	0.793	0.793	0.783	0.783	0.783	0.783	0.783

Table A4. Data center and municipal bond spread by use of proceeds

Use of Proceeds	(1)	(2)	(3) Healthcare	(4)	(5)	(6)	(7)	(8) Transportation	(9)	(10)
Dep. Var.	Adjusted Spread (%)									
After Entry	-0.162					-0.195				
	(0.203)					(0.214)				
Space		-0.012					-0.092			
		(0.220)					(0.102)			
Utility Power			0.619					-0.946		
			(1.017)					(0.690)		
UPS Power				0.338					-1.749	
				(2.388)					(1.157)	
Racks					1.478					-15.315**
					(15.041)					(7.474)
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,048	56,048	56,048	56,048	56,048	41,995	41,995	41,995	41,995	41,995
R-squared	0.764	0.764	0.764	0.764	0.764	0.842	0.842	0.842	0.842	0.842

Table A5. Data center and water bond spread excluding large data center counties

This table reports the estimates of β coefficients from OLS regression:

$$\text{Adjusted Yield}_{i(c),t,g} = \beta \text{DC Exposure}_{c,t} + \boldsymbol{\theta}'\mathbf{B}_{i,t} + \boldsymbol{\lambda}'\mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g},$$

where i indexes bonds, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is defined in Table A4. Counties that rank among the top five in 2025 by any measure of data center scale, including the number of facilities, total data center space, total utility power capacity, total UPS capacity, or total number of racks, are excluded. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Use of Proceeds			Water		
Dep. Var.			Adjusted Spread (%)		
After Entry	0.126**				
	(0.053)				
Space		0.212***			
		(0.058)			
Utility Power			1.542***		
			(0.432)		
UPS Power				2.724***	
				(0.789)	
Racks					16.817***
					(3.797)
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	241,972	241,972	241,972	241,972	241,972
R-squared	0.734	0.735	0.735	0.735	0.735

Table A6. The effects of data centers on water GO bond yields

This table reports the estimates of β coefficients from OLS regression:

$$\text{Adjusted Yield}_{i(c),t,g} = \beta \text{DC Exposure}_{c,t} \times \text{Water Scarce}_c + \boldsymbol{\theta}'\mathbf{B}_{i,t} + \boldsymbol{\lambda}'\mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g},$$

where i indexes bonds, c indexes counties, t indexes years, and g indexes treatment cohort. $\text{DC Exposure}_{c,t}$ is defined in Table 3. *Water Scarce*$_c$ is an indicator variable equal to one if county c's Water Scarcity Index in 2010 is above the sample median. The sample is restricted to water GO bonds. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	Adjusted Spread (%)				
	(1)	(2)	(3)	(4)	(5)
After Entry	0.007				
	(0.195)				
Space		-0.193			
		(0.125)			
Utility Power			-0.087		
			(0.593)		
UPS Power				0.318	
				(0.816)	
Racks					0.699
					(6.072)
Water Scarce×After Entry	-0.042				
	(0.206)				
Water Scarce×Space		0.080			
		(0.192)			
Water Scarce×Utility Power			-0.691		
			(1.177)		
Water Scarce×UPS Power				-1.187	
				(2.106)	
Water Scarce×Racks					-3.102
					(11.414)
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	56,962	56,962	56,962	56,962	56,962
R-squared	0.808	0.808	0.808	0.808	0.808

Table A7. The effects of data centers on water revenue bond yields

This table reports the estimates of β coefficients from OLS regression:

$$\text{Adjusted Yield}_{i(c),t,g} = \beta \text{DC Exposure}_{c,t} \times \text{Water Scarce}_c + \boldsymbol{\theta}' \mathbf{B}_{i,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g},$$

where i indexes bonds, c indexes counties, t indexes years ,and g indexes treatment cohort. DC Exposure$_{c,t}$ is defined in Table 3. *Water Scarce*$_c$ is an indicator variable equal to one if county c's Water Scarcity Index in 2010 is above the sample median. The sample is restricted to water revenue bonds. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	Adjusted Spread (%)				
	(1)	(2)	(3)	(4)	(5)
After Entry	0.003				
	(0.060)				
Space		-0.107***			
		(0.023)			
Utility Power			-0.686***		
			(0.185)		
UPS Power				-0.959***	
				(0.259)	
Racks					-5.993***
					(1.370)
Water Scarce×After Entry	0.260**				
	(0.107)				
Water Scarce×Space		0.330***			
		(0.059)			
Water Scarce×Utility Power			1.779***		
			(0.583)		
Water Scarce×UPS Power				3.715***	
				(0.656)	
Water Scarce×Racks					21.278***
					(3.481)
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	164,087	164,087	164,087	164,087	164,087
R-squared	0.771	0.771	0.771	0.771	0.771

Table A8. Data center and primary and secondary bond spread excluding large data center counties

This table reports the estimates of β coefficients from OLS regression:

$$\text{Adjusted Yield}_{i(c),t,g} = \beta \text{DC Exposure}_{c,t} + \boldsymbol{\theta}' \mathbf{B}_{i,t} + \boldsymbol{\lambda}' \mathbf{C}_{c,t} + \alpha_{c,g} + \delta_{s(c),t,g} + \varepsilon_{i(c),t,g},$$

where i indexes bonds, c indexes counties, t indexes years, and g indexes treatment cohort. DC Exposure$_{c,t}$ is defined in Table A4. Counties that rank among the top five in 2025 by any measure of data center scale, including the number of facilities, total data center space, total utility power capacity, total UPS capacity, or total number of racks, are excluded. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Use of Proceeds	Primary and Secondary Education				
Dep. Var.	Adjusted Spread (%)				
After Entry	0.076**				
	(0.031)				
Space		0.065			
		(0.041)			
Utility Power			0.181		
			(0.174)		
UPS Power				0.391	
				(0.290)	
Racks					2.037
					(1.991)
County Controls	Yes	Yes	Yes	Yes	Yes
County-Cohort FE	Yes	Yes	Yes	Yes	Yes
State-Year-Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	671,193	671,193	671,193	671,193	671,193
R-squared	0.737	0.737	0.737	0.737	0.737