Who Pays For Data Centers?

Evidence From Municipal Financing

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CONFERENCE ON MUNICIPAL BOND MARKETS

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Motivation

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  This paper: Neighboring municipalities and in tax-incentive states, school districts.

This paper

- We identify the impact of data centers (DCs) on muni bond spreads and issuance.
  - Map issuers, DCs, and school districts to municipalities using spatial geography.
  - Instrument data center presence with proximity to high-voltage transmission lines, built before 2021.

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- DC proximity raises neighbors' bond spreads by 4–10 bps on average.
  - Bond spreads of host municipalities see little effect.
  - The repricing is concentrated in general-purpose bonds.

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- DC proximity raises neighbors' bond spreads by 4–10 bps on average.
  - Bond spreads of host municipalities see little effect.
  - The repricing is concentrated in general-purpose bonds.
- This translates to higher borrowing, but only in states that offer DC tax incentives.
  - Incentive states: No spread widening. Education bond issuance rises over 12–24 months.
  - Non-incentive states: Spreads widen, no issuance response.

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  - Adoption reduces state transfers to school districts by about $485 per student.
  - The effect is concentrated in school employee benefits.
  - Education bond spreads also increase by about 12 bps after incentive adoption.

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Takeaway: The incidence of the fiscal costs of data centers depends on state policy.

- In non-incentive states, neighbor bond spreads rise when data centers expand.
- In incentive states, education bond spreads rise when states adopt tax incentives.

Related literature

- Municipal bond market: liquidity and default risk [Schwert, 2017, Haughwout, Hyman, and Shachar, 2022]; municipal finance and distress [Giesecke and Rauh, 2023, Gao, Lee, and Murphy, 2019, Ivanov and Zimmermann, 2024].
- AI in finance: asset pricing [Eisfeldt, Schubert, and Zhang, 2023, Babina, Fedyk, He, and Hodson, 2025]; municipal finance [Andreadis, Chatzikonstantinou, Kalotychou, Louca, and Makridis, 2024]; data centers in local economies [Andreadis et al., 2024, Gargano and Giacoletti, 2026, Yue and Zeng, 2025, Chia, Cornaggia, Haushalter, and Wang, 2026, Israelsen and Yun, 2026].
- Vertical externalities and fiscal federalism: [Slattery and Zidar, 2020, Keen and Kotsogiannis, 2002, Devereux, Lockwood, and Redoano, 2007].

Outline

- Data and sample construction.
- Identifying the causal impact of data centers on:
  1. Municipal bond spreads.
  2. Municipal debt issuance.
- Disentangling the potential mechanisms.

Data and Sample Construction

Data

- **Data centers:** S&P 451 Research (2014–2025). ▸ Power capacity
- **Municipal bond data:**
  - MSRB (2008–2025), Mergent (2008–2020), Bloomberg (2021–2025).
- **Time-varying state data:**
  - House prices: FHFA.
  - GDP, unemployment, population: BEA, BLS, Census.
  - Unemployment insurance claims: FRED.
- **Time-varying municipality data:**
  - County sectoral employment: BLS QCEW, NAICS 518210 and 236220 ("Data Processing, Hosting" and construction).
  - House prices in cities and counties: Zillow Home Value Index.
  - School district finances and enrollment: NCES CCD Fiscal data.
- **Municipality and power line geography:**
  - High-voltage transmission lines: U.S. Electric Power Transmission Lines.
  - Municipality boundaries: U.S. Census TIGER/Line shapefiles.

Geographic mapping to municipalities

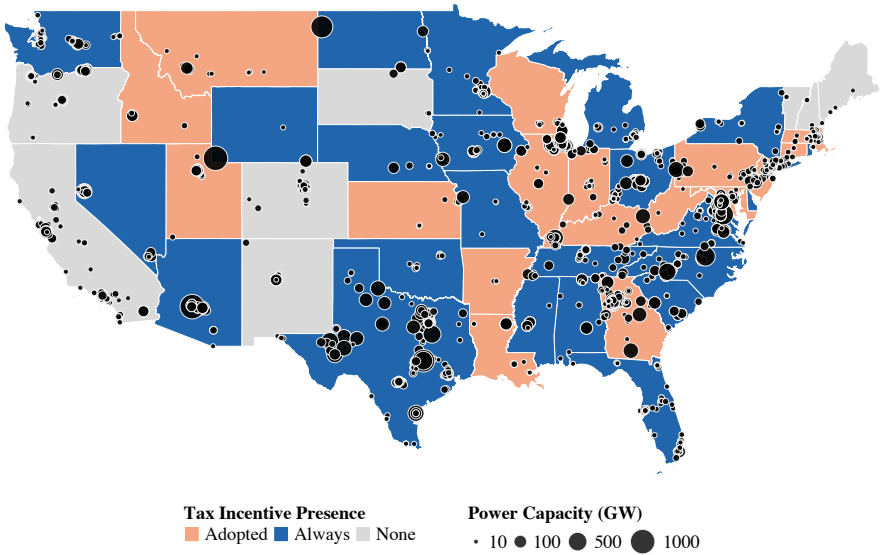
We map municipal issuers, data centers, and school districts to municipalities.

1. Map municipal issuers to municipalities:
   - Map issuers to counties, cities, towns, etc. by parsing issuer names.
   - Issuer match rates of 92% for counties, 90% for local population centers, and 62% for other issuers.

2. Map data centers to municipalities:
   - Map DC coordinates using place centroids.
   - Locate 3,655 data centers in 741 municipalities.

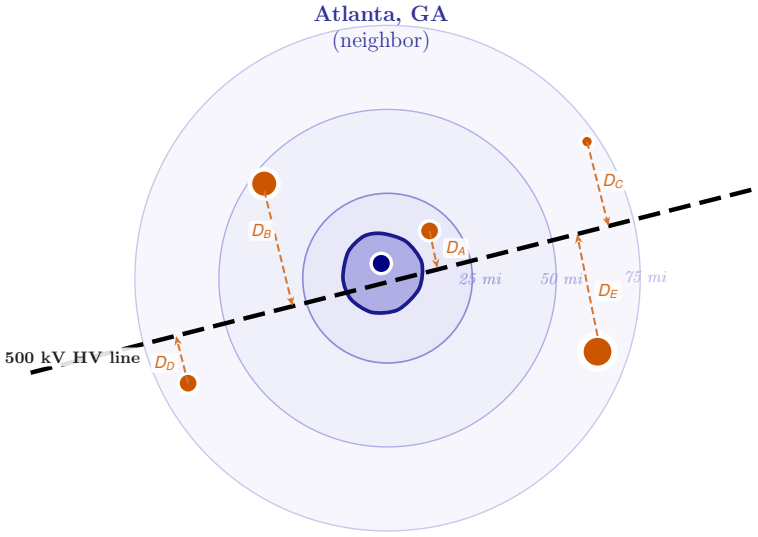
3. Map school districts to municipalities:
   - Use point-in-polygon containment and if muni centroid is outside district polygon, nearest-centroid.
   - Match 13,316 school districts to 4,255 municipalities.

Data centers are spread out across the U.S.



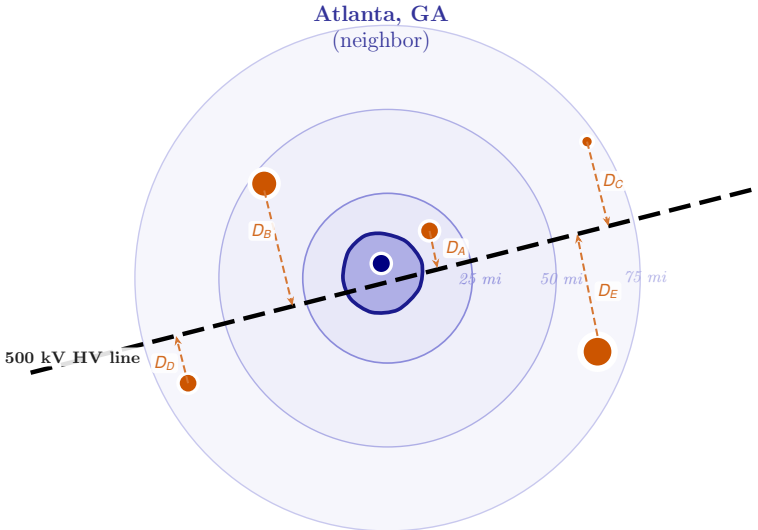
Classify host vs. neighbor municipalities

- 30.5% (44.3%, 53.4%) of municipalities have at least 1 DC within 25 (50, 75) miles.
- A host municipality has 6 DCs on average.
- A neighboring municipality has on average 14 (25, 30) DCs within 25 (50, 75) miles.



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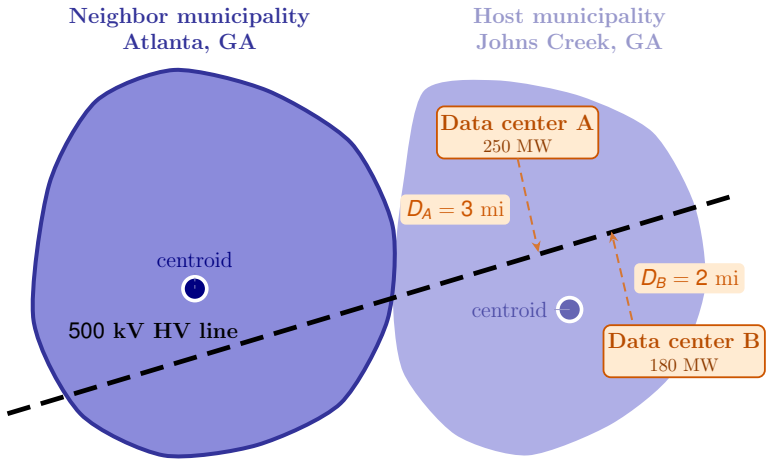


$N_{mt} = \{N^h_{mt}$ for hosts; $N(r)_{mt}$ for neighbors$\}$.

Impact of Data Centers on Municipal Bond Spreads

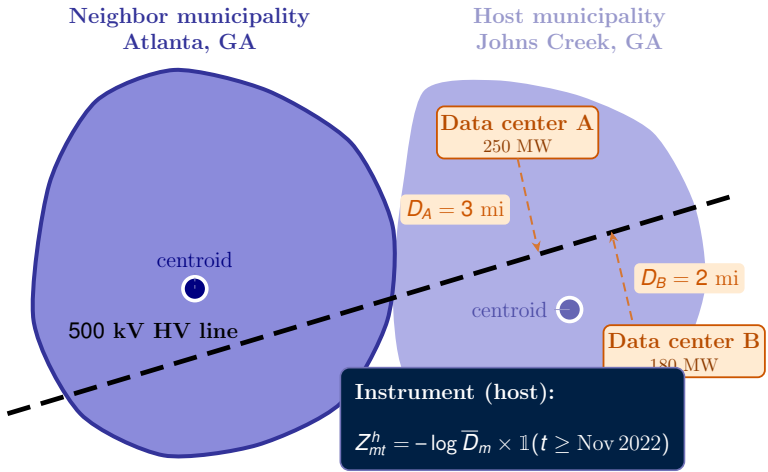
Instrument data center presence using power lines

- Exploit high-voltage transmission lines HV lines ($\geq$ 345 kV) mapped pre-2021.



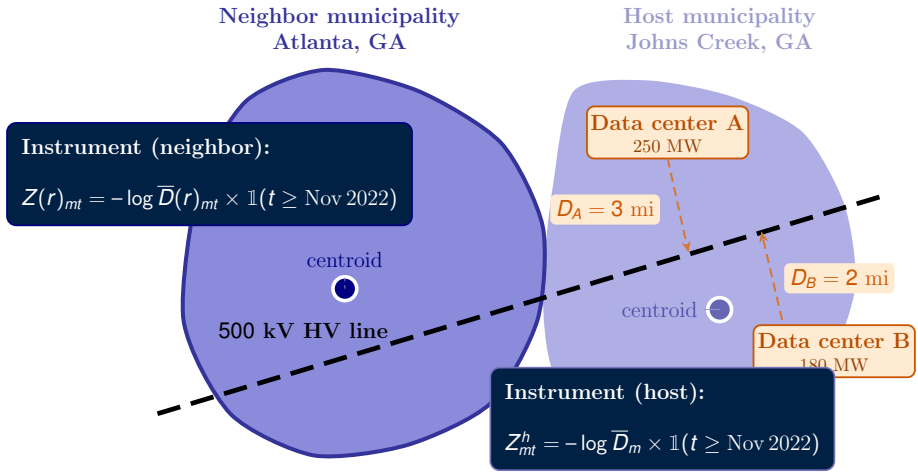
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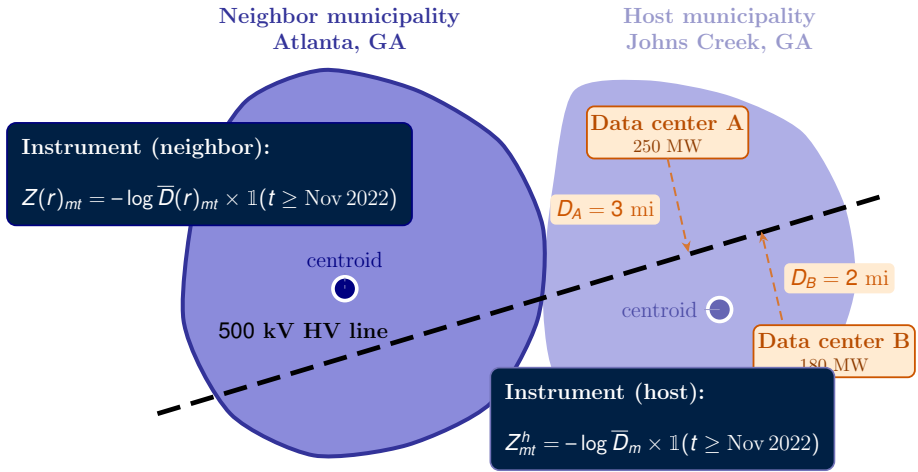
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$Z_{mt} = \{Z^h_{mt}$ for hosts; $Z(r)_{mt}$ for neighbors$\}$ with $r = \{25, 50, 75\}$ miles.

Do data centers persistently affect muni bond spreads?

For issuer i in municipality m and month t:

$$N_{mt} = \alpha_{ms} + \lambda_t + \psi_i + \delta Z_{mt} + \eta X_{st} + \gamma L_{imt} + \varepsilon_{imt},$$
$$\text{Spread}_{imt} = \alpha_{ms} + \lambda_t + \psi_i + \beta \widehat{N}_{mt} + \gamma X_{st} + \phi L_{imt} + \epsilon_{imt}.$$

- Distinguish among isolated hosts, dense hosts, and neighboring municipalities.
- Controls include bid-ask spreads, GDP, unemployment claims.
- Identification assumption: HV line locations are conditionally orthogonal to unobserved residual municipal bond spreads.

Data center proximity widens bond spreads of exposed municipalities

Dependent Variable:	Spread (%)				
Municipality:	Isolated Host	Dense Host	Neighbor		
	(1)	(2)	(3)	(4)	(5)
$\widehat{N}^{h}_{mt}$	0.013	0.099*			
	(0.020)	(0.051)			
$\widehat{N}(25)_{mt}$			0.100***		
			(0.030)		
$\widehat{N}(50)_{mt}$				0.049***	
				(0.015)	
$\widehat{N}(75)_{mt}$					0.041***
					(0.012)
Observations	6,597	27,013	31,868	47,868	57,745
Clusters	66	331	1,241	1,936	2,402
F-statistic	4.94	7.69	32.17	34.17	54.10
Fixed effects:					
Issuer, Date	✓	✓	✓	✓	✓
State×County×Municipality	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

▸ DCs in the pipeline ▸ Fiscal fundamentals ▸ HPI ▸ Falsification test

Neighbors' spread impact is driven by general-purpose bonds

Dependent Variable:	Spread (%)									
Bond Sample:	Utility & Transportation					General Purpose				
Municipality:	Isolated Hosts	Dense Hosts	Neighbor			Isolated Hosts	Dense Hosts	Neighbor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\widehat{N}^h_{mt}$	−1.122	0.103				−1.233	0.154			
	(1.286)	(0.103)				(1.836)	(0.097)			
$\widehat{N}(25)_{mt}$			0.198*					0.077**		
			(0.108)					(0.036)		
$\widehat{N}(50)_{mt}$				0.055*					0.044***	
				(0.032)					(0.017)	
$\widehat{N}(75)_{mt}$					0.060**					0.046***
					(0.028)					(0.015)
Observations	892	5,924	4,813	6,720	7,921	1,437	10,344	12,255	17,076	19,672
F-statistic	0.29	1.79	4.83	6.89	9.38	0.59	2.48	11.45	16.51	14.38

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

- General-purpose bonds include refunding and public improvements bonds.

No detectable spread impact in incentive states

Dependent Variable:	Spread (%)								
State Sample:	States With Data Center Tax Incentives								
Bond Sample:	Utility & Transportation			General Purpose			Education		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{N}(25)_{mt}$	0.415			0.055			0.019		
	(0.359)			(0.044)			(0.032)		
$\widehat{N}(50)_{mt}$		0.038			0.026			0.009	
		(0.030)			(0.016)			(0.013)	
$\widehat{N}(75)_{mt}$			0.044			0.021			0.004
			(0.030)			(0.017)			(0.011)
Observations	3,253	4,725	5,712	8,770	12,680	14,325	8,247	14,693	18,076
F-statistic	1.54	9.10	10.76	11.98	30.45	27.92	11.35	12.56	21.93

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

▸ Cumulative bond returns

Impact of Data Centers on Municipal Debt Issuance

DC proximity also predicts future issuance of neighbor municipalities

$$\text{Offering}_{im,t+1\to t+12} = \alpha_{ms} + \lambda_t + \psi_i + \beta \widehat{N}_{mt} + \gamma \text{X}_{st} + \gamma L_{imt} + \varepsilon_{imt}.$$

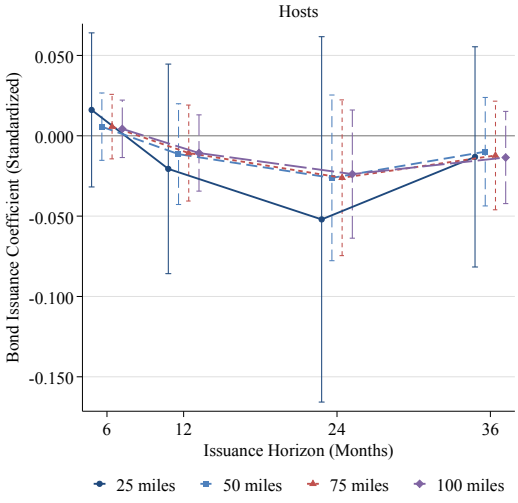
Dependent Variable:	*Future Offering Amount (Standardized)*			
Municipality:	Hosts	Neighbors		
	(1)	(2)	(3)	(4)
$\widehat{N}^h_{mt}$	−0.009			
	(0.012)			
$\widehat{N}(25)_{mt}$		0.009**		
		(0.004)		
$\widehat{N}(50)_{mt}$			0.005**	
			(0.002)	
$\widehat{N}(75)_{mt}$				0.004***
				(0.001)
Observations	33,455	31,124	46,617	56,179
F-statistic	4.53	30.57	32.01	50.94
Mean Dep. Var.	689.54	73.56	73.56	73.56
Mean Indep. Var.	8.29	7.50	20.41	29.55

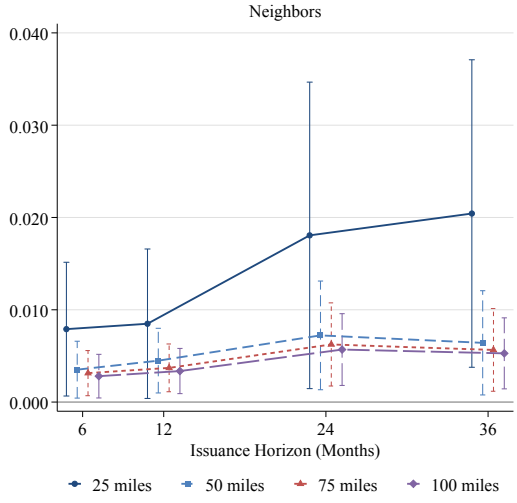
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Interpretation:

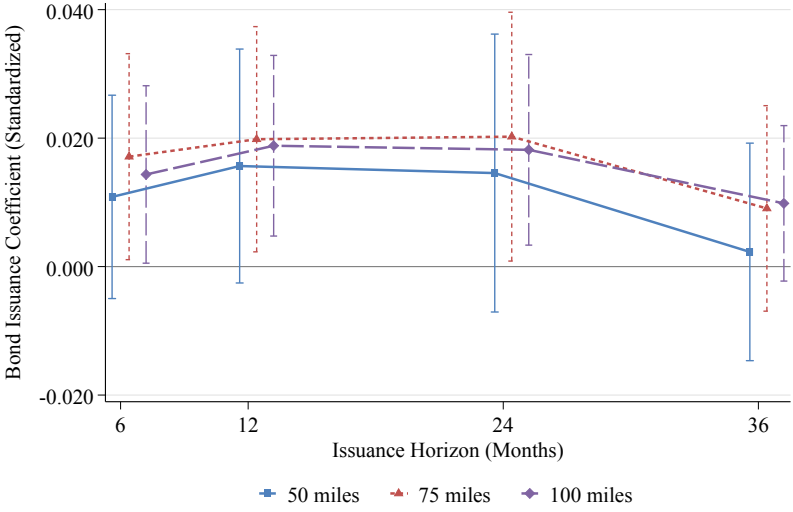
- 8 DCs within 25 miles $\implies$ 0.07 SD ↑ in offering volume, ≈ \$34 million in 1 year.
- 20 DCs within 50 miles $\implies$ 0.1 SD ↑ in offering volume, ≈ \$47 million in 1 year.

Slow-moving fiscal stress for DC neighbors





Issuance is concentrated in education bonds in incentive states



▸ Non-education bond issuance in incentive states ▸ Bond issuance in non-incentive states

Summary so far

	Incentive states	**Non-incentive states**
Spreads	No effect **No detectable repricing.** Anticipated DC entry and negotiated fiscal terms contain spread pressure across all bond types.	General purpose **Spreads widen significantly.** Unanticipated externality repriced by markets.
Issuance	Education **Issuance rises over 12–24 months.** Education: significant at 75–100 mi over 6–24 months. General-purpose and utility issuance flat.	No effect **No issuance response.** Fiscal stress absorbed entirely through spread widening. No bond type shows a significant quantity response.

Disentangling Potential Mechanisms

Ruling out an employment or housing boom

At the municipality-quarter frequency, examine:

$$\text{Outcome}_{mst} = \alpha_m + \lambda_t + \phi_s + \beta \widehat{N}_{mst} + \gamma \text{X}_{mst} + \varepsilon_{mst},$$

$$N_{mst} = \alpha_m + \lambda_t + \phi_s + \delta Z_{mst} + \eta \text{X}_{mst} + \epsilon_{mst}.$$

Dependent variable:	Data Center Employment Level				Zillow Home Value Index (Log)			
Municipality:	Host	Neighbor			Host	Neighbor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{N}^h_{mt}$	157.666				0.014			
	(262.796)				(0.011)			
$\widehat{N}(25)_{mt}$		−270.827***				0.010*		
		(99.427)				(0.005)		
$\widehat{N}(50)_{mt}$			−213.791***				0.006*	
			(69.667)				(0.003)	
$\widehat{N}(75)_{mt}$				−181.046***				0.005**
				(56.703)				(0.002)
Observations	4,582	9,156	10,831	11,601	6,459	12,043	18,282	22,561
F-statistic	6.30	26.54	31.05	33.90	11.97	42.41	64.90	72.15

Specifications (1)–(5) control for the employment level in the construction sector.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

▸ Horizon tests

Why does education finance in incentive states increase?

$$\text{Outcome}_{mst} = \alpha_{ms} + \lambda_t + \beta \times \mathbb{1}(\text{Incentive}_{st}) + \varepsilon_{mst}.$$

- Use the staggered adoption of DC incentives among 16 states over 2017–2025.
- Examine education financing over $[-4; 8]$ years around incentive adoption.
- E.g., compare education financing in Kansas (eff. in 2025) to Georgia (2018).
- Use the Borusyak, Jaravel, and Spiess [2024] estimator and cluster observations at the state level.
- Identification assumption: parallel trends between treated and not-yet-treated municipalities.

Incentive adoption reduces state contributions to school districts

Dependent Variable	Total Students	Total Revenue ($ Per Student)	Total State Revenue ($ Per Student)	State Contributions Employee Benefits ($ Per Student)
Coefficient	−104.255	−1,462.746***	−485.115***	−537.094**
	(146.700)	(237.943)	(185.660)	(266.729)
Pre_1	291.261	−2,914.430	−1,420.382	260.411
	(198.409)	(1,897.077)	(1,240.711)	(325.976)
Pre_2	130.442	−1,240.776	−431.359	331.269
	(100.478)	(941.456)	(619.043)	(208.521)
Observations	1,353	797	797	806
Mean Dep. Var.	10,640	20,048	8,723	1,458

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

- This is echoed by industry reports [Elmo, Gizis, and LeRoy, 2025, Elmo and Gizis, 2026].

Spreads of education bonds also increase

Examine education bond spreads over $[-4; 8]$ years around incentive adoption:

$$\text{Spread}_{mst} = \alpha_{ms} + \lambda_t + \beta \times \mathbb{1}(\text{Incentive}_{st}) + \gamma \text{X}_{mst} + \varepsilon_{mst}.$$

Dependent variable:	Spread (%)		
Bond sample:	Utility & Transp.	General Purpose	Education
	(1)	(2)	(3)
$\mathbb{1}(\text{Incentive}_{st})$	0.036	0.088*	0.115***
	(0.123)	(0.051)	(0.033)
Pre_1	−0.265	−0.109	0.186
	(0.517)	(0.112)	(0.230)
Pre_2	−0.035	−0.059	−0.004
	(0.365)	(0.078)	(0.204)
Pre_3	0.111	0.032	0.007
	(0.256)	(0.064)	(0.097)
Pre_4	−0.027	0.006	−0.064
	(0.250)	(0.050)	(0.085)
Observations	285	1,167	1,041

Standard errors clustered at the state level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Conclusion

- Data center proximity raises bond spreads of neighboring municipalities by 4–10 bps.
- In non-incentive states, markets reprice risk at DC entry, not incentive adoption.
- In incentive states, the fiscal cost is shifted to school districts.
- The AI infrastructure boom creates fiscal burdens in municipalities that never negotiated the deal.

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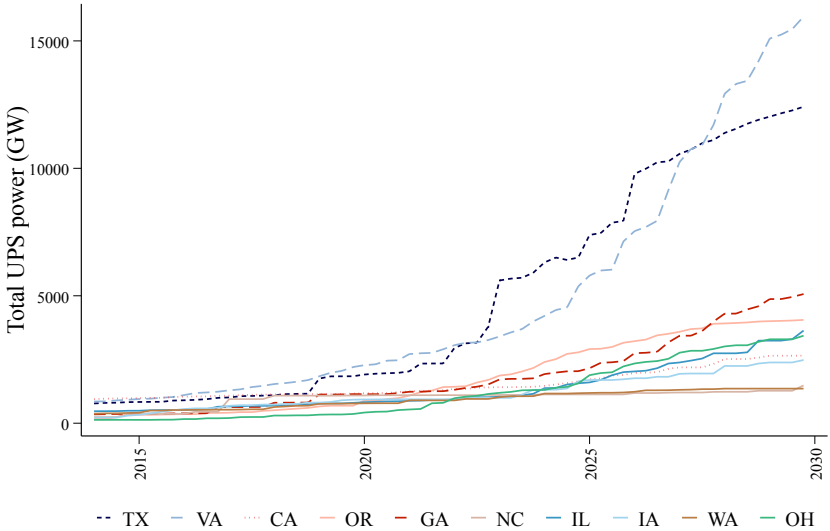
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States with highest DC power capacity

Back



Falsification test using post June 2018 as a shock

- Randomize shock to June 2018 and exclude AI-boom era (post-2021).

Dependent variable:	Spread (%)				
Municipality:	Isolated Host	Dense Host	Neighbor		
Radius (miles):			25	50	75
	(1)	(2)	(3)	(4)	(5)
$\widehat{N}^h_{mt}$	−0.100	−0.214			
	(0.062)	(0.318)			
$\widehat{N}(25)_{mt}$			−0.008		
			(0.047)		
$\widehat{N}(50)_{mt}$				−0.014	
				(0.022)	
$\widehat{N}(75)_{mt}$					−0.007
					(0.022)
Observations	3,743	13,352	13,870	21,025	25,496
F-statistic	6.44	1.02	12.75	33.86	37.40
Fixed effects:					
Issuer	✓	✓	✓	✓	✓
Date	✓	✓	✓	✓	✓
State×County×Municipality	✓	✓	✓	✓	✓

Standard errors clustered at the municipality level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

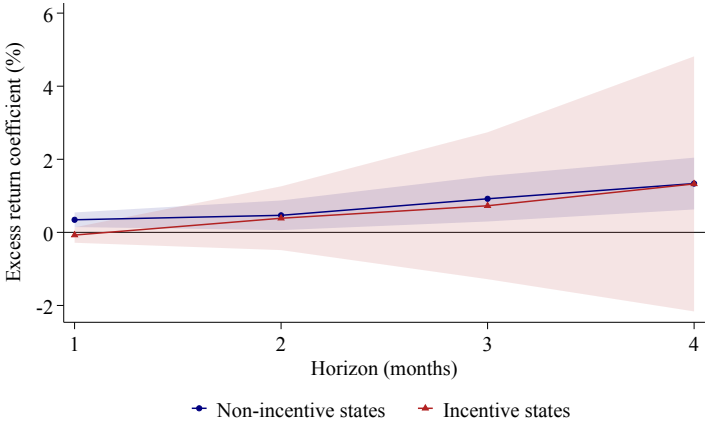
Back

Some general-purpose bond return predictability

Back

$$\text{Returns}_{im,t\to t+h} = \alpha_{ms} + \lambda_t + \psi_i + \beta \mathbf{N}_{mt} + \gamma \mathrm{X}_{st} + \varepsilon_{imt}.$$

- Examine cumulative excess general-purpose bond returns in neighbor municipalities over $h = [1; 4]$ months.



Results are robust to including DCs in the pipeline

Back

Dependent Variable:	Spread (%)				
Municipality:	Isolated Host	Dense Host	Neighbor		
Radius (Miles):			25	50	75
	(1)	(2)	(3)	(4)	(5)
$\widehat{N}^h_{mt}$	0.021	0.086*			
	(0.025)	(0.048)			
$\widehat{N}(25)_{mt}$			0.098***		
			(0.031)		
$\widehat{N}(50)_{mt}$				0.047***	
				(0.015)	
$\widehat{N}(75)_{mt}$					0.040***
					(0.012)
Observations	5,898	27,712	31,162	46,823	56,529
Clusters	57	340	1,224	1,908	2,367
F-statistic	4.30	7.78	30.06	34.08	53.33
Fixed effects:					
Issuer	✓	✓	✓	✓	✓
Date	✓	✓	✓	✓	✓
State×County×Municipality	✓	✓	✓	✓	✓

Standard errors clustered at the municipality level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Pricing impact of DCs is concentrated in high-HPI states

▸ Back

Dependent variable:	Spread (%)							
	Panel A: High-HPI states				*Panel B: Low-HPI states*			
Municipality:	Host	Neighbor			Host	Neighbor		
Radius (miles):		25	50	75		25	50	75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N^h_{mt}	0.036*				−0.033			
	(0.021)				(0.054)			
$\widehat{N}(25)_{mt}$		0.118***				−0.046*		
		(0.035)				(0.024)		
$\widehat{N}(50)_{mt}$			0.043***				−0.042*	
			(0.012)				(0.021)	
$\widehat{N}(75)_{mt}$				0.035***				−0.039**
				(0.009)				(0.018)
Observations	21,874	21,864	32,156	37,974	11,692	9,908	15,538	19,549
F-statistic	6.01	24.76	37.33	68.02	4.74	7.60	12.74	21.43

Standard errors clustered at the municipality level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results are driven by states with strong fiscal fundamentals

Back

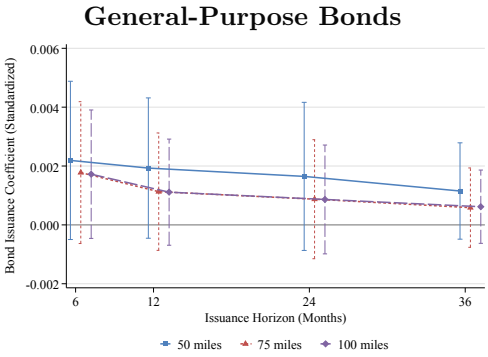
Dependent variable:	Spread (%)							
	Panel A: High lagged rev/exp				*Panel B: Low lagged rev/exp*			
Municipality:	Host	Neighbor			Host	Neighbor		
Radius (miles):		25	50	75		25	50	75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N^h_{mt}	0.014				0.041			
	(0.024)				(0.038)			
$\widehat{N}(25)_{mt}$		0.140***				0.012		
		(0.053)				(0.058)		
$\widehat{N}(50)_{mt}$			0.079**				0.027	
			(0.034)				(0.035)	
$\widehat{N}(75)_{mt}$				0.084**				−0.020
				(0.033)				(0.057)
Observations	17,744	16,843	25,652	31,353	15,758	14,818	21,890	25,978
F-statistic	3.67	29.29	33.37	32.46	2.58	2.40	1.60	0.36

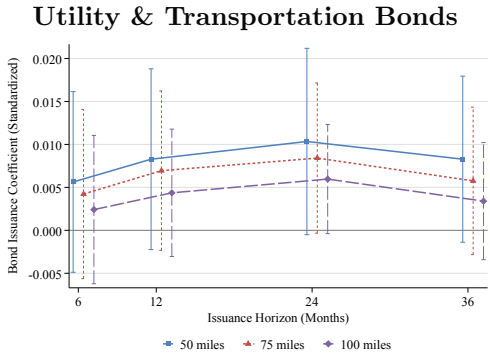
Standard errors clustered at the municipality level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Non-education bond issuance in incentive states is unchanged

Back





No detectable bond issuance in non-incentive states

▸ Back

Dependent Variable:	Future Offering Amount (Standardized)								
Bond Sample:	Utility & Transportation			General Purpose			Education		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{N}(25)_{mt}$	0.054			−0.009			−0.027		
	(0.067)			(0.012)			(0.040)		
$\widehat{N}(50)_{mt}$		−0.058			−0.414			0.000	
		(0.108)			(15.897)			(0.006)	
$\widehat{N}(75)_{mt}$			−0.014			0.035			0.005
			(0.019)			(0.118)			(0.003)
Observations	1,520	1,942	2,147	3,354	4,226	5,156	3,623	5,188	6,577
F-statistic	0.81	0.32	0.44	2.35	0.00	0.10	1.31	1.65	16.48
Fixed effects:									
Issuer	✓	✓	✓	✓	✓	✓	✓	✓	✓
Date	✓	✓	✓	✓	✓	✓	✓	✓	✓
State×County×Municipality	✓	✓	✓	✓	✓	✓	✓	✓	✓

Absence of an employment or housing boom

▸ Back

Dependent variable:	Data Center Employment Level				Zillow Home Value Index ($)			
Horizon (quarter):	1	2	3	4	1	2	3	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{N}(50)_{mt}$	−107.191**	−97.519**	−71.360**	−50.568	0.006**	0.005**	0.004*	0.002
	(41.803)	(39.799)	(34.415)	(31.781)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	12,744	12,633	12,757	12,811	19,830	19,540	19,643	19,676
F-statistic	50.65	46.15	48.52	47.58	90.94	88.39	86.92	86.31

Standard errors clustered at the municipality level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.