Artificial Intelligence, Agglomeration, and US Metropolitan Credit Risk

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Technology and Labor

- Tech breakthroughs allow workers to shift away from mundane tasks and toward productive ones
    - The ATM: for bank tellers, a shift away from cash-handling and toward relationship banking
- However, tech breakthroughs can also render some occupations completely obsolete due to their exposed makeup of tasks
    - The smartphone: rendered some occupations obsolete (photo developers, travel agents, physical map manufacturers)
- The broader impact of a general purpose tech breakthrough largely depends on which mechanism dominates (productivity vs employment losses)





Generative AI

- Generative AI has the potential to fundamentally alter local labor markets and productivity

- OpenAI’s ChatGPT is credited with accelerating the GenAI boom, with 100M users signing up in just two months after its release

    - Examples of ChatGPT tasks: writing and debugging computer programs, customer service, drafting and copyediting, scheduling, generating images

    - 5.4 billion web visits in 2/2026

- Anthropic’s Claude has similarly seen massive growth in recent months, with 290.3 million web visits in 2/2026 (up 43% from 1/2026)

    - Claude excels at tasks that involve nuanced long-form writing, complex coding, and data visualization

Generative AI and Agglomeration

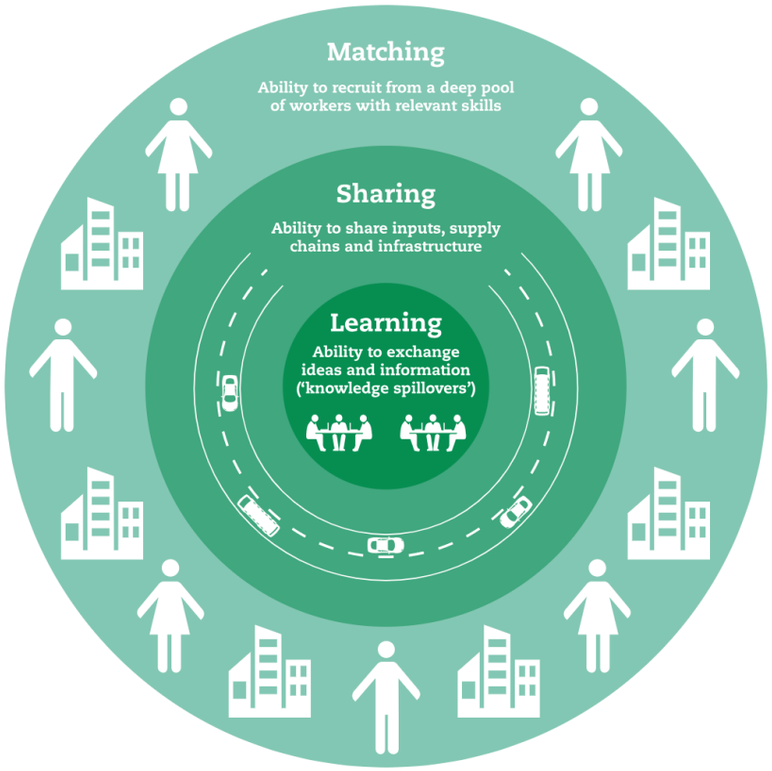
- Marshallian theory (1920) predicts that agglomeration is associated with productivity benefits in metropolitan areas (MSAs) such as:

    1) Labor market pooling (improved matching between workers and firms)

    2) Knowledge spillovers (increase the speed in the flow of ideas and technology)

- GenAI has the potential to fundamentally alter the set of tasks associated with each occupation, allowing workers to shift away from “mundane” tasks

    - This reshuffling of tasks can accelerate positive agglomeration forces by enhancing the associated productivity benefits outlined above



Generative AI and Unemployment

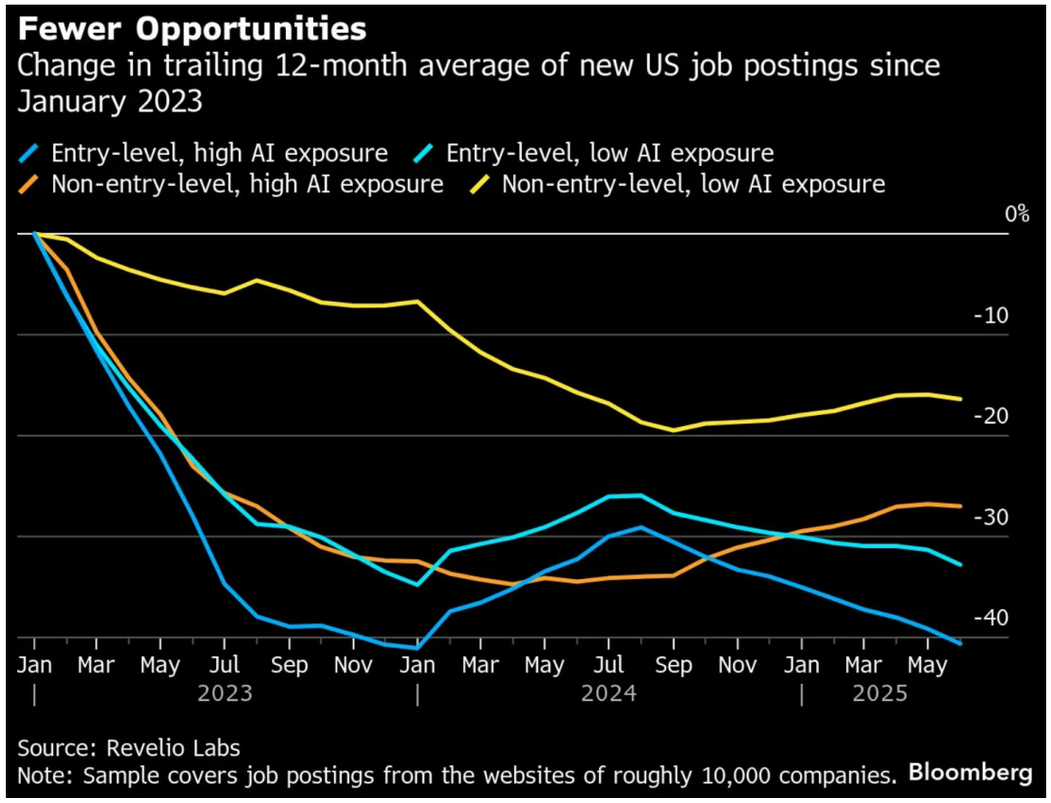
- However, the reshuffling of occupation-tasks is likely to render some jobs obsolete if all of their tasks can be handled by GenAI

- This concern is not a mere hypothetical, especially for entry-level jobs that are often necessary to train new generations of workers:

  - In the US, entry-level postings are down by 35% since early 2023, with generative AI accelerating a “white-collar recession”

  - In 2024, there was a 35% decline in junior tech positions across major EU countries

  - Indian IT companies have reduced entry-level roles by 20-25% due to automation and AI



Our Central Research Question

How does GenAI affect credit risk and asset value of US cities?

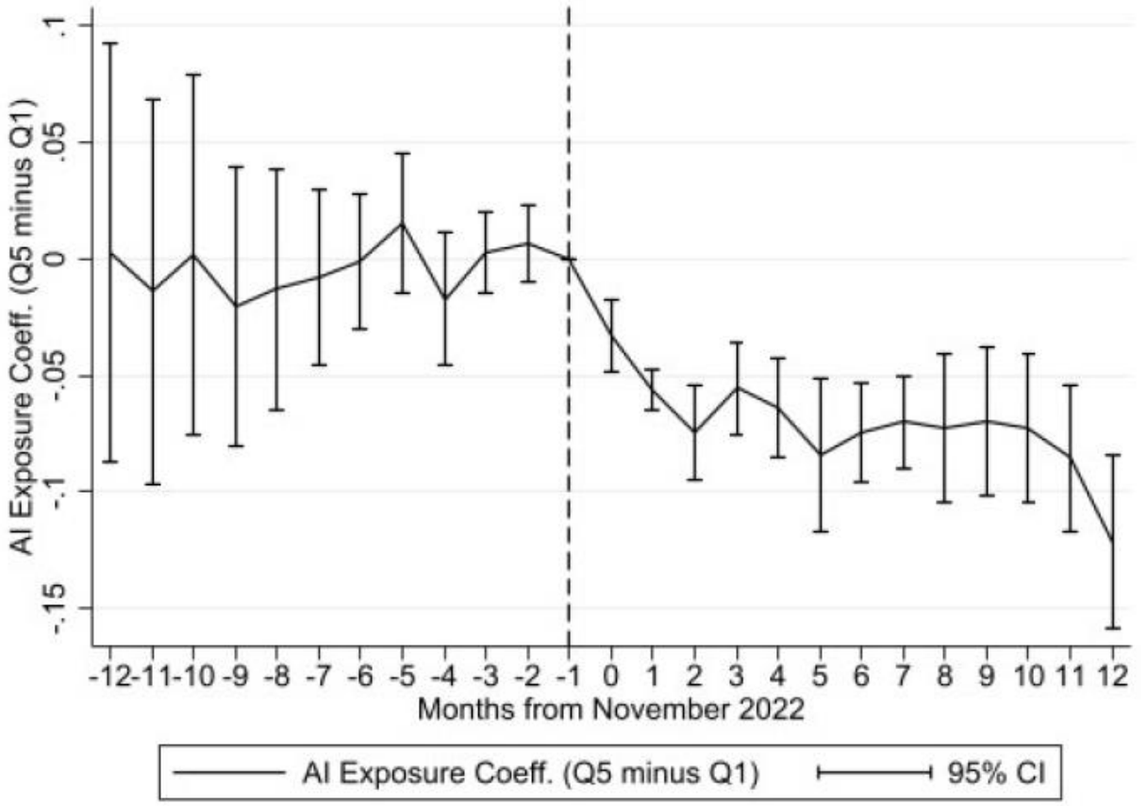
- The $4.4T US municipal bond market is an ideal laboratory for this question:
    - The associated yields are forward-looking and incorporate the opinions of investors on the quality of the tax base in the long-run, and the associated uncertainties
    - The anticipated quality of the tax base is directly tied to anticipated productivity gains and employment effects
    - Information on secondary yields allows us to focus on *within-bond* changes in yields in response to a GenAI shock
    - A structural analysis using the Merton (1974) model allows us to estimate the changes in MSA asset value and uncertainty that accompany any GenAI-induced yield changes

Our Central Research Findings (1)

Following a shock to GenAI capabilities in November 2022 (introduction of ChatGPT), we observe the following changes:

1) Within-bond secondary yields decrease by 7.4 bps in high AI exposure MSAs relative to low AI exposure MSAs

2) Our structural analysis indicates that the yield increase corresponds to a 5.0% increase in expected MSA asset value and a 1.5% increase in MSA asset volatility.



Our Central Research Findings (2)

1) A shift-share instrument using pre-existing occupation shares and national occupation growth supports the labor market channel.

2) Using LinkedIn data, we find that the yield reduction is stronger in thick labor markets with a higher rate of within-MSA labor movements.



3) The yield reduction is driven by supplementary task AI exposure, supporting the labor substitution channel.

4) Surveys indicate local govts have been slow to react to AI due to continuing uncertainties on revenue, expenditure, and jobs projections.



Related Literature

- Acemoglu and Restrepo (2018, 2019): their foundational task-based framework emphasizes an AI labor displacement effect that is counterbalanced by a productivity effect
- Eisfeldt et al. (2025): following the introduction of ChatGPT, firms with high AI exposure saw a 5% stock price increase through the worker substitution channel (lower labor costs)
- Andrews and Farboodi (2025): long-term Treasury and corporate bond yields fell around major AI model releases
- Hampole et al. (2025): while AI substitutes for labor at the task level, aggregate employment effects are muted because workers reallocate efforts to complementary tasks
- Autor and Thompson (2025): the effects of automation on wage and employment depend on the expertise level of tasks lost to automation; the same technology replaces experts in some occupations and augments expertise in others
- Babina et al. (2024): firms that invest in AI see higher growth in sales and employment due to increase product innovation

Measuring AI Exposure (AIE)

- The US Department of Labor O*NET database provides a menu of tasks associated with each occupation
- For each occupation, Eloundou et al. (2024) (EMMR) determine the % of tasks that could be replaced by an LLM like ChatGPT
    - Their finding: on average, 30% of an occupation's tasks are exposed to AI, in that access to an LLM and related software would lead to at least 50% time savings
- We obtain the data on occupation-level AIE from EMMR

Top and Bottom Occupations by AIE (2022)

Panel A: Top Ten Occupations by AI Exposure

	AI Exposure	Agg Emp. (M)	Agg. Wage (B)
Software Developers	0.868	1.36	165.05
Accounting Clerks	0.783	1.51	68.13
Web Administrators	0.735	3.33	327.11
Human Resources Specialists	0.635	0.74	52.39
Sales Representatives, Services	0.633	1.03	72.99
Administrative Assistants	0.625	1.83	75.01
Computer Systems Analysts	0.610	1.01	103.26
Sales Representatives, Manufacturing	0.605	1.24	89.94
Business Continuity Planners	0.587	4.12	326.57
Office Clerks	0.571	2.58	100.52

Panel B: Bottom Ten Occupations by AI Exposure

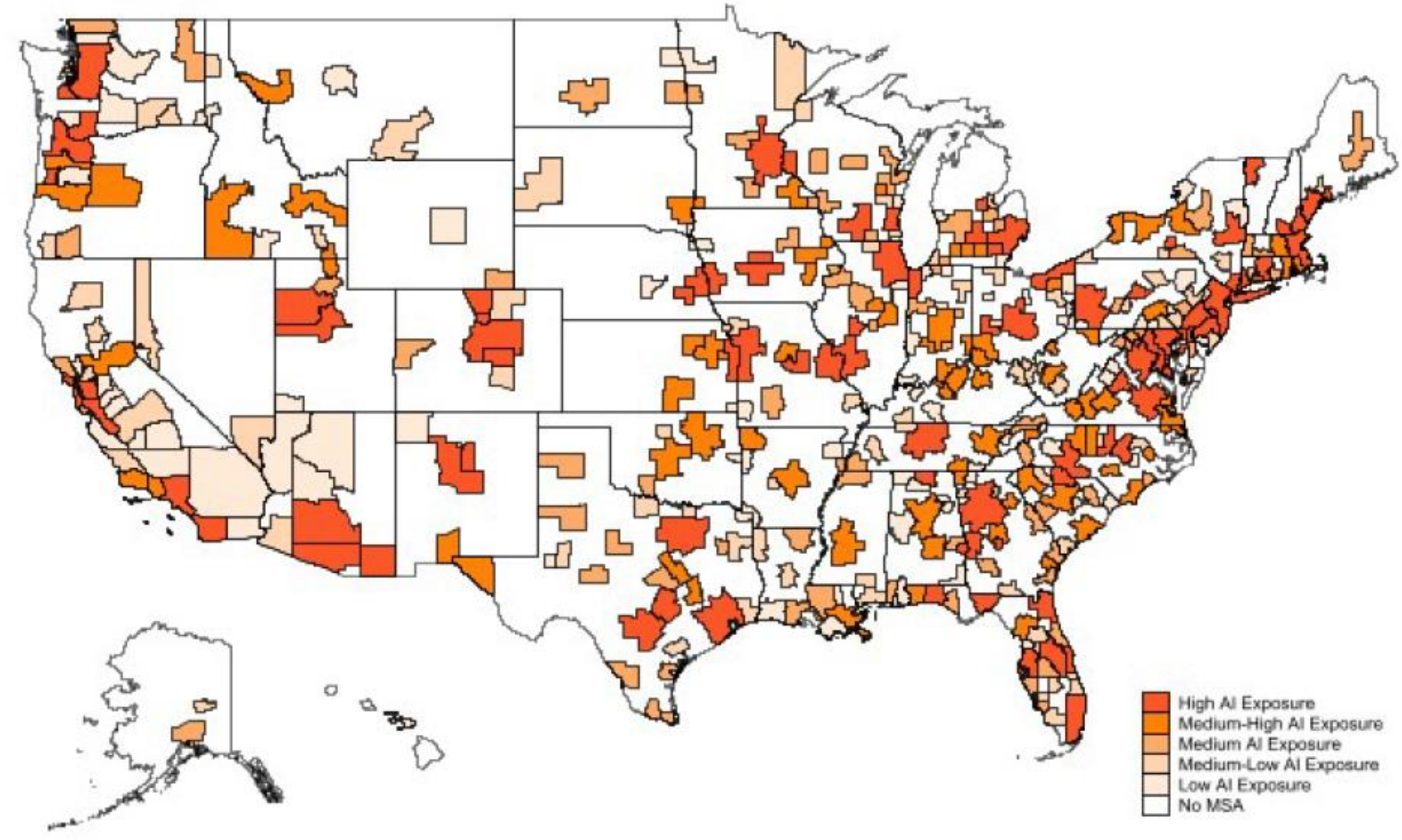
	AI Exposure	Agg Emp. (M)	Agg. Wage (B)
Janitors and Cleaners	0.000	2.04	64.89
Laborers and Frieght Movers	0.052	5.46	190.76
Plumbers and Pipefitters	0.074	0.84	52.91
Fast Food Workers	0.110	6.19	161.32
Maintenance and Repair Workers	0.117	1.42	63.64
Waiters and Waitresses	0.180	1.80	52.33
Stockers and Order Fillers	0.183	2.45	80.95
Cashiers	0.241	3.32	88.82
Heavy Truck Drivers	0.242	1.90	95.82
Elementary School Teachers	0.303	1.33	89.17

Methodology – Measuring MSA AIE

- The BLS OEWS database provides total employment and total wage statistics for each MSA-occupation
    - 389 MSAs, 923 occupations
    - We calculate MSA-level AI exposure as the wage-weighted average AI exposure across occupations
- Ex post validation: observed AIE (Massenkoff and McCrory, 2026) and EMMR AIE have a correlation of 0.90

	Mean	Median	P25	P75	SD
AI Exposure	0.401	0.399	0.384	0.422	0.029
Core AI Exposure	0.299	0.298	0.284	0.314	0.025
Supp. AI Exposure	0.102	0.103	0.099	0.104	0.006
% Supp. Exposure	0.255	0.256	0.248	0.261	0.012
Agg Emp. (M)	1.935	1.049	0.287	3.018	2.298
Agg Wage (B)	131.593	62.115	16.629	180.917	174.345

AI Exposure Heat Map



Top Ten MSAs by AIE

Panel A: Top Ten Metro Areas by AI Exposure

	AI Exposure	Agg Emp. (M)	Agg. Wage (B)
San Jose, CA	0.473	1.10	122.11
Washington, DC	0.460	3.02	247.27
San Francisco, CA	0.458	2.35	214.40
Seattle, WA	0.457	1.99	157.83
Austin, TX	0.451	1.16	73.12
Raleigh, NC	0.441	0.66	39.90
Denver, CO	0.438	1.53	108.88
Boston, MA	0.433	2.64	209.54
Atlanta, GA	0.430	2.69	166.02
Baltimore, MD	0.430	1.27	85.31

Bottom Ten MSAs by AIE

Panel B: Bottom Ten Metro Areas by AI Exposure

	AI Exposure	Agg Emp. (M)	Agg. Wage (B)
Riverside, CA	0.338	1.61	92.71
Las Vegas, NV	0.361	1.01	52.93
Memphis, TN	0.368	0.61	31.52
Grand Rapids, MI	0.374	0.54	29.47
Louisville, KY	0.379	0.63	34.00
Indianapolis, IN	0.382	1.04	59.16
Buffalo, NY	0.391	0.51	29.97
Oklahoma City, OK	0.392	0.62	31.96
Providence, RI	0.392	0.55	33.58
Sacramento, CA	0.392	1.01	68.25

Primary Outcome Variable

- Our primary outcome variable is the secondary municipal bond yield spread (y) for bond i in MSA m and year-month t
- For each bond x year-month, we calculate the trade size-weighted average yield using customer buy transactions from MSRB EMMA
- We tax-adjust this average yield using the tax adjustment procedure from Garrett et al. (2023)
- We subtract the duration-matched risk-free rate based on the yield curve from Gürkaynak, Sack, and Wright (2007) to obtain the tax-adjusted yield spread
- We match this information to bond characteristics from the Mergent database

Bond Summary Statistics

	Mean	Median	P25	P75	SD
Yield (%)	4.97	5.08	3.89	6.19	1.79
Yield Spread (%)	1.67	1.54	0.75	2.47	1.22
Bond Size (M)	3.73	0.81	0.32	2.35	13.99
Issue Size (M)	59.06	16.47	6.57	51.14	137.13
Years to Maturity	10.71	9.49	5.01	15.13	7.02
Duration	8.19	7.96	4.55	11.55	4.33
Rating Number	18.30	19.00	17.00	20.00	2.21
Unrated	0.08	0.00	0.00	0.00	0.27
General Obligation	0.66	1.00	0.00	1.00	0.47
Insured	0.23	0.00	0.00	0.00	0.42
Callable	0.53	1.00	0.00	1.00	0.50
Negotiated	0.49	0.00	0.00	1.00	0.50

Baseline Methodology – Event Study

- We examine yield spread outcomes for top quintile AIE MSAs (AIE_m^{Q5}) vs bottom quintile AIE MSAs around the introduction of ChatGPT in November 2022

$$y_{imt} = \beta^t \times (AIE_m^{Q5} \times t) + \delta_i + \gamma_t + \varepsilon_{imt}$$

- In this model, δ_i is a vector of bond fixed effects and γ_t is a vector of year-month fixed effects
- We focus on a two-year period around the event

Background on the Introduction of ChatGPT

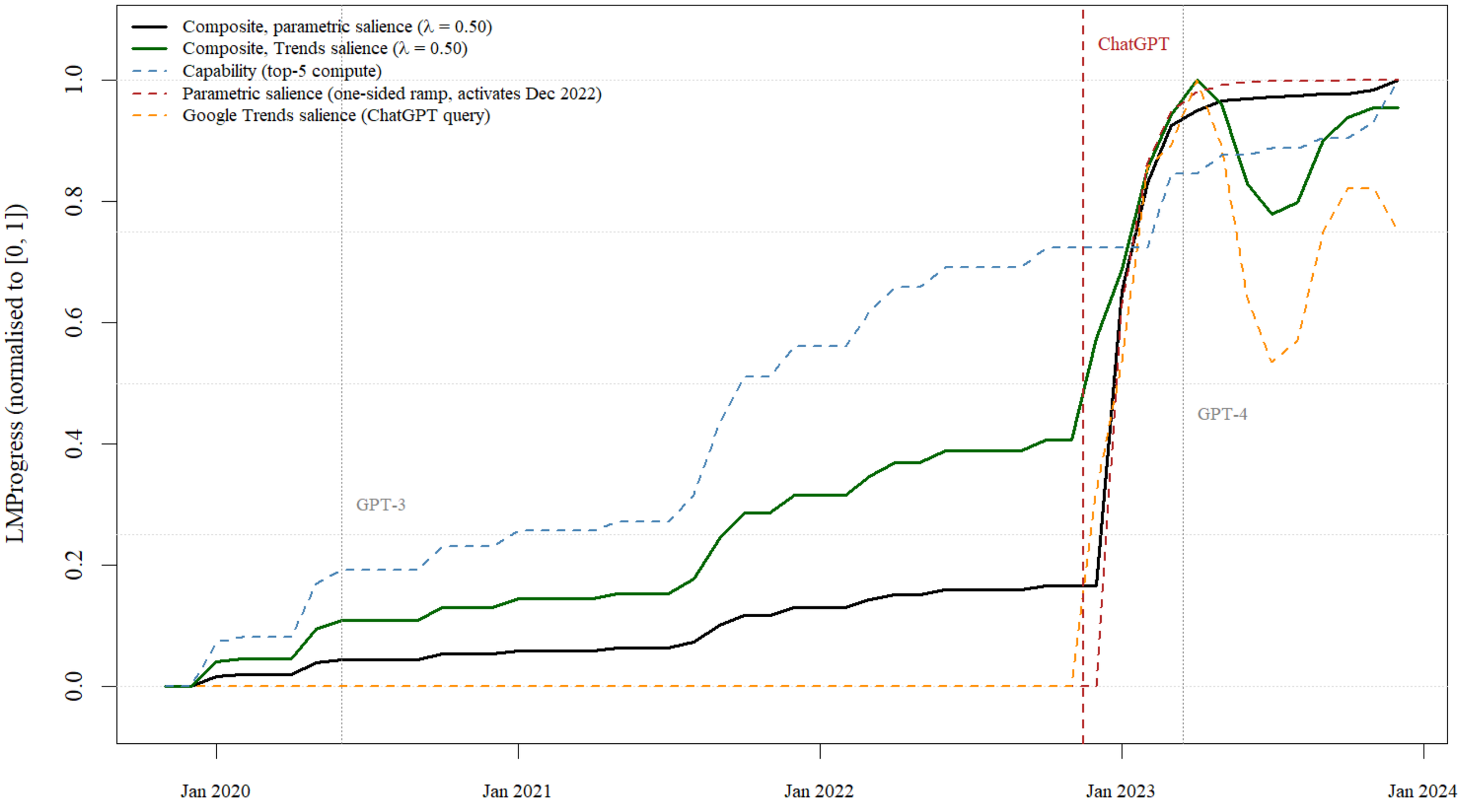
The introduction of ChatGPT is widely seen as the primary shock to GenAI:

- 1M users five days after its release; 100M users after two months

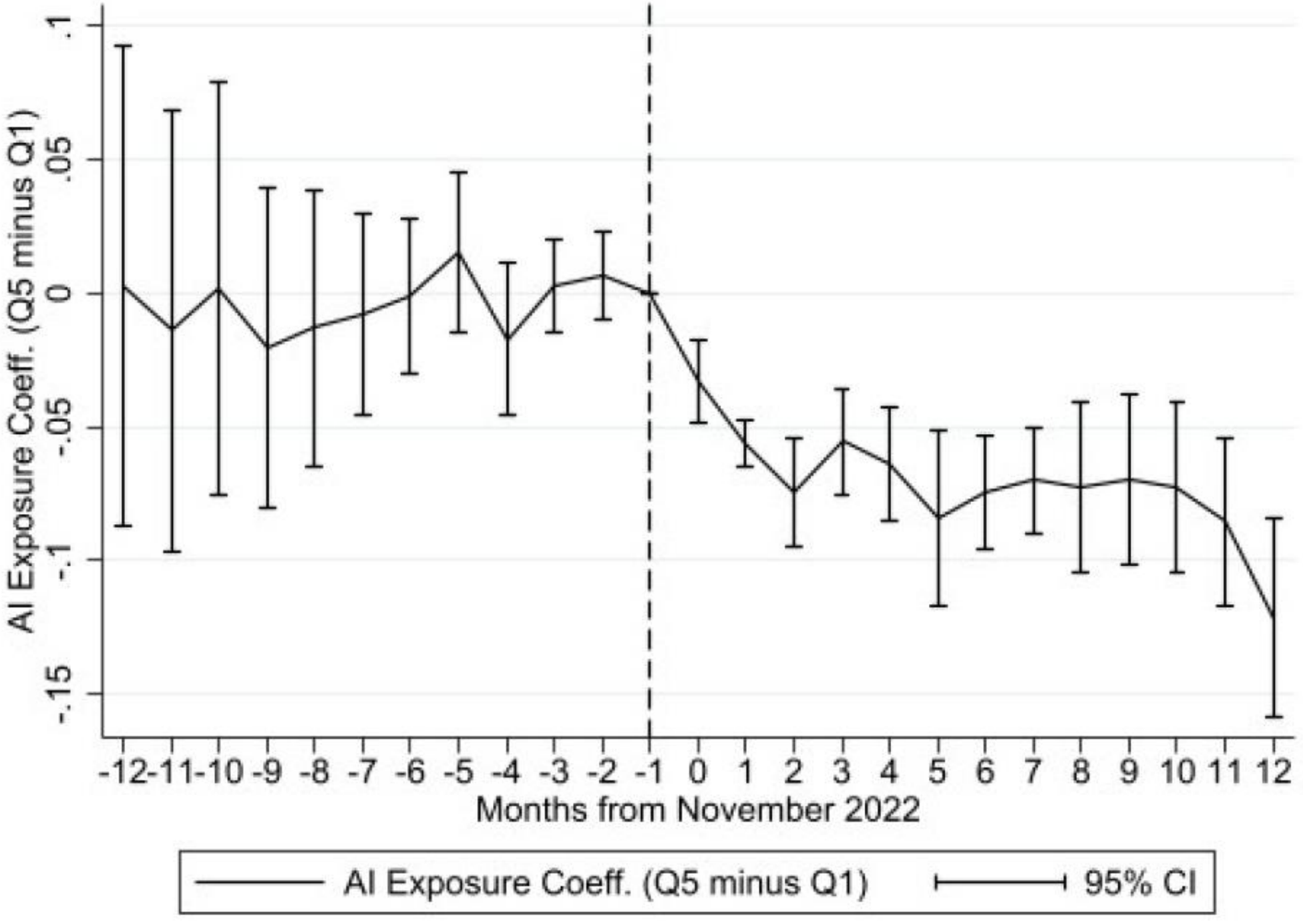
This was also associated with a massive shock to GenAI awareness:

- 275M web searches in 12/2022; 830M web searches in 1/2023
- Google Trends similarly indicates a massive and permanent spike in search volume after its release

Background on the Introduction of ChatGPT



Event Study Results



Secondary Market Regression Results

	(1) Yield Sp.	(2) Yield Sp.	(3) Yield Sp.	(4) Yield Sp.	(5) Yield Sp.
Post × AI Exp. Q5	-0.068***	-0.070***	-0.062**	-0.083***	-0.074**
	(0.020)	(0.024)	(0.024)	(0.021)	(0.030)
Bond FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Pop × YM	No	Yes	No	No	Yes
PCInc × YM	No	No	Yes	No	Yes
BSize × YM	No	No	No	Yes	Yes
Adj. R^2	0.802	0.802	0.802	0.804	0.804
N	984,601	984,601	984,601	984,601	984,601

- The 7.4 bps reduction = 6.1% of one SD in y; 9.5% of the Aaa-Baa1 credit spread; $4.2B in interest savings for ten years of issues in high AIE MSAs
- Also robust to interactions with percentage vote for Democratic candidates, midterm elections, or the exclusion of high-AI investment states such as CA, NY, and MA

Primary Market Offering Regression Results

	(1) Yield Sp.	(2) Rating
Post × AI Exposure Q5	-0.111**	0.357**
	(0.049)	(0.165)
CBSA FE	Yes	Yes
Year-Month FE	Yes	Yes
Sector FE	Yes	Yes
Adj. R^2	0.704	0.461
N	55,376	51,272

- Offering spreads decrease by 11.1 bps
- Credit rating improves by 0.36 notches

Structural Analysis

- The Merton (1974) credit risk model can be used to determine the joint changes in MSA asset value and uncertainty that accompany the 7.4 bps decrease in yield spread
- The value of a risky bond (D) equals a long position in an asset with value outcome V and a short call option with strike K (face value):

$$
\begin{aligned}
D &= V - (V\Phi(d_1) - Ke^{-rT}\Phi(d_2)), \text{ where} \\
d_1 &= (\ln(V/K) + (r + \tfrac{1}{2}\sigma^2)T)/(\sigma\sqrt{T}), \\
d_2 &= d_1 - \sigma\sqrt{T}
\end{aligned}
$$

Structural Analysis

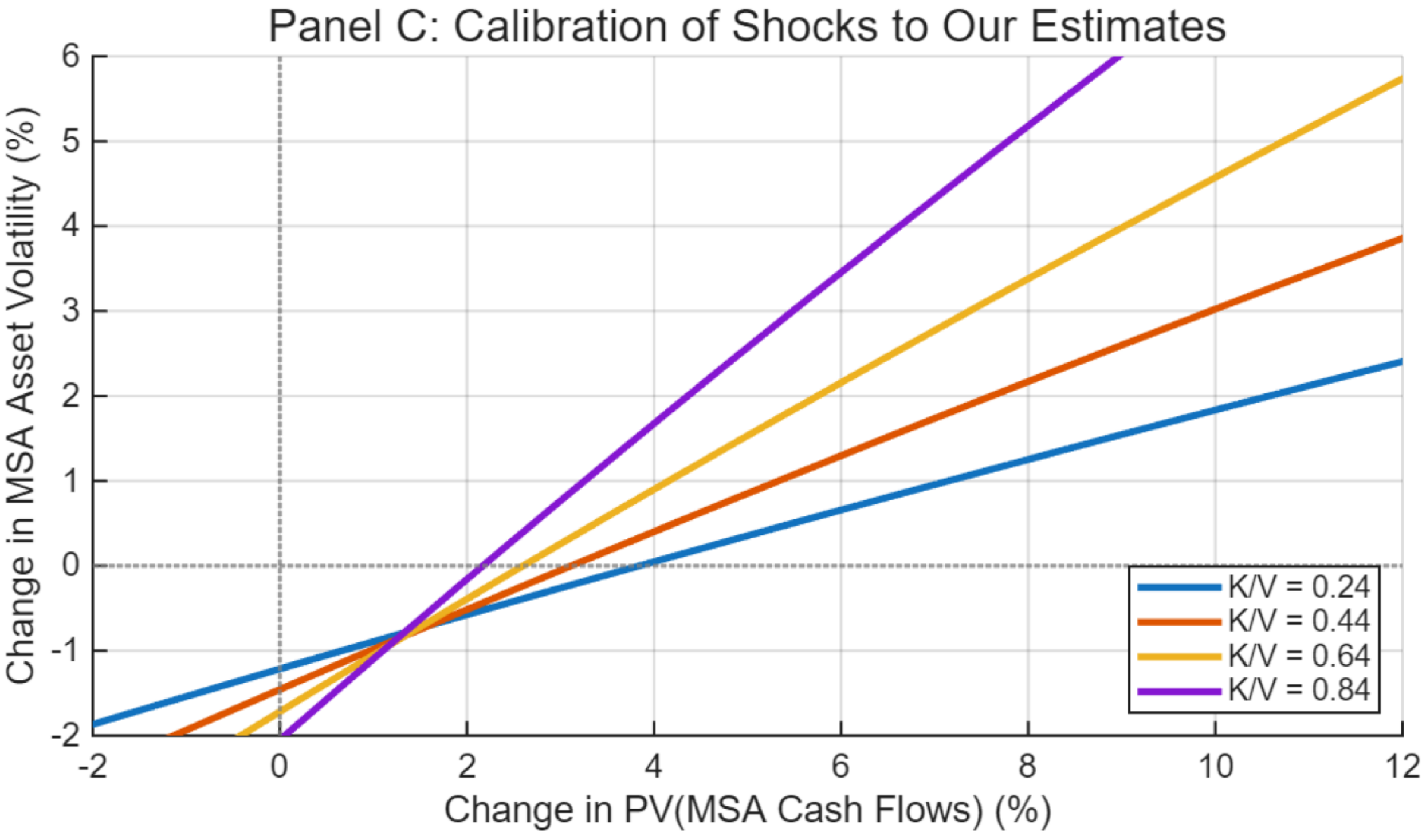
- We can rearrange this equation so that yield spread $s \equiv y - r$ is the LHS variable, where $y = (T)^{-1}\ln(K/D)$:

$$s \equiv y - r = -T^{-1}\ln\{e^{-rT}\Phi(d_2) + (V/K)(1 - \Phi(d_1))\} - r$$

- This equation is a function of the inverse leverage ratio (V/K), MSA asset volatility (σ), maturity (T), and the risk-free rate (r)
- We difference this equation based on joint changes in V and σ, and set the difference to our reduced form estimate of -7.4 bps:

$$\Delta s = s(V/K \times (1+\omega), \sigma \times (1+z), r, T) - s(V/K, \sigma, r, T) = -7.4 \text{ bps}$$

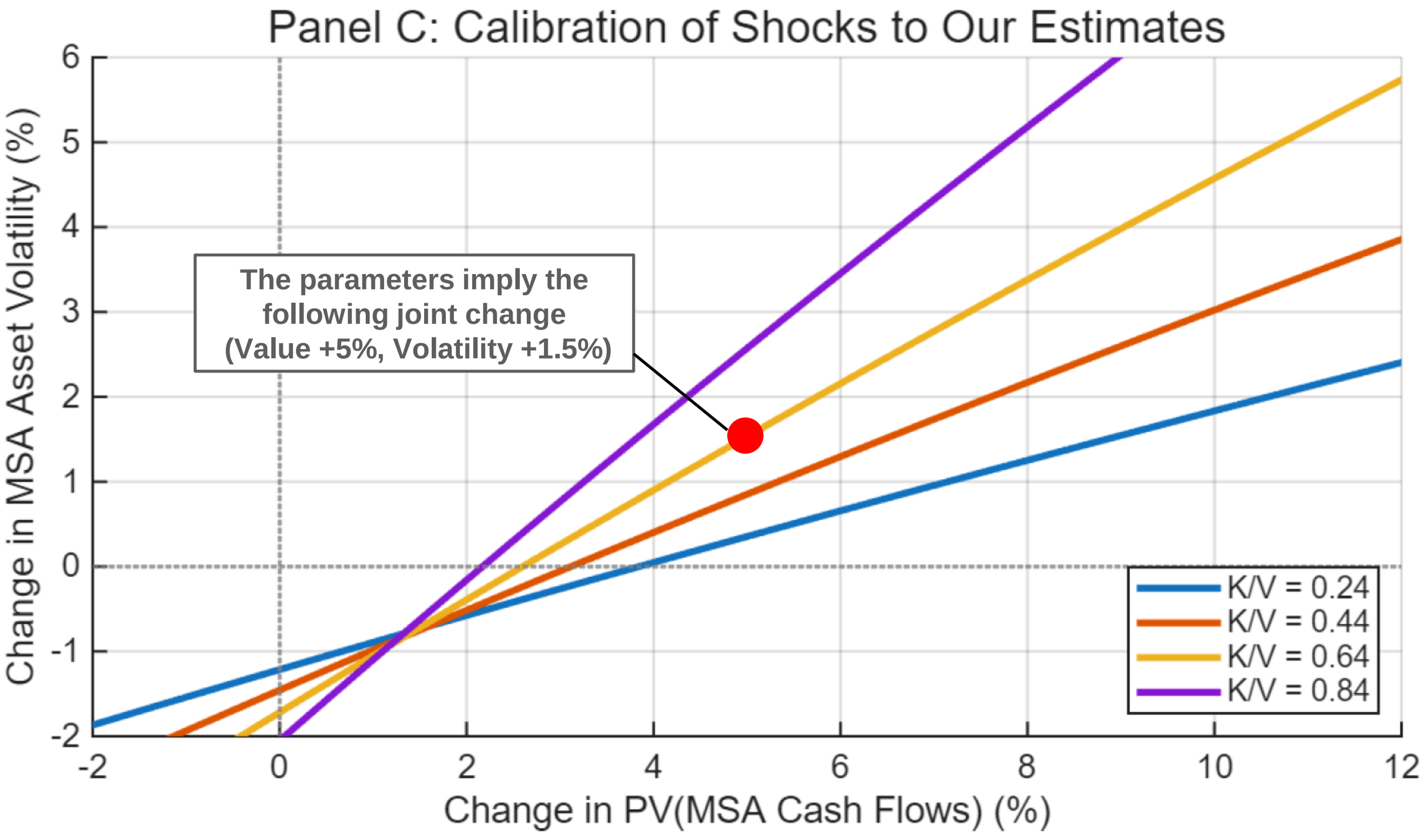
Results of Structural Analysis



Identifying the Value/Volatility Effect

- The previous figure shows a wide range of value/volatility effects that are consistent with the 7.4 bps reduction
- We narrow down the joint effect using the following estimates:
  - 64% leverage ratio ($K/V = 0.64$) from the Reason Foundation
  - Median elasticity of MSA value to productivity of 2.5 (Hornbeck and Moretti, 2024)
  - Estimate of percentage change in labor productivity after 2022 in high-AIE MSAs (+2.0%)

Results of Structural Analysis



Identifying the Labor Channel (Shift-Share)

- We use a time-varying AIE variable that is driven by changes in the MSA's labor market

$$AIE_{m,t} = \sum_j AIE_j \times \frac{E_{m,j,t}}{E_{m,t}}$$

- More growth in high-AIE occupations should decrease yields if markets anticipate greater productivity

- Local growth may be driven by confounders, so we use the product of national occ. growth (g) and pre-existing MSA occ. shares (s) as an instrument for $AIE_{m,t}$

$$B_{m,t} = \sum_j s_{m,j,2014} \times \tilde{g}_{j,t}$$

Shift-Share IV Results

	(1) $AIE_{m,t}$	(2) Yield Sp.	(3) Yield Sp.	(4) Yield Sp.
$B_{m,t}$	0.344***			
	(0.041)			
$AIE_{m,t}$		-0.294**	-0.299**	-0.369**
		(0.128)	(0.135)	(0.160)
Bond FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Pop × YM FE	Yes	Yes	Yes	Yes
PCInc × YM FE	Yes	Yes	Yes	Yes
Size × YM FE	Yes	Yes	Yes	Yes
LOO CBSA	No	No	Yes	No
LOO State	No	No	No	Yes
First-Stage F		70.4	61.4	41.6
Partial R^2		0.059	0.060	0.061
N	2,274,510	2,274,510	2,274,510	2,274,510

Labor Market Tests (1)

- We provide further support for the labor market channel using job transitions data from Revelio Labs (>2M LinkedIn profiles)
- MSA labor market thickness is the ratio of within-MSA job transitions to within-MSA plus out-of-MSA jobs transitions (mean = 91.7%; SD = 7.8%)
- Labor market thickness is a classic Marshallian agglomeration mechanism where the local economy efficiently matches firms and workers
- In thick markets, AI-displaced workers can transition to other local employers, often in occupations that use complementary skills

Labor Market Tests (1)

	(1) Yield Sp.	(2) Yield Sp.	(3) Yield Sp.	(4) Yield Sp.
Post × AI Exp. Q5	-0.103***	-0.036	-0.070**	-0.039
	(0.020)	(0.026)	(0.027)	(0.033)
Post × AI Exp. Q5 × LThick			-0.056***	-0.052***
			(0.017)	(0.014)
Post × LThick			0.027**	0.026**
			(0.011)	(0.011)
Post × AI Exp. Q5 × Unemp				0.043*
				(0.024)
Post × Unemp				0.004
				(0.009)
Bond FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Labor Thickness Sample	High	Low	All	All
Adj. R^2	0.804	0.800	0.802	0.802
N	717,195	738,624	969,171	969,171

Labor Market Tests (2)

- An alternative measure of thickness is based on the ratio of occupation-switching job transitions to all job transitions within an MSA
- Intuitively, MSAs with high occupation switching rates absorb AI-induced displacement without productivity losses
- This measure relates to the mechanism in Hampole et al. (2025): AI reallocates labor toward complementary tasks but does not reduce aggregate employment

Labor Market Tests (2)

	(1) Yield Sp.	(2) Yield Sp.
Post × AI Exp. Q5	-0.108***	-0.088***
	(0.031)	(0.028)
Post × AI Exp. Q5 × OccSwitchRate	-0.069**	
	(0.028)	
Post × OccSwitchRate	0.034**	
	(0.013)	
Post × AI Exp. Q5 × IndSwitchRate		-0.075
		(0.061)
Post × IndSwitchRate		0.022*
		(0.013)
Bond FE	Yes	Yes
Year-Month FE	Yes	Yes
Adj. R^2	0.802	0.802
N	974,388	974,388

Labor Market Tests (3)

- We measure MSA AI exposure for core vs supplementary tasks
- An occupation-task is “core” if it has high relevance and importance ratings
    - Occupations with high core AIE are more likely to be **replaced by AI** (Eisfeldt et al, 2025)
- An occupation-task is “supplemental” if it has low relevance, or high relevance and low importance
    - Occupations with high supplemental AIE are more likely to be **complemented by AI**
- Information on occupation-level core and supplemental AI exposure is provided by Eisfeldt et al (2025); we use this information to construct MSA-level measures

Labor Market Tests (3)

	(1) Yield Sp.	(2) Yield Sp.	(3) Yield Sp.
Post × Core AI Exp. Q5	-0.064***		-0.023
	(0.020)		(0.025)
Post × Supp. AI Exp. Q5		-0.106***	-0.100**
		(0.029)	(0.037)
Bond FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Adj. R^2	0.797	0.797	0.797
N	2,525,323	2,525,323	2,525,323

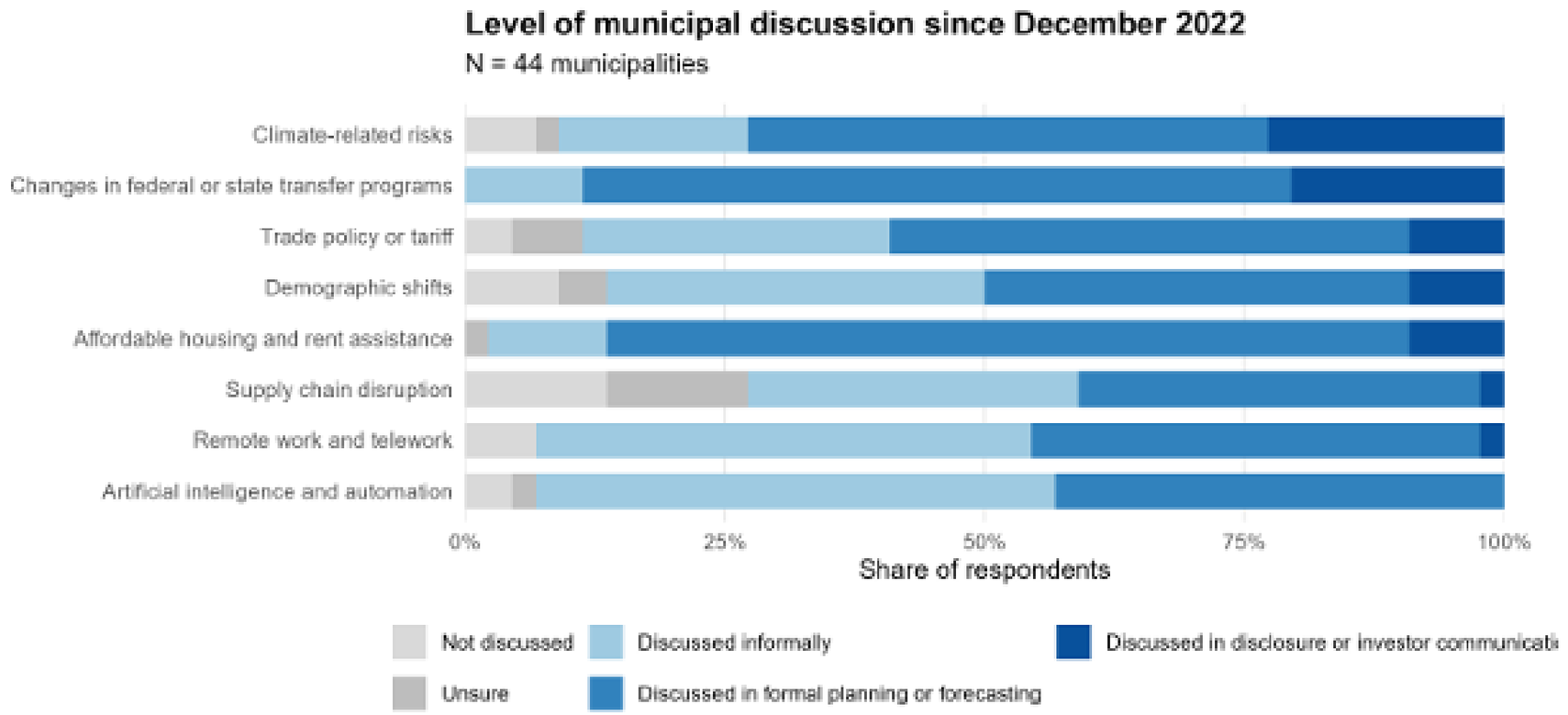
- The strong supplemental AI effect indicates that GenAI reduces credit risk by enhancing complementarities among workers in high-AIE MSAs, thereby increasing the expected productivity of the MSA

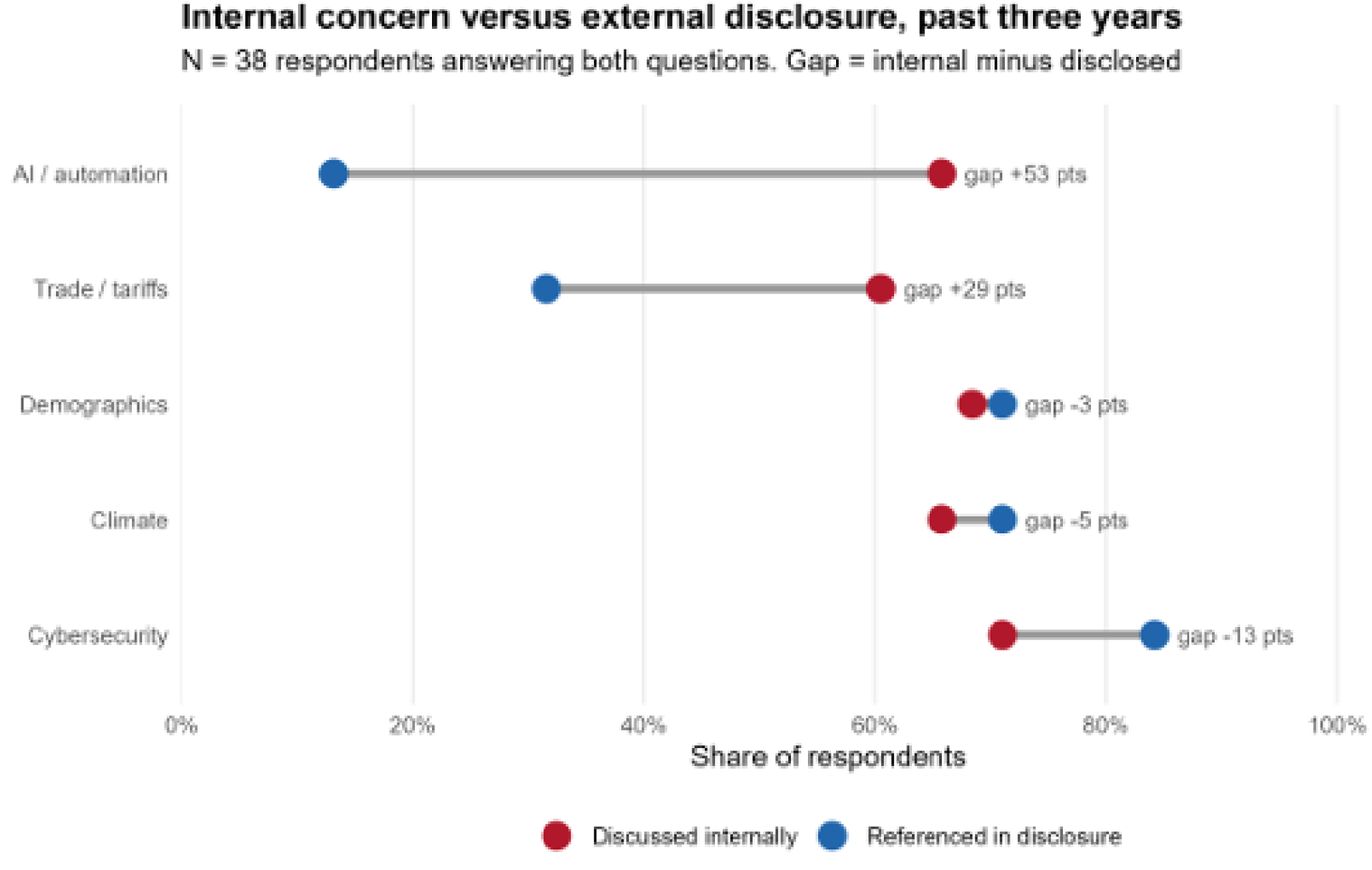
Survey Evidence

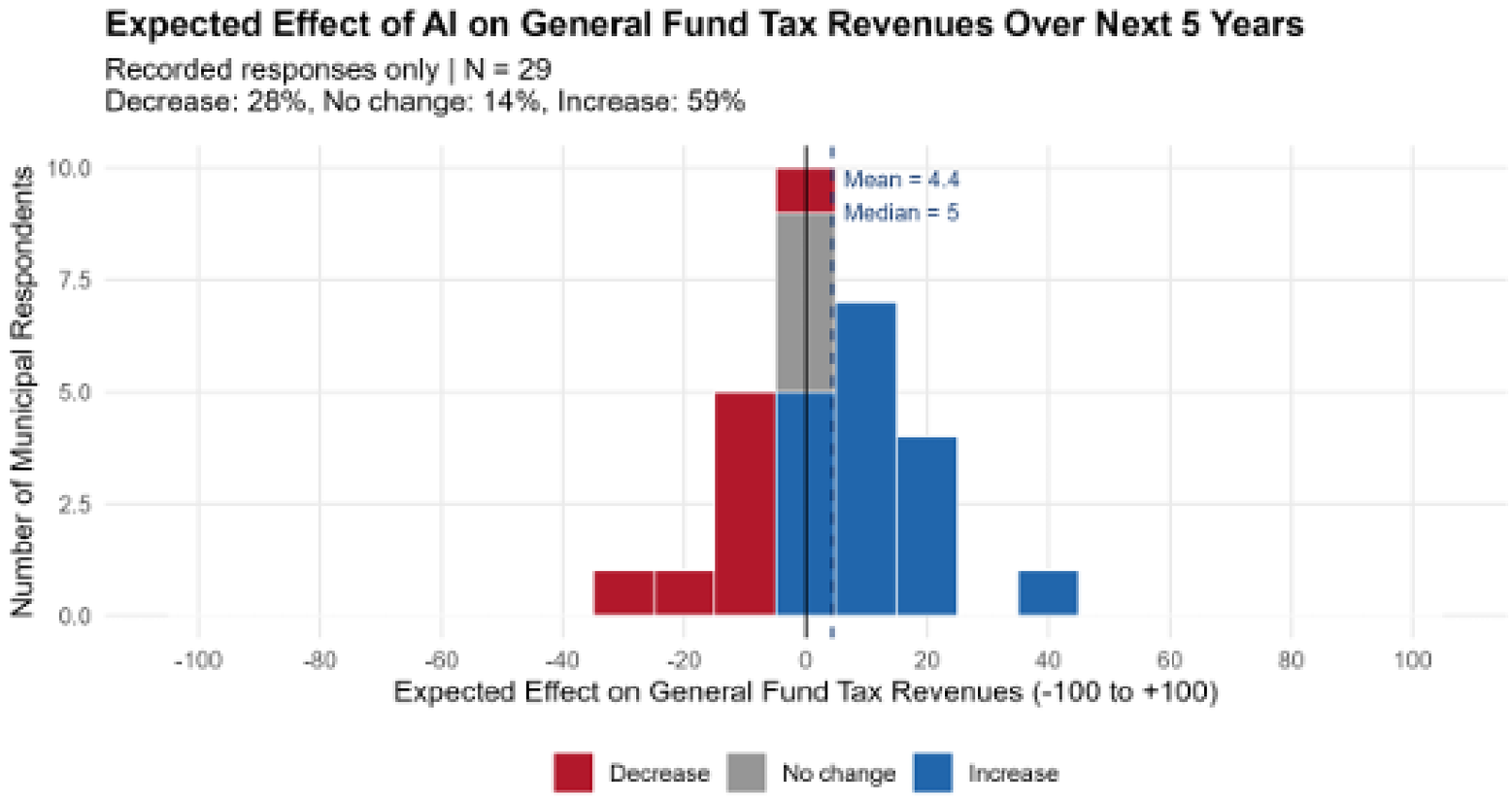
- The muni market reacted strongly to ChatGPT

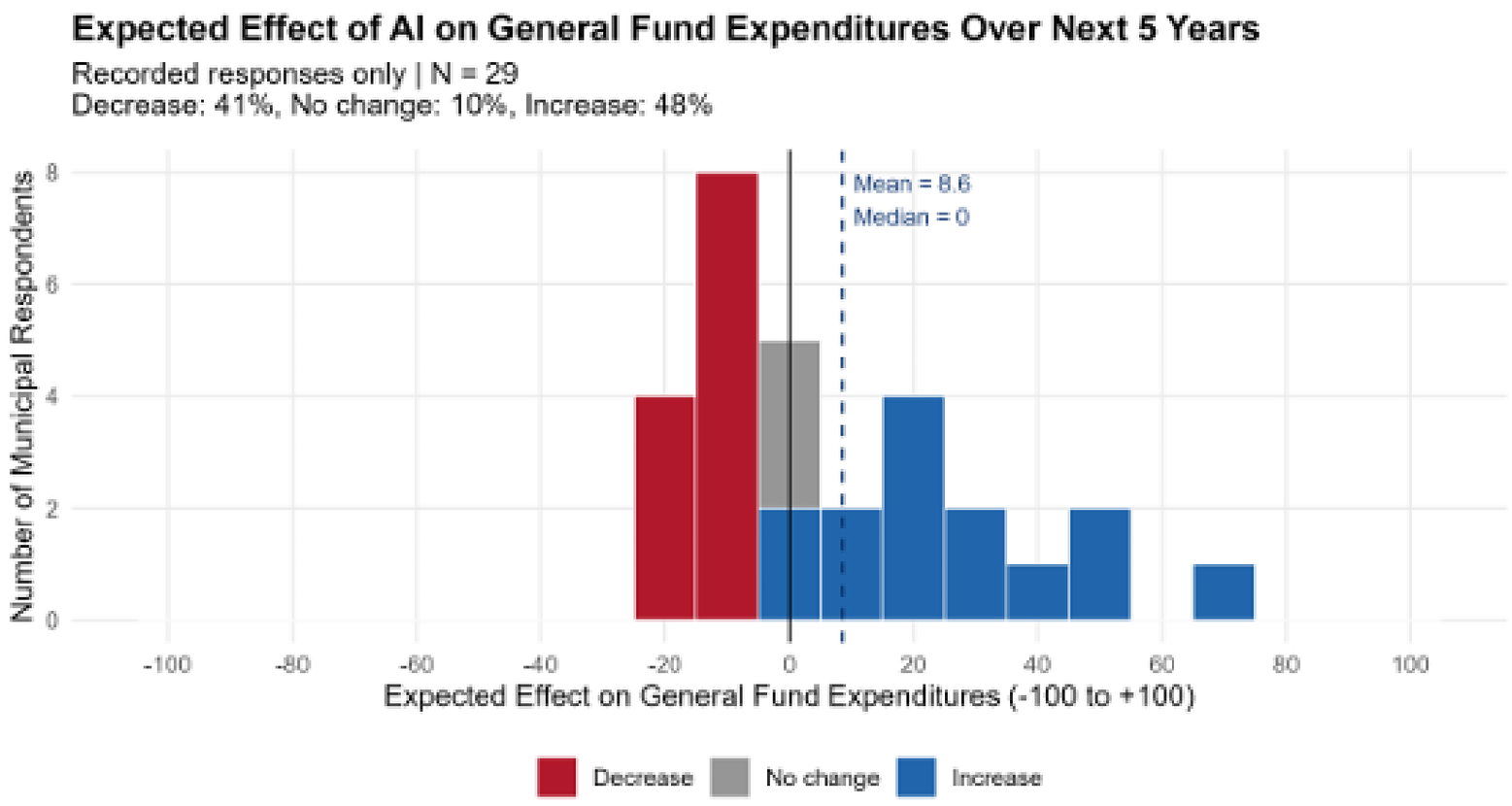
How did local governments respond?

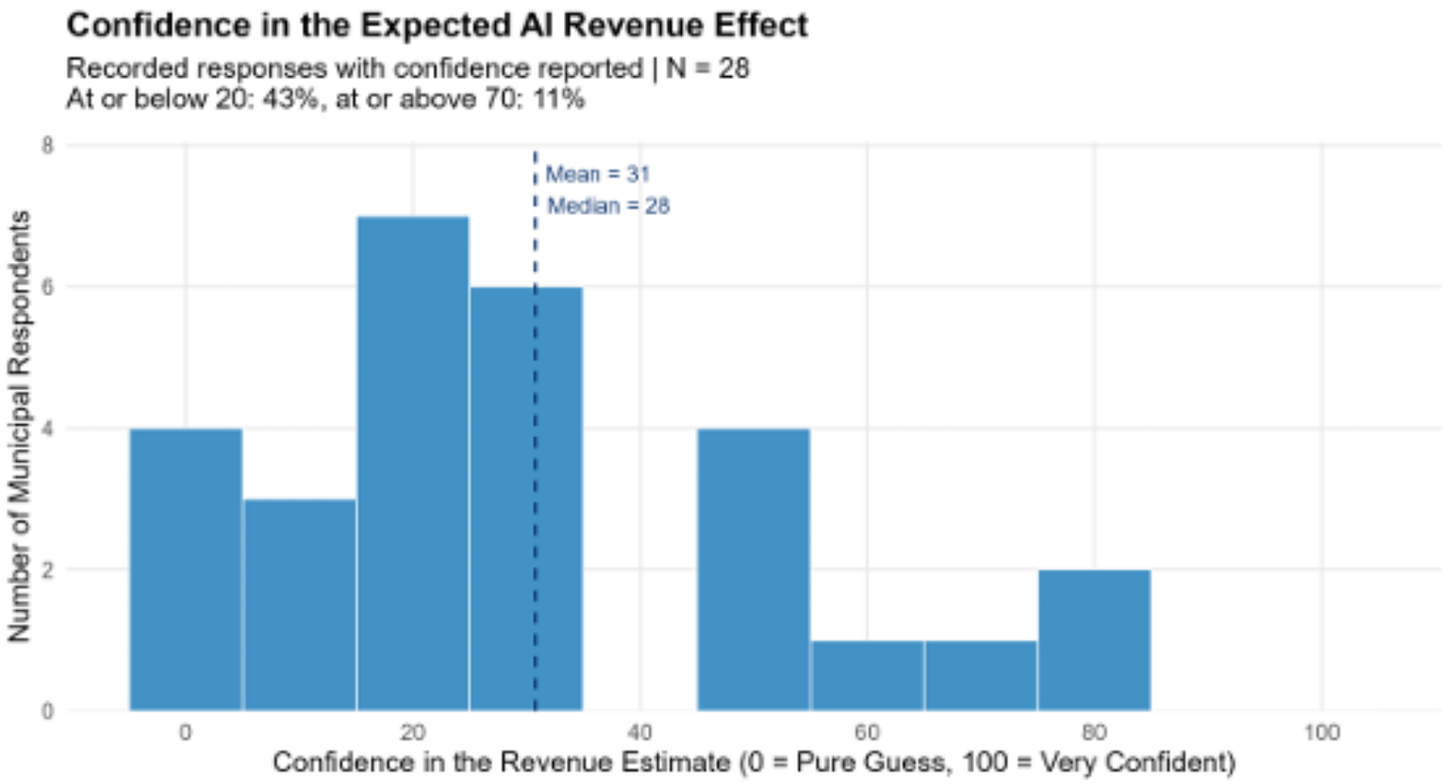
- We surveyed local government finance officers in 150 MSAs from 7/20/2026 to 8/31/2026, and received 44 responses
- We find that local governments are strongly aware of AI, but the anticipated impacts on revenues, expenditures, and employment are absent from public disclosures
- Forecasts of AI's impact on economic outcomes are highly dispersed, as are the confidence levels in those forecasts
- Institutional inertia stems from the high uncertainty

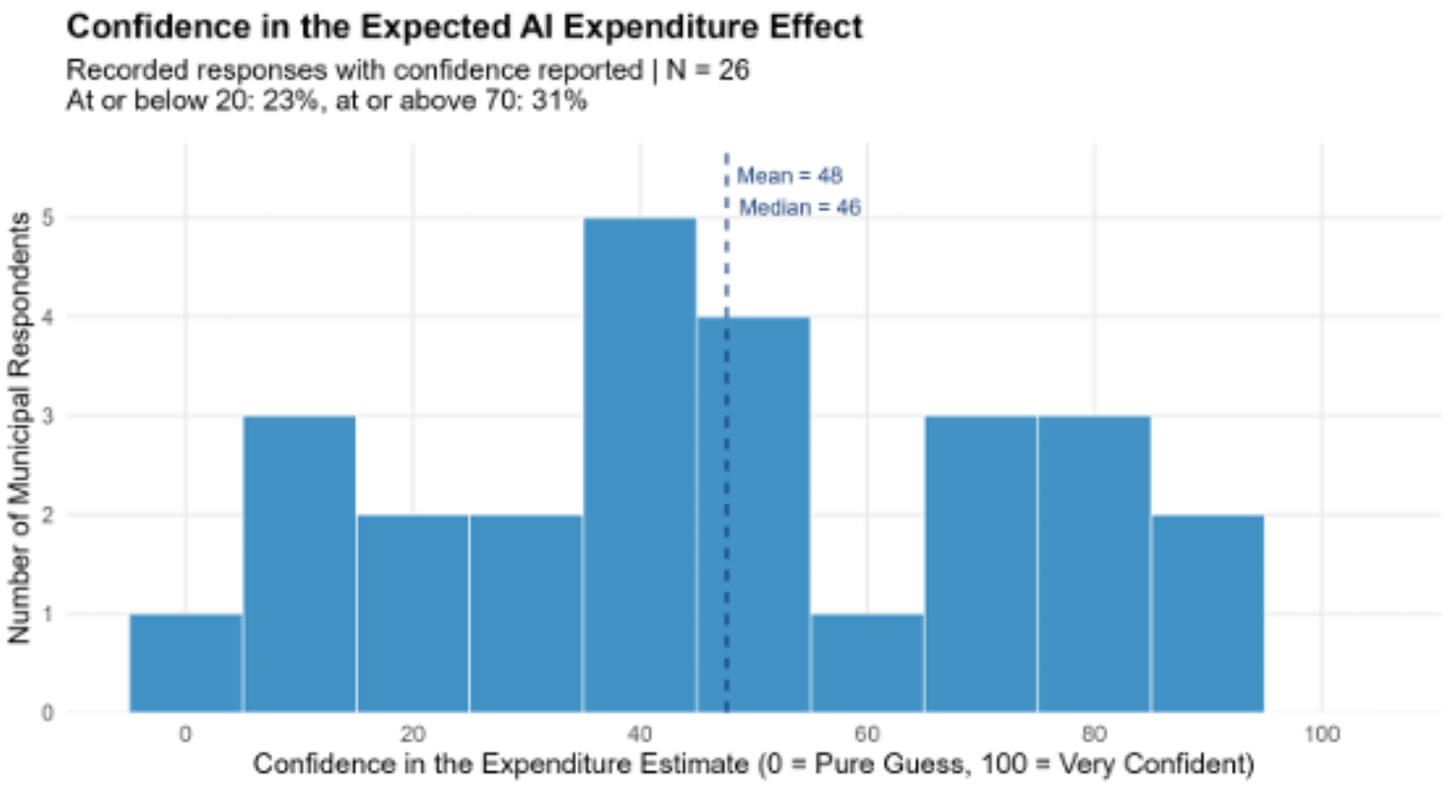

Level of municipal discussion since December 2022
N = 44 municipalities
Climate-related risks
Changes in federal or state transfer programs
Trade policy or tariff
Demographic shifts
Affordable housing and rent assistance
Supply chain disruption
Remote work and telework
Artificial intelligence and automation
0%
25%
50%
75%
100%
Share of respondents
Not discussed
Discussed informally
Discussed in disclosure or investor communicati
Unsure
Discussed in formal planning or forecasting

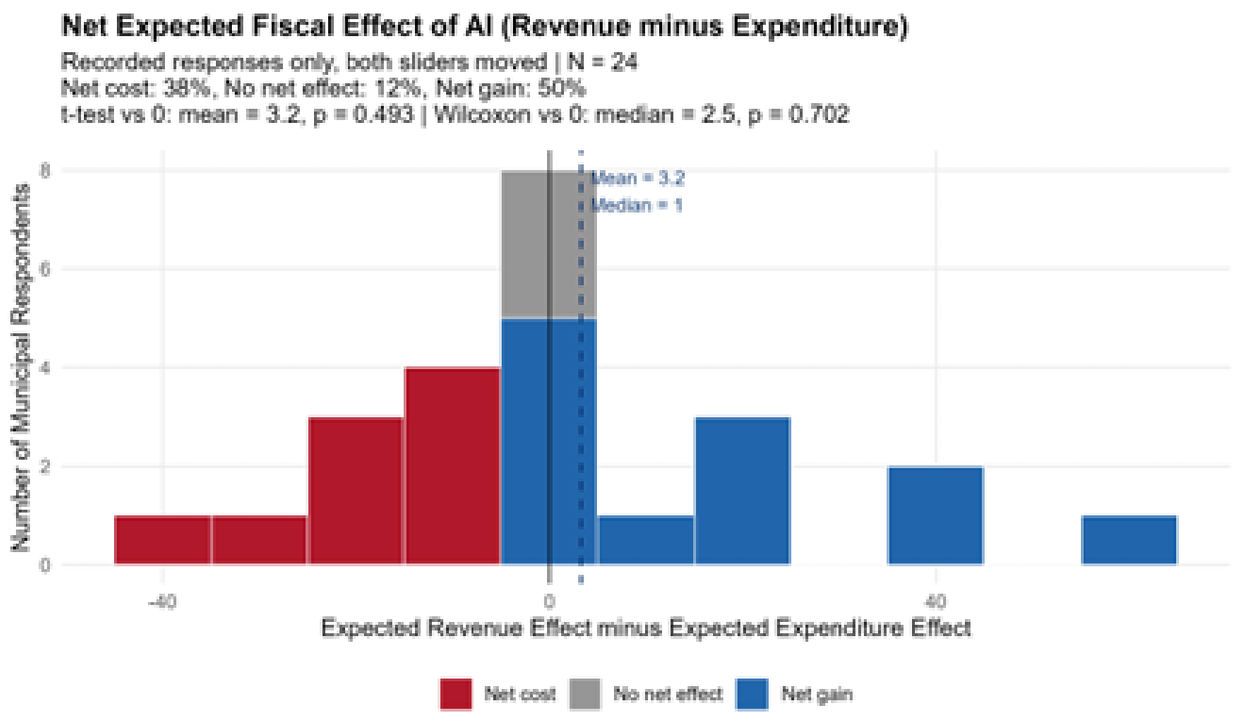

Internal concern versus external disclosure, past three years
N = 38 respondents answering both questions. Gap = internal minus disclosed
AI / automation
gap +53 pts
Trade / tariffs
gap +29 pts
Demographics
gap -3 pts
Climate
gap -5 pts
Cybersecurity
gap -13 pts
0%
20%
40%
60%
80%
100%
Share of respondents
Discussed internally
Referenced in disclosure

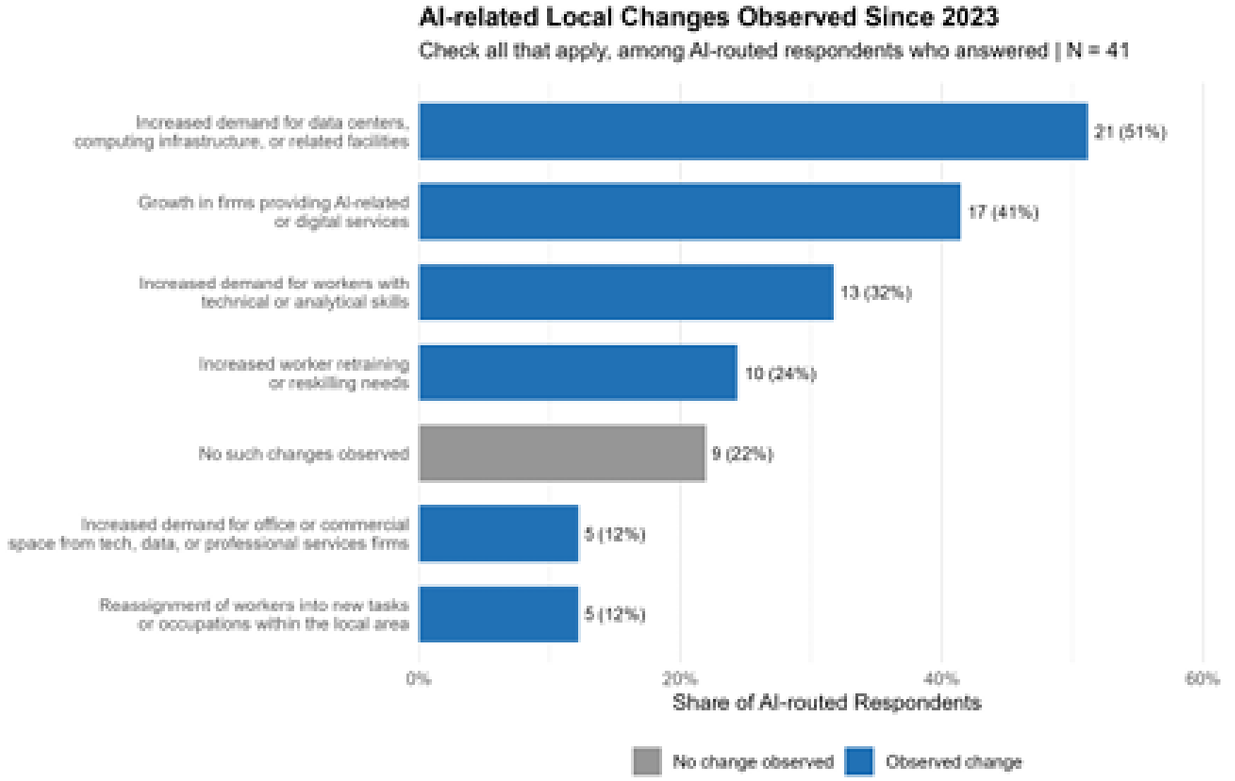

Expected Effect of AI on General Fund Tax Revenues Over Next 5 Years
Recorded responses only | N = 29
Decrease: 28%, No change: 14%, Increase: 59%
Mean = 4.4
Median = 5
Number of Municipal Respondents
10.0
7.5
5.0
2.5
0.0
-100
-80
-60
-40
-20
0
20
40
60
80
100
Expected Effect on General Fund Tax Revenues (-100 to +100)
Decrease
No change
Increase


Expected Effect of AI on General Fund Expenditures Over Next 5 Years
Recorded responses only | N = 29
Decrease: 41%, No change: 10%, Increase: 48%
Mean = 8.6
Median = 0
Number of Municipal Respondents
8
6
4
2
0
-100
-80
-60
-40
-20
0
20
40
60
80
100
Expected Effect on General Fund Expenditures (-100 to +100)
Decrease
No change
Increase


Confidence in the Expected AI Revenue Effect
Recorded responses with confidence reported | N = 28
At or below 20: 43%, at or above 70: 11%
Mean = 31
Median = 28
Number of Municipal Respondents
0
2
4
6
8
0
20
40
60
80
100
Confidence in the Revenue Estimate (0 = Pure Guess, 100 = Very Confident)


Confidence in the Expected AI Expenditure Effect
Recorded responses with confidence reported | N = 26
At or below 20: 23%, at or above 70: 31%
Mean = 48
Median = 46
Number of Municipal Respondents
0
1
2
3
4
5
0
20
40
60
80
100
Confidence in the Expenditure Estimate (0 = Pure Guess, 100 = Very Confident)


Net Expected Fiscal Effect of AI (Revenue minus Expenditure)
Recorded responses only, both sliders moved | N = 24
Net cost: 38%, No net effect: 12%, Net gain: 50%
t-test vs 0: mean = 3.2, p = 0.493 | Wilcoxon vs 0: median = 2.5, p = 0.702
Mean = 3.2
Median = 1
Number of Municipal Respondents
0
2
4
6
8
-40
0
40
Expected Revenue Effect minus Expected Expenditure Effect
Net cost
No net effect
Net gain


AI-related Local Changes Observed Since 2023
Check all that apply, among AI-routed respondents who answered | N = 41
Increased demand for data centers, computing infrastructure, or related facilities
21 (51%)
Growth in firms providing AI-related or digital services
17 (41%)
Increased demand for workers with technical or analytical skills
13 (32%)
Increased worker retraining or reskilling needs
10 (24%)
No such changes observed
9 (22%)
Increased demand for office or commercial space from tech, data, or professional services firms
5 (12%)
Reassignment of workers into new tasks or occupations within the local area
5 (12%)
0%
20%
40%
60%
Share of AI-routed Respondents
No change observed
Observed change

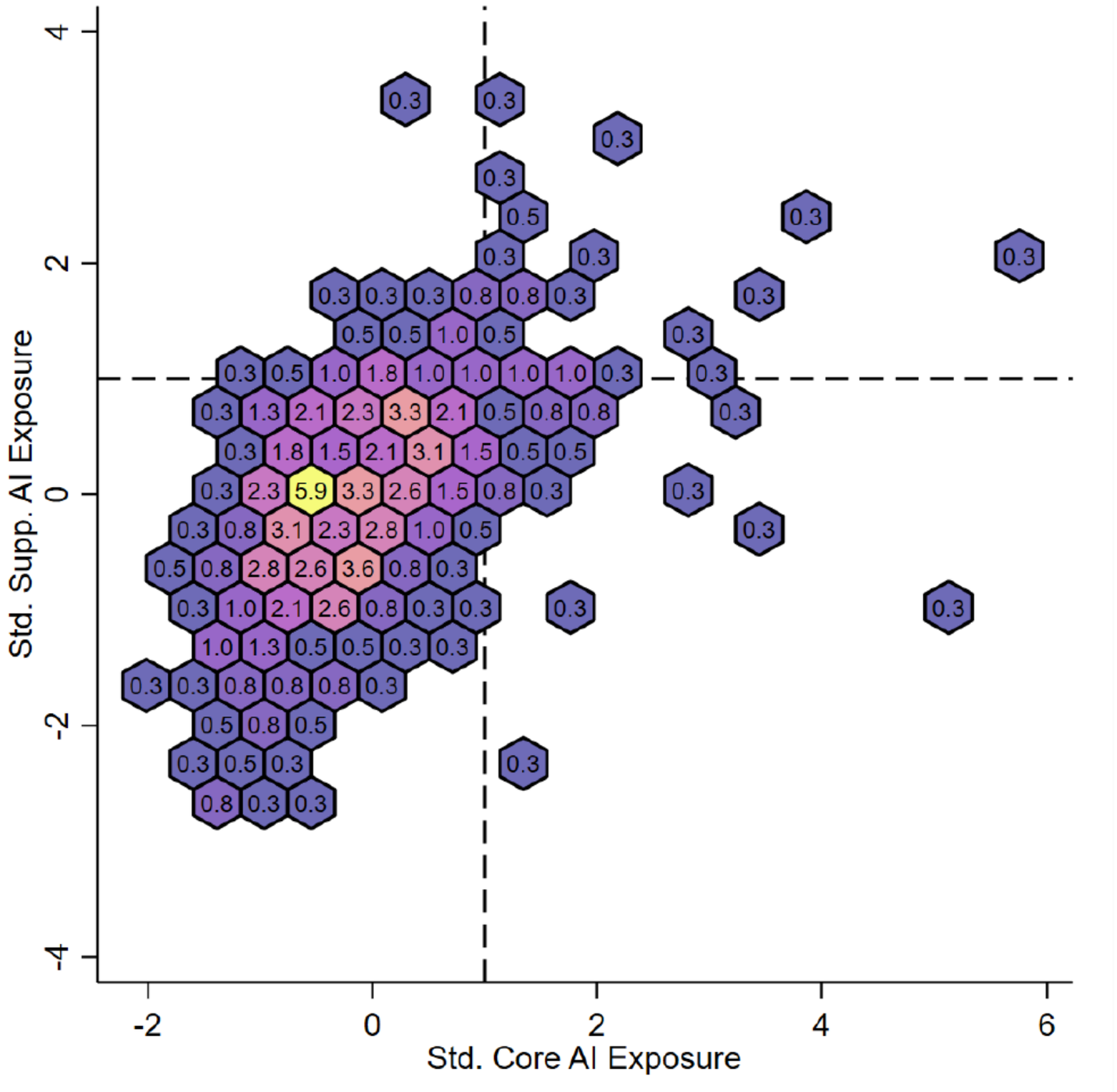
Conclusion

- GenAI has the potential to accelerate MSA productivity through the labor complementarity channel, but also has the potential to increase unemployment through the substitution channel
- Municipal markets recognize the upsides and downsides to GenAI and price the associated bonds accordingly
- We find that a GenAI shock is associated with a significant decrease in the average yield in high AIE MSAs, and significant increases in MSA expected asset value and uncertainty
- These results indicate that the complementarity channel dominates, although market opinions may shift if worries about an AI investment bubble end up being justified
- Policymakers in high-AIE MSAs can reinforce agglomeration benefits by investing in workforce adaptability; policies that support retraining and labor market intermediation help maintain thick labor markets and facilitate task reallocation over displacement

THANKS FOR LISTENING!

SUPPLEMENTAL SLIDES

Core-Supplemental AIE Hexmap



MSAs by Core-Supplemental AIE

Panel A: High Core, High Supplemental AI Exposure

	Core AI Exp.	Supp. AI Exp.	Agg Emp. (M)	Agg. Wage (B)
Austin, TX	0.334	0.117	1.16	73.12
Boulder, CO	0.364	0.109	0.18	14.19
Durham, NC	0.365	0.108	0.28	19.35

Panel B: Low Core, High Supplemental AI Exposure

	Core AI Exp.	Supp. AI Exp.	Agg Emp. (M)	Agg. Wage (B)
Lubbock, TX	0.273	0.105	0.14	6.49
College Station, TX	0.285	0.106	0.11	5.27
Boise City, ID	0.285	0.105	0.35	18.01

Panel C: Low Core, Low Supplemental AI Exposure

	Core AI Exp.	Supp. AI Exp.	Agg Emp. (M)	Agg. Wage (B)
Visalia, CA	0.238	0.082	0.15	8.01
Salinas, CA	0.243	0.083	0.17	9.78
Bakersfield, CA	0.258	0.081	0.31	17.80

Panel D: High Core, Low Supplemental AI Exposure

	Core AI Exp.	Supp. AI Exp.	Agg Emp. (M)	Agg. Wage (B)
San Jose, CA	0.375	0.098	1.10	122.11
Washington, DC	0.363	0.096	3.02	247.27
Trenton, NJ	0.351	0.098	0.23	16.87

Cross-Sectional Tests 1: Sector

	(1) Yield Sp.	(2) Yield Sp.	(3) Yield Sp.	(4) Yield Sp.	(5) Yield Sp.
Post × AI Exp. Q5	-0.099***	-0.046*	-0.055*	-0.017	-0.173***
	(0.024)	(0.024)	(0.027)	(0.055)	(0.044)
Bond FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Sector	Gen. Purpose	Education	Utility	Transportation	Healthcare
Adj. R^2	0.800	0.798	0.767	0.784	0.830
N	292,872	311,580	176,681	71,681	53,163

Cross-Sectional Tests 2: Maturity

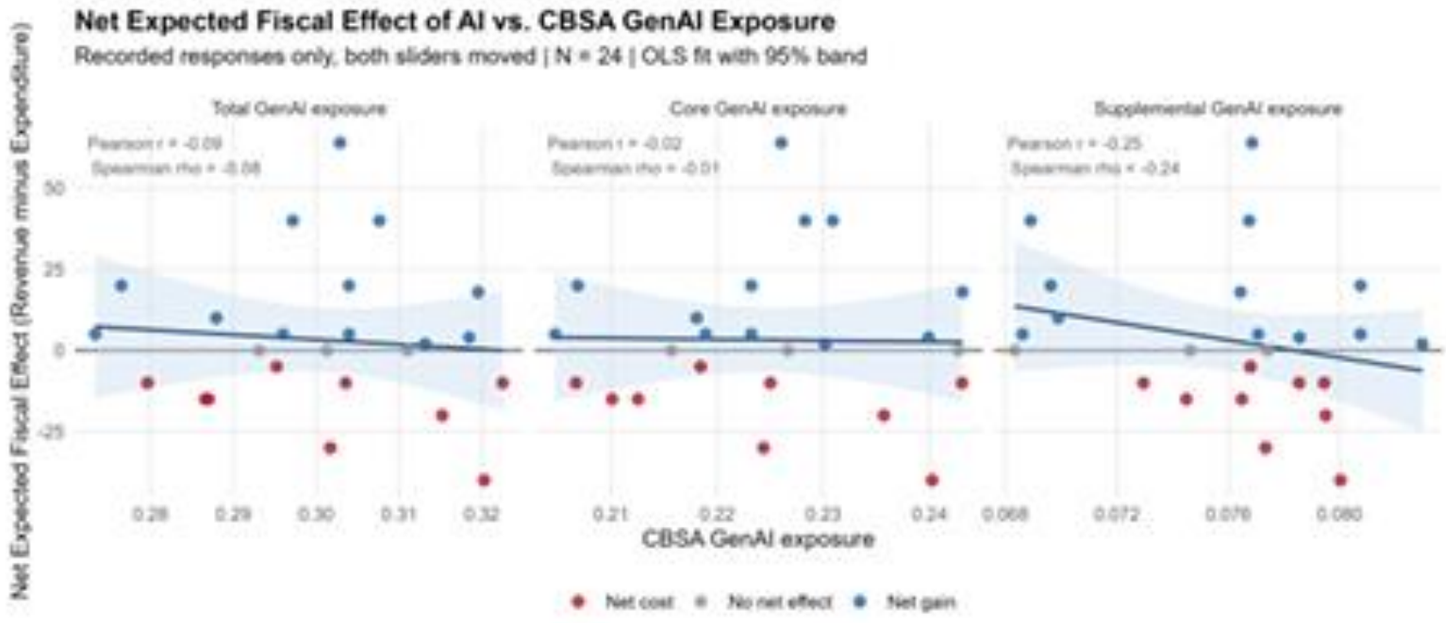
	(1) Yield Sp.	(2) Yield Sp.	(3) Yield Sp.
Post × AI Exp. Q5	-0.046**	-0.080***	-0.081***
	(0.022)	(0.024)	(0.022)
Bond FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Maturity	Low	Medium	High
Adj. R^2	0.647	0.741	0.838
N	320,525	322,329	330,011

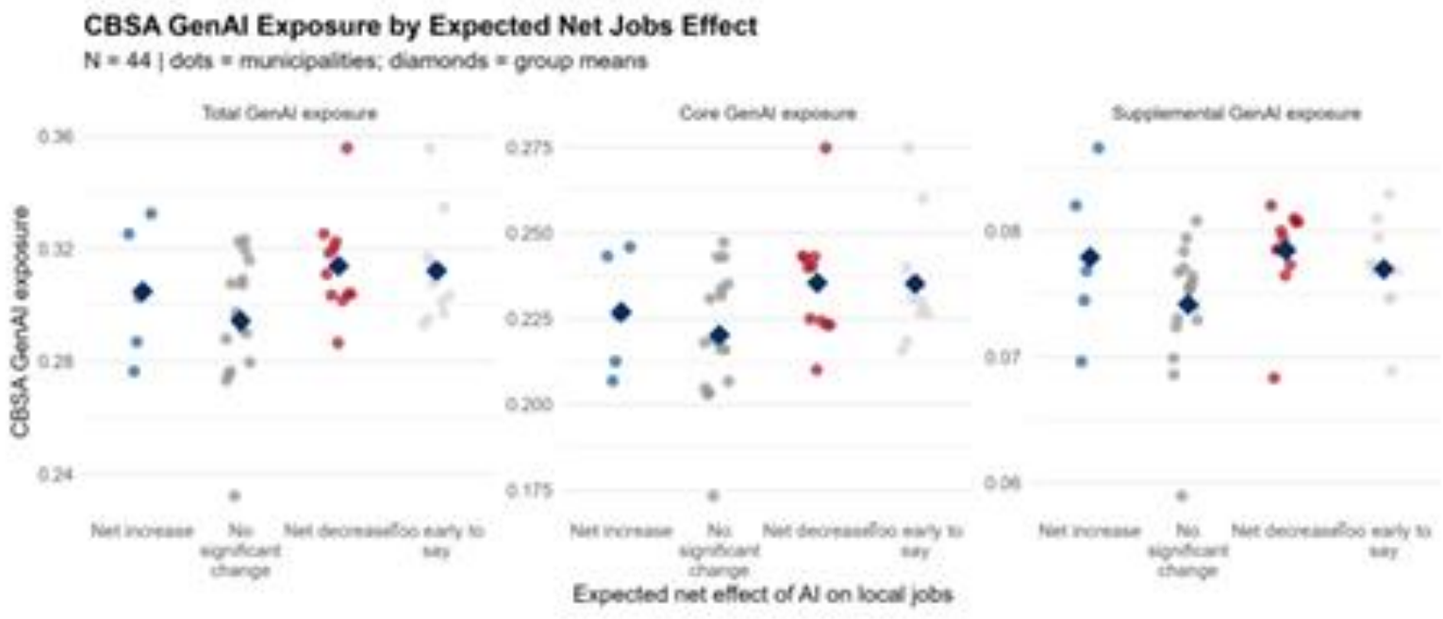
Cross-Sectional Tests 3: Fiscal Stability

	(1) Yield Sp.	(2) Yield Sp.	(3) Yield Sp.	(4) Yield Sp.	(5) Yield Sp.
Post × AIE Q5	-0.056**	-0.059***	-0.063***	-0.071***	-0.065***
	(0.024)	(0.020)	(0.020)	(0.018)	(0.019)
Post × AIE Q5 × σ(GVR)	0.047	0.068***	0.055**	0.054	-0.048***
	(0.028)	(0.017)	(0.026)	(0.034)	(0.002)
Post × σ(GVR)	0.006	-0.011*	-0.003	-0.010*	0.005*
	(0.011)	(0.006)	(0.008)	(0.005)	(0.002)
GVR	Rev/GDP	PRev/GDP	Exp/GDP	Capx/GDP	Rev/Exp
Bond FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.802	0.802	0.802	0.802	0.802
N	967,035	967,035	967,035	967,035	967,035

Robustness Tests

	(1) Yield Sp.	(2) Yield Sp.	(3) Yield Sp.	(4) Yield Sp.	(5) Yield Sp.
Post × AI Exp. Q5	-0.083***	-0.067***	-0.078***	-0.068***	-0.057***
	(0.022)	(0.021)	(0.022)	(0.020)	(0.018)
Post × AI Exp. Q5 × DemVote	0.029				
	(0.019)				
Post × DemVote	0.002				
	(0.015)				
Post × AI Exp. Q5 × NoMTE	0.003				
	(0.037)				
Post × NoMTE	-0.028				
	(0.033)				
Bond FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Sample	All	All	No CA	No NY	No MA
Adj. R^2	0.802	0.802	0.803	0.802	0.802
N	840,558	984,601	893,789	984,601	907,738


Net Expected Fiscal Effect of AI vs. CBSA GenAI Exposure
Recorded responses only, both sliders moved | N = 24 | OLS fit with 95% band
Total GenAI exposure
Core GenAI exposure
Supplemental GenAI exposure
Pearson r = -0.09
Spearman rho = -0.08
Pearson r = -0.02
Spearman rho = -0.01
Pearson r = -0.25
Spearman rho = -0.24
Net Expected Fiscal Effect (Revenue minus Expenditure)
50
25
0
-25
0.28
0.29
0.30
0.31
0.32
0.21
0.22
0.23
0.24
0.068
0.072
0.076
0.080
CBSA GenAI exposure
Net cost
No net effect
Net gain


CBSA GenAI Exposure by Expected Net Jobs Effect
N = 44 | dots = municipalities; diamonds = group means
Total GenAI exposure
Core GenAI exposure
Supplemental GenAI exposure
CBSA GenAI exposure
0.36
0.32
0.28
0.24
0.275
0.250
0.225
0.200
0.175
0.08
0.07
0.06
Net increase
No significant change
Net decrease
Too early to say
Expected net effect of AI on local jobs