

The Fracture Line: Firm Size, Digital Infrastructure, Industry Structure and the Geography of Artificial Intelligence Adoption among U.S. Employer Businesses

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Abstract

Purpose. Federal statistics on business ownership, broad band connectivity, workforce skills and the adoption of artificial intelligence (AI) are generated and analyzed independently. This study asks whether the disadvantages they record co-locate in the same firms, sectors and places, a pattern we call a “fracture line”, and which structural factors explain why AI adoption differs across U.S. states.

Methodology. Based on the technology–organisation–environment (TOE) framework and the digital-divide theory, a state-level dataset (50 states and the District of Columbia) is constructed using data from the Business Trends and Outlook Survey (BTOS) of the Census Bureau, the American Community Survey, the Annual Business Survey, County Business Patterns and BLS payroll data. The analysis has four parts: (i) inverse-variance-weighted tests of the national firm-size gradient from the BTOS AI Supplement (November 2025–February 2026); (ii) a shift-share decomposition separating industry-mix from within-industry effects; (iii) OLS models with HC3 robust errors and five robustness checks; and (iv) spatial diagnostics (Moran’s I and a spatial lag model).

Findings. AI adoption is flat among firms with 1–19 employees (slope $p = .35$) and rises sharply from 20 employees (slope change = 4.47 points, $p = .002$). The gap separating micro firms from those with 250+ employees is 13.0 points in current use and 19.2 points in planned use. Across states, adoption ranges from 10.8% to 23.2%. Industry mix explains only 12–19% of that variation; the remaining four-fifths arises within industries. Household broadband subscription is the most robust correlate of adoption (about 1.7 points per standard deviation) in every specification and in an independent replication window. Ownership composition has no independent association, which supports a compositional rather than a constraint-based “double divide”. Five disadvantage indicators co-locate strongly (Cronbach’s $\alpha = .83$), and their composite correlates $-.55$ with AI adoption.

Originality/value. This is the first study to combine these federal programmes in a formal test of whether digital disadvantages co-locate. It shows that the AI divide among firms has a threshold rather than a linear shape, that it is mainly a within-industry phenomenon, and that among the measured place-level conditions it follows digital access most closely. Each of these findings points to a different policy lever.

Keywords: Artificial Intelligence Adoption; Digital Divide; Small Business; Broadband; TOE Framework; Shift-Share; United States **JEL Codes:** O33; L25; R12; J15.

I. INTRODUCTION

Generative and predictive AI are spreading across the business sector faster than any general-purpose technology before them, yet the spread is uneven. Early federal evidence shows that AI use is concentrated in large, young and technology-intensive firms and in a handful of “superstar” metropolitan areas (McElheran et al., 2024; Bonney et al., 2024). When a general-purpose technology is adopted unevenly, the gap is significant, lagging adopters may become more disadvantaged, while early-adopting businesses and regions benefit from complementing investments and productivity gains (Brynjolfsson et al., 2021; Forman et al., 2005). Understanding the regions where AI dissemination is weakest and why is therefore crucial for small businesses, the workforce, and regional policy.

For example, U.S. statistical authorities have begun to release comprehensive but separate data on the conditions for adoption. The Annual Business Survey (ABS) provides information on the number of people who own businesses and in which sectors while the American Community Survey (ACS) provides data on education and broadband in households. The National Center for Science and Engineering Statistics (NCSES) tracks who works in science and engineering. Since 2023, the Business Trends and Outlook Survey (BTOS) has measured AI use directly. Because these programmes are released and studied independently, the literature has not tested whether the negative correlations they find are redundant, that is, whether the states with low rates of broadband adoption, many small firms and industries that are resistant towards new technologies are also the states that are slow to adopt AI. This means that if there is overlap, national programmes with a “one size fits all” approach will be most effective in the places that need them the least. In contrast, if there is no overlap, then single-channel programmes (e.g., only broadband or only skills) may be sufficient.

This paper tests this “fracture line” claim directly. It asks three research questions:

- RQ¹. What shape does the relationship between firm size and AI adoption take, and does it rise steadily with size or jump at a threshold?
- RQ². How much of the cross-state variation in AI adoption is due to differences in industry mix, and how much to within-industry differences?
- RQ³. Once industry mix and firm-size structure are accounted for, are digital infrastructure, human capital and business-ownership composition independently associated with state AI adoption, and do these disadvantages cluster geographically?

Three contributions are made in this study. First, it presents the AI size gap as a threshold. According to the latest BTOS AI Supplement, adoption of AI remains stagnating in companies with fewer than 20 people and rapidly increases at that size demarcation. This supports an increasing body of research showing that adoption simply tends to rise with size (Zolas et al., 2020; McElheran et al., 2024) and implies the absence of fixed adoption costs and some complimentary capabilities. Second, it employs a shift-share decomposition to examine the adoption of AI at the state level and finds that roughly four-fifths of regional variance occurs within industries; the portion that place-based policy may affect. Household broadband is the most reliable place-level factor. Third, it challenges the “double divide” presumption: the assertion that minority and women-owned business industries are experiencing a dual AI disadvantage. Once sector, scale and infrastructure are controlled for, ownership composition carries no independent information, and the paper is explicit about the limits of ecological inference (Robinson, 1950).

The rest of the paper is organised as follows. Section 2 reviews the theory and prior evidence and develops the hypotheses. Section 3 describes the data and methods. Section 4 presents the results, and Section 5 discusses implications for theory and policy and sets out agency-specific recommendations. Section 6 sets out the limitations, and Section 7 concludes.

II. THEORETICAL BACKGROUD AND HYPOTHESES

2.1 The Technology Organisation Environment (TOE) framework

The Technology Organisation Environment (TOE) framework (Tornatzky & Fleischer, 1990) holds that whether a firm adopts an innovation depends on three things: the technology’s characteristics, the organisation’s resources and structure, and the environment it operates in. The framework is widely used for firm-level adoption of information technology (Oliveira & Martins, 2011) and, more recently, of AI (Chatterjee et al., 2021; Kinkel et al., 2022). This study works with aggregate data, so it uses TOE as an organising lens rather than a firm-level behavioural model. Organisational factors appear as the size distribution of a state’s firms. Environmental factors appear as digital infrastructure, local human capital and industry structure. Diffusion theory (Rogers, 2003) adds that adoption spreads through networks of information and imitation, which implies spatial dependence: states next to high-adoption states may adopt more themselves.

2.2 Firm size and the adoption threshold

Firm size is one of the most consistent predictors of technology adoption. Larger firms spread the fixed costs of adoption (data infrastructure, integration and specialised staff) over more output, and they are more likely to have the managerial practices and data assets that complement digital technologies (Bloom et al., 2012; Brynjolfsson et al., 2021). Evidence from the ABS technology module shows that use of advanced technologies, including AI, is heavily skewed towards large firms (Zolas et al., 2020; Acemoglu et al., 2022). BTOS evidence shows the same pattern for current AI use (Bonney et al., 2024). Fixed-cost and complementarity arguments, however, predict a *threshold* rather than a straight line. Below a certain scale, firms lack the specialised roles (an IT function, data staff) that make AI integration possible, so adoption among the very smallest firms should be similarly low and flat. Above the threshold it should rise steeply.

H1. The relationship between firm size and AI adoption is nonlinear: adoption is flat among the smallest size classes and increases significantly above a size threshold.

2.3 Industry structure

How useful AI is depends heavily on the task content of an industry. Information, professional services and finance work with codified information and adopt at high rates, whereas construction, accommodation and food services, and agriculture rely on physical and interpersonal tasks (McElheran et al., 2024; Bonney et al., 2024). Industries are spread unevenly across space, so a state's AI adoption partly reflects its industrial mix. The shift-share tradition in regional analysis (Dunn, 1960) separates this compositional component from a within-industry ("competitive" or local) component. Only the second can plausibly be changed by place-based policy.

H2. State AI adoption is positively associated with the adoption rate implied by the state's industry mix, and industry mix accounts for a substantial share of cross-state variation.

2.4 Digital infrastructure and human capital

Digital-divide theory distinguishes a first-level divide in physical and material access from a second-level divide in skills and usage (Hargittai, 2002; van Deursen & van Dijk, 2019). For businesses, broadband serves as the essential input for cloud-based AI services, and rural broadband shortages are associated with slower local economic growth (Whitacre et al., 2014). While access is necessary, it is not enough, as adoption also depends on workers and managers who can identify where AI is relevant and apply it, which is roughly indicated by local tertiary educational attainment. Forman et al. (2005) show that during internet diffusion, advanced business uses concentrated in places rich in complementary skills and infrastructure.

H3a. State AI adoption is positively associated with broadband connectivity.

H3b. State AI adoption is positively associated with human capital (tertiary educational attainment).

2.5 Business ownership composition: the "double divide"

A large literature documents that minority-owned firms face tighter capital constraints, smaller networks and fewer inherited business assets, and that these differences limit scale and growth (Fairlie & Robb, 2008). Similar constraints could limit technology investment, which predicts a compounding "double divide". An alternative explanation is compositional: minority- and women-owned firms are concentrated in particular sectors and size classes, so differences in adoption may reflect *where* firms operate rather than *who* owns them. These explanations make different predictions in state-level data. The constraint explanation predicts that ownership composition remains negatively associated with AI adoption after controlling for sector mix, size structure and infrastructure. The compositional explanation predicts that the association weakens towards zero. We state both as competing hypotheses.

H4a (constraint). The minority-owned (women-owned) share of employer firms is negatively associated with state AI adoption, net of industry mix, size structure and infrastructure.

H4b (composition). Once industry mix, size structure and infrastructure are controlled for, ownership composition has no independent association with state AI adoption.

2.6 Co-location of disadvantage

The overarching proposition of the paper is that these disadvantages are not independent: they co-locate in the same states and cluster across neighbouring states.

H5. Indicators of digital disadvantage (low broadband connectivity, low human capital, small establishment scale, a low-adoption industry mix and low population density) are positively correlated across states, and AI adoption is spatially autocorrelated.

III. DATA AND METHODS

3.1 Data sources

The analysis matches five public federal data products to the 50 states and the District of Columbia (N = 51). Table 1 lists the variables, their definitions and their sources.

AI adoption. The dependent variable comes from the U.S. Census Bureau's Business Trends and Outlook Survey (BTOS). BTOS is a biweekly survey of a sample of approximately 1.2 million single-unit employer businesses, excluding farms (Bonney et al., 2024). Since the December 2025 questionnaire revision, BTOS has asked whether a business used AI "in any of its business functions" in the previous two weeks. The primary measure is the state share of employer businesses answering "yes", averaged over the six biweekly releases published between 15 January and 26 March 2026 (Visual Capitalist, 2026). This window overlaps the end of the AI Supplement collection (17 November 2025–8 February 2026). Averaging six releases reduces the sampling noise of any single biweekly state estimate. For replication, a second, non-overlapping six-release average (18 May–9 August 2026; Keyhole Software, 2026) is used as an alternative dependent variable. The two measures correlate at $r = .83$ across states. National estimates by employment-size class and two-digit NAICS sector, with their standard errors, come from the BTOS AI Supplement (U.S. Census Bureau, 2026a).

Digital infrastructure, human capital and income. American Community Survey (ACS) 5-year estimates for 2020–2024 (U.S. Census Bureau, 2026b): the percentage of households with a broadband internet subscription; the percentage of adults aged 25+ holding a bachelor's degree or higher; and median household income.

Business ownership. Annual Business Survey (ABS), reference year 2023 (U.S. Census Bureau, 2026b): counts of minority-owned, nonminority-owned, women-owned and men-owned employer firms. The minority-owned share is $\text{minority} / (\text{minority} + \text{nonminority})$. The women-owned share is $\text{women} / (\text{women} + \text{men})$, which excludes equally owned and unclassifiable firms. Kentucky's women-owned count is suppressed for not meeting publication standards, so models that include the women-owned share use $N = 50$.

Establishment size. County Business Patterns (CBP) 2023: total employer establishments and total employment, from which we compute mean establishment size (employees per establishment). We use this measure in place of a micro-firm share because enterprise-size distributions by state are not available in a form that can be harmonised with the other sources. Mean establishment size captures the same organisational-scale dimension.

Industry mix. Bureau of Labor Statistics (BLS) Current Employment Statistics, State Employment and Unemployment release of 18 September 2026, Table 3 (seasonally adjusted, August 2026 preliminary): nonfarm payroll employment by state in seven private supersectors plus government (Bureau of Labor Statistics, 2026). Private employment in mining and logging, information and other services is obtained as a residual. As a validation check, this residual lies between 4.6% and 11.6% of total employment in every state.

Rurality. We measure rurality with population density from the 2020 Decennial Census (persons per square mile, log-transformed).

3.2 Measures

Industry-implied AI adoption. For each state, the adoption rate expected from its industry mix alone is

$$E_s = \sum_k w_{sk} \cdot A_k,$$

where w_{sk} is supersector k 's share of the state's private employment and A_k is the national BTOS AI Supplement adoption rate for the corresponding sector. The supersector rates use the dominant two-digit sector in each supersector:

- construction: 9.2%
- manufacturing: 12.4%

- Trade, Transportation And Utilities: 12.6% (The Retail Trade Rate)
- Financial Activities: 30.4% (The Finance And Insurance Rate)
- Professional And Business Services: 34.2% (The Professional, Scientific And Technical Services Rate)
- Education And Health: 20.7% (The Health Care Rate)
- Leisure And Hospitality: 8.0% (The Accommodation And Food Services Rate)
- The Residual Group: 17.9% (The National Average)

E_s is the adoption a state would have if every one of its sectors adopted AI at the national rate for that sector. Because the supersector mapping is approximate, we also use a second, assumption-free measure: the knowledge-intensive employment share, defined as financial activities plus professional and business services as a percentage of private employment.

Shift-share decomposition. Each state's adoption rate is split into an industry-mix component and a within-industry (local) component, both expressed as deviations from their cross-state means:

$$A_s = E_s + (A_s - E_s), \text{ so that } \text{Var}(A_s) = \text{Var}(E_s) + \text{Var}(A_s - E_s) + 2\text{Cov}(E_s, A_s - E_s).$$

The mix component reflects industrial structure. The local component reflects every other place-specific influence (infrastructure, skills, organisational scale and diffusion), and these are the influences place-based policy can reach (Dunn, 1960).

3.3 Estimation

Firm-size gradient (H1). We model the seven national size-class estimates with weighted least squares (WLS), weighting each class by $1/SE^2$. The regressor is the log of the size-class midpoint. A piecewise term lets the slope change at the 20–49 class. Adjacent classes are compared with two-sided z-tests based on the published standard errors. At state level, H1 corresponds to the coefficient on mean establishment size.

State models (H2–H4). We estimate

$$A_s = \alpha + \beta_1 E_s + \beta_2 \text{EstabSize}_s + \gamma_1 \text{Broadband}_s + \gamma_2 \text{Tertiary}_s + \delta_1 \text{Minority}_s + \delta_2 \text{Women}_s + \theta' \text{Ctrl}_s + \varepsilon_s$$

by OLS with HC3 heteroskedasticity-robust standard errors, which behave well in small samples (Long & Ervin, 2000). Predictors are standardised, so each coefficient is the percentage-point change in AI adoption associated with a one-standard-deviation

increase in the predictor. Blocks are entered in sequence:

- M1: structure (industry mix and establishment size)
- M2: adds infrastructure and human capital
- M3: adds ownership composition
- M4: adds log density and log median income

M0 includes ownership composition alone, to show its unconditional association with adoption. Because $N = 51$, we report variance inflation factors (VIFs) and read coefficients through their confidence intervals.

Robustness. The full model is re-estimated in five ways:

1. Without The District Of Columbia;
2. Without High-Influence States (Cook's $D > 4/N$);
3. With Knowledge-Intensive Employment Share In Place Of E_s ;
4. With The May–August 2026 Adoption Measure As The Dependent Variable;
5. The Parsimonious M2 Specification Without DC.

Spatial dependence and co-location (H5). For the 48 contiguous states and DC, we compute global Moran's I using a row-standardised queen-contiguity matrix with 9,999 permutations. We compute it for AI adoption, for the industry-mix and local components, and for the residuals of the full model. A maximum-likelihood spatial lag model (Anselin, 1988) tests whether diffusion between neighbouring states changes the substantive results.

To test whether disadvantages co-locate, we standardise five indicators: low broadband subscription, low tertiary attainment, small mean establishment size, low industry-implied adoption, and low population density. We then examine their correlation matrix, the variance explained by the first principal component and Cronbach's α . The mean of the five standardised indicators forms a composite fracture index.

3.4 Unit of analysis and ecological inference

All state-level relationships are ecological. Whether states with more minority-owned firms adopt more or less AI says nothing direct about whether minority-owned firms themselves adopt more or less (Robinson, 1950). H4 is therefore interpreted strictly as a test of whether ownership composition carries information about state adoption beyond industry mix, scale and infrastructure. It is not a test of how individual owners behave.

Table 1. Variables, definitions and sources

Variable	Definition	Source (period)
AI adoption	% of employer businesses using AI in any business function, mean of six biweekly state estimates	BTOS (15 Jan–26 Mar 2026)
AI adoption (replication)	As above	BTOS (18 May–9 Aug 2026)
Industry-implied adoption	$\sum_k w_{sk} A_k$; employment-weighted national sector AI rates	BLS CES (Aug 2026); BTOS AI Supplement
Knowledge-intensive share	Financial activities + professional and business services, % of private employment	BLS CES (Aug 2026)
Mean establishment size	Employees per employer establishment	CBP (2023)
Broadband	% of households with a broadband internet subscription	ACS 5-year (2020–2024)
Tertiary attainment	% of adults 25+ with a bachelor's degree or higher	ACS 5-year (2020–2024)
Minority-owned share	Minority-owned / (minority + nonminority) employer firms, %	ABS (2023)
Women-owned share	Women-owned / (women + men-owned) employer firms, %	ABS (2023)
Population density (log)	$\ln(\text{persons per square mile})$	Decennial Census (2020)
Median income (log)	$\ln(\text{median household income})$	ACS 5-year (2020–2024)

Authors' Compilation, (2026).

IV. RESULTS

4.1 Descriptive overview

Table 2 reports descriptive statistics. In January–March 2026, state AI adoption averaged 17.3% of employer businesses. It ranged from 10.8% in West Virginia to 23.2% in Colorado, a spread of more than four standard deviations. Adoption rose between the two measurement windows: the May–August 2026 mean was 20.8%. The ranking of states stayed stable, however: the two measures correlate at $r = .83$. Broadband subscription varies over a narrow range (84.1%–93.6%), yet it is the variable most strongly correlated with AI adoption ($r = .67$; Figure 2). Tertiary attainment ($r = .51$), median income ($r = .54$) and knowledge-intensive employment ($r = .62$) are also positively correlated with adoption.

The two ownership measures are *positively* correlated with AI adoption: $r = .34$ for the minority-owned share and $r = .31$ for the women-owned share. This is the opposite of what a simple “double divide” would predict.

Table 2. Descriptive statistics (States and DC)

Variable	N	Mean	SD	Min	Max
AI adoption, Jan–Mar 2026 (%)	51	17.31	2.86	10.80	23.20
Industry-implied adoption	51	18.26	0.99	16.31	22.28
Knowledge-intensive share	51	21.79	3.90	14.85	36.21
Mean establishment size	51	16.10	2.54	8.89	23.47
Broadband subscription	51	90.44	2.09	84.10	93.60
Tertiary attainment	51	35.25	6.80	24.10	64.20
Minority-owned share	51	18.58	11.38	4.43	62.10
Women-owned share	50	26.38	3.03	20.86	35.09

Population density (log)	51	4.65	1.54	0.26	9.33
Median income (log)	51	11.28	0.16	10.94	11.61
AI adoption, May–Aug 2026 (%)	51	20.77	3.61	14.10	32.00

Authors' Computation, (2026). Note. Income and density are in natural logs (mean of state median household income = \$80,412; median density $\approx$ 109 persons per sq. mi.).

4.2 The firm-size threshold (H1)

Figure 1 and Table 3 show that the national firm-size gradient is not monotonic. Current AI use in the three smallest size classes cannot be statistically distinguished: 17.6%, 17.0% and 17.2%. The 1–4 versus 5–9 contrast is -0.6 points ($z = -1.62$, $p = .106$), and the 5–9 versus 10–19 contrast is $+0.2$ points ($p = .682$). The inverse-variance-weighted slope across these classes is effectively zero ($p = .349$).

From the 20–49 class onward, each successive step is significant: $+1.3$, $+2.8$, $+4.0$ and $+5.3$ points, all with $p < .01$. At the threshold, the piecewise model predicts a slope shift of $+4.47$ points/log size ($SE = 0.58$, $p = .002$). Planned use shows a greater difference and the same form. It is 13.0 points for current use and 19.2 points for anticipated use for businesses ranging from micro to 250+. As a result, H1 is endorsed nationally; the size division is a threshold rather than a slope.

In state levels, average establishment size shows no clear relationship with adoption in any model. Estimates range from -0.12 to $+0.52$, and all p -values exceed .2 (Tables 5–6). There are two possible reasons. First, every state except DC has an average establishment size below the national threshold of roughly 20 employees; state averages range from 8.9 to 23.5. The number of enterprises above the threshold, when the breadth of adoption variance starts, is unlikely to be indicated by these averages. Second, variations in adoption within a state may be influenced by size. That latter point will be revisited in section 5.

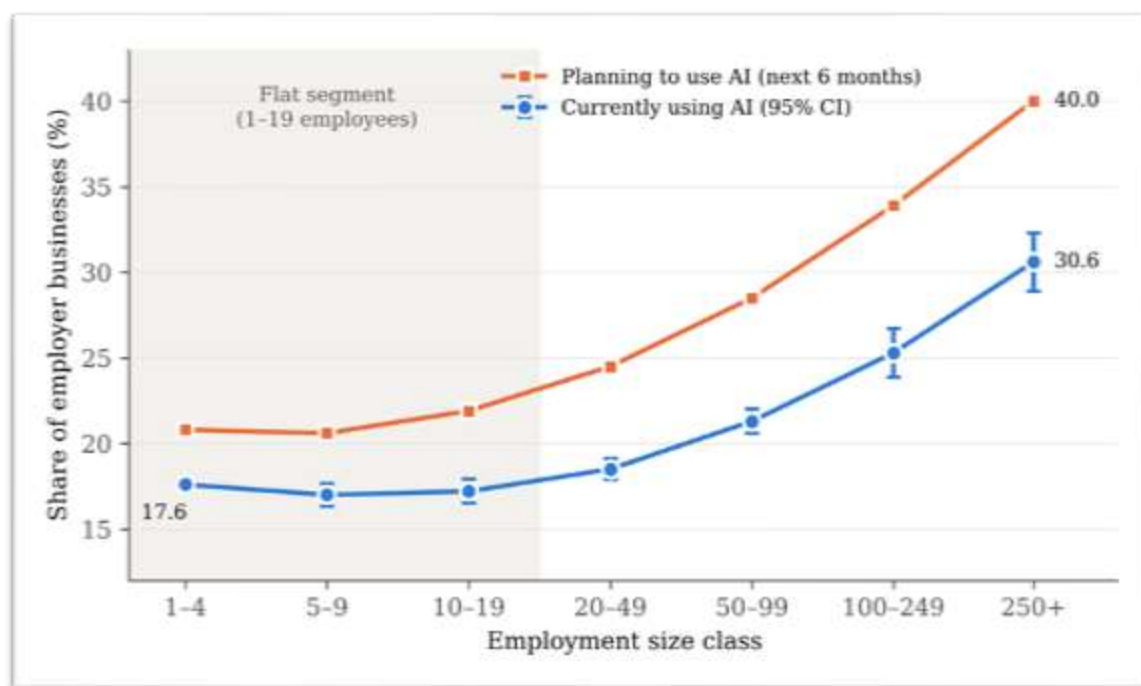


Figure 1. Current and planned AI use by employment-size class (BTOS AI Supplement, Nov 2025–Feb 2026). Error bars are 95% confidence intervals from published standard errors.

Figure 1 presents this national pattern visually. For the three smallest size groups, both planned and current use of AI are practically flat; for businesses with 20 or more people, it develops quickly, and planned use is always greater than current use. By presenting the differences between neighboring size classes along with their standard errors and significance levels, Table 3 explicitly tests this pattern. The compares confirm that the gap only begins between 10 and 19 versus 20 and 49, and that it grows with each further step.

Table 3. Firm-size gradient in current AI use: adjacent-class contrasts

Contrast	Difference (pp)	SE	Z	p
1–4 vs 5–9	-0.6	0.37	-1.62	0.106
5–9 vs 10–19	+0.2	0.49	0.41	0.682
10–19 vs 20–49	+1.3	0.48	2.70	0.007
20–49 vs 50–99	+2.8	0.49	5.72	<.001
50–99 vs 100–249	+4.0	0.81	4.94	<.001
100–249 vs 250+	+5.3	1.13	4.69	<.001
1–4 vs 250+	+13.0	0.89	14.67	<.001

Authors' Computation, (2026). Note. SEs of differences are $\sqrt{SE_1^2 + SE_2^2}$, from published BTOS AI Supplement standard errors. Inverse-variance-weighted piecewise regression on log size midpoint: slope below 20 employees = 0.16 (SE 0.19, $p = .445$); change in slope from the 20–49 class onward = +4.47 (SE 0.58, $p = .002$). WLS slope within the 1–19 segment alone = -0.31 ($p = .349$).

4.3 Industry structure and the shift-share decomposition (H2)

Industry-implied adoption predicts actual state adoption on its own (M1: $\beta = 1.36$, $p = .001$). A one-point higher industry-implied rate is associated with a 1.31-point higher actual rate ($R^2 = .21$; Table 4).

The decomposition shows, however, that industry mix accounts for only a modest part of cross-state variation. The mix component explains 12.0% of the variance in state adoption. A further 7.4% comes from the covariance term, because states with favourable industry mixes also tend to adopt more *within* industries. The within-industry (local) component explains 80.6%.

The states furthest below their industry-implied rate are West Virginia (-6.2 points), Arkansas (-5.0), North Dakota (-3.9), Oklahoma (-3.7), New York (-3.6) and New Mexico (-3.4). New York stands out: it has the second most favourable industry mix in the sample, yet adopts 3.6 points less than its mix predicts. Colorado, Arizona (both +5.2), Nevada (+4.7), Oregon (+3.9), Utah (+3.7) and Florida (+3.1) adopt the most above their industry-implied rates. In short, most of the geography of AI adoption reflects how much firms within the same industries adopt, not which industries a state has.

Once broadband and tertiary attainment enter (M2), the industry-implied coefficient falls to 0.41 and is no longer significant. This reflects its strong correlation with tertiary attainment ($r = .79$). The assumption-free knowledge-intensive employment share remains significant in the full specification (R3: $\beta = 1.31$, $p = .021$). H2 is partly supported: industry mix matters, but it is neither the main source of geographic variation nor robust to controls for human capital in every specification.

Table 4. Shift-share decomposition of state AI adoption

Panel A. Variance decomposition

Component	Variance	Share of Var(A)
Industry mix, Var(E)	0.98	12.0%
Within-industry (local), Var(A – E)	6.57	80.6%
2 × Covariance	0.60	7.4%
Total, Var(A)	8.15	100.0%

Panel B. States with the largest negative and positive local components (pp)

State	AI adoption	Industry-implied	Mix component	Local component
West Virginia	10.8	17.9	-0.34	-6.17
Arkansas	11.8	17.7	-0.56	-4.95
North Dakota	12.3	17.2	-1.10	-3.91
Oklahoma	13.3	18.0	-0.27	-3.74
New York	15.3	19.9	+1.62	-3.63
New Mexico	14.1	18.4	+0.18	-3.39
Florida	20.9	18.8	+0.52	+3.07
Utah	21.1	18.4	+0.10	+3.69
Oregon	21.1	18.2	-0.08	+3.87
Nevada	20.9	17.1	-1.13	+4.73
Arizona	22.9	18.7	+0.43	+5.16
Colorado	23.2	19.0	+0.73	+5.16

Authors' Computation, (2026) Note. Components are deviations from cross-state means. Regressing A on E gives $b = 1.31$ (HC3 SE 0.32, $p < .001$), $R^2 = .21$.

4.4 Infrastructure, Human Capital and Ownership (H3–H4)

Broadband subscription is the most robust correlate of state AI adoption (Table 5). In M2, a one-standard-deviation increase in broadband subscription (2.1 points) is associated with 1.73 points higher AI adoption ($p = .002$). This is about 0.8 points of AI adoption per point of broadband, roughly 60% of a standard deviation of the dependent variable. The coefficient stays significant and of similar or larger size in every specification (Tables 5–6):

- with ownership composition, density and income added (M4: $\beta = 3.09$, $p = .001$);
- without DC ($\beta = 3.25$, $p < .001$);
- without high-influence states ($\beta = 3.02$, $p < .001$);
- with the knowledge-intensive share measure ($\beta = 2.28$, $p = .023$);
- with the May–August 2026 adoption measure ($\beta = 3.13$, $p = .002$);
- in the spatial lag model ($\beta = 1.86$, $p < .001$).

H^{3a} is supported. The larger coefficients in M4 reflect partial collinearity with median income ($r = .87$, VIF = 12.5). For that reason, the parsimonious M2 and M3 estimates (about 1.7–1.8 points per SD) are the more conservative reading.

Tertiary attainment has no association with adoption independent of broadband and industry mix: coefficients range from -0.49 to $+1.85$, and none is significant. H3b becomes insignificant when broadband penetration is considered. This does not imply, in our view, that skills are unimportant. Income, skills, employment in knowledge-intensive industries, and broadband penetration are all strongly correlated (inter-correlations .43–.87). Because there are only 51 observations, the models cannot isolate all of these effects. The models indicate that among these characteristics, the digital-access dimension has the highest explanatory weight.

Ownership composition is unaffected by the structural and infrastructure composition (M3: minority-owned $\beta = -0.28$, $p = .72$; women-owned $\beta = 0.79$, $p = .33$). The corrected R² rises from .447 to just .473 due to the ownership barrier. Both coefficients are positive and not significant in M0, which simply takes ownership composition into account (joint F-test $p = .19$). Only in the absence of influential governments does the women-owned share become significant, and even then, it has a positive sign ($\beta = 1.22$, $p = .037$). As a result, the data supports H4b, the compositional explanation, and disproves H4a, the constraint explanation. Once industry, scale, and infrastructure are taken into account, there is no evidence at the state level that a greater minority or women-owned company sector lowers the adoption of AI technologies.

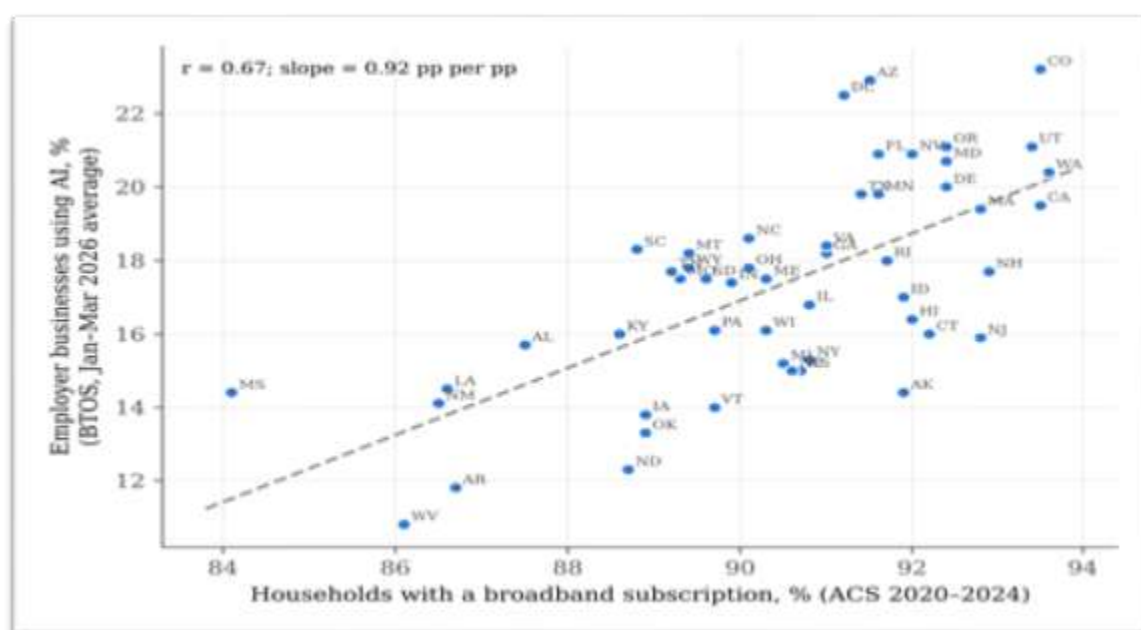


Figure 2. Household broadband subscription and business AI adoption across states. Dashed line: OLS fit.

Figure 2 depicts the bivariate relationship that anchors these results: states with higher household broadband subscription record consistently higher business AI adoption, and the fitted line rises steadily across the observed range of 84.1% to 93.6%. Whether

this association survives once industry mix, establishment size, human capital and ownership composition are held constant is examined in Table 5, which reports the five nested OLS specifications (M0–M4) with standardised predictors and HC3 robust standard errors.

Table 5. OLS models of state AI adoption (standardised predictors)

	M0	M1	M2	M3	M4
Industry-implied adoption		1.36** (0.42)	0.41 (0.63)	0.43 (0.90)	-0.09 (1.08)
Mean establishment size		-0.12 (0.41)	0.27 (0.41)	0.52 (0.43)	0.47 (0.49)
Broadband subscription			1.73** (0.55)	1.78** (0.57)	3.09** (0.96)
Tertiary attainment			-0.01 (0.87)	-0.21 (0.90)	1.36 (1.64)
Minority-owned share	0.68 (0.68)			-0.28 (0.78)	0.22 (0.83)
Women-owned share	0.55 (0.67)			0.79 (0.80)	0.54 (0.81)
Population density (log)					-0.06 (0.79)
Median income (log)					-2.44 (1.81)
R ²	0.138	0.207	0.491	0.538	0.596
Adj. R ²	0.102	0.174	0.447	0.473	0.518
N	50	51	51	50	50

Authors' Computation, (2026). Note. Dependent variable: share of employer businesses using AI, Jan–Mar 2026 (%; SD = 2.86). Coefficients are percentage-point changes per one-SD increase in the predictor; HC3 robust SEs in parentheses. M0, M3 and M4 exclude Kentucky (women-owned count suppressed). Maximum VIF: M2 = 3.7; M3 = 3.9; M4 = 12.5 (median income). † p < .10, * p < .05, ** p < .01, *** p < .001.

Because the models are estimated on only 50–51 observations, and the full specification shows elevated collinearity (maximum VIF = 12.5), the stability of these estimates is assessed in Table 6. The five robustness checks re-estimate the model without the District of Columbia, without high-influence states, with the knowledge-intensive employment share in place of industry-implied adoption, with the May–August 2026 adoption measure as the dependent variable, and in the parsimonious M2 form without DC. Across all five checks, broadband subscription remains positive and statistically significant, while ownership composition remains non-significant except for the women-owned share in R2.

Table 6. Robustness Checks

	(R1) Excl. DC	(R2) Excl. influential	(R3) Knowledge share	(R4) May–Aug 2026 DV	(R5) M2 excl. DC
Industry-implied adoption	-0.09 (0.88)	0.06 (0.86)		0.00 (1.77)	0.32 (0.49)
Knowledge-intensive share			1.31* (0.57)		
Mean establishment size	0.32 (0.44)	0.48 (0.40)	0.20 (0.47)	0.03 (0.97)	0.11 (0.37)
Broadband subscription	3.25*** (0.98)	3.02*** (0.69)	2.28* (1.01)	3.13** (1.02)	2.10*** (0.52)
Tertiary attainment	0.75 (1.64)	0.03 (1.28)	0.21 (1.35)	1.85 (2.45)	-0.49 (0.61)
Minority-owned share	0.16 (0.87)	-0.32 (0.54)	-0.21 (0.69)	-0.47 (1.40)	
Women-owned share	0.50 (0.85)	1.22* (0.58)	0.54 (0.81)	1.01 (0.99)	
Population density (log)	0.03 (0.67)	0.06 (0.57)	-0.31 (0.66)	0.86 (1.48)	
Median income (log)	-2.24 (2.01)	-1.15 (1.29)	-1.23 (1.76)	-2.84 (1.73)	
R ²	0.575	0.726	0.637	0.514	0.484
Adj. R ²	0.490	0.662	0.566	0.420	0.438
N	49	43	50	50	50

Authors' Computation, (2026) Note. R1: M4 excluding DC. R2: M4 excluding high-influence states (AK, DC, HI, MS, SD, VT, WY). R3: knowledge-intensive share replaces industry-implied adoption. R4: dependent variable = May–Aug 2026 BTOS average. R5: M2 excluding DC. HC3 SEs. † p < .10, * p < .05, ** p < .01, *** p < .001.

4.5 Spatial Dependence and Co-location of Disadvantage (H5)

The industry mix is highly spatially autocorrelated (Moran's I = .378, p < .001). AI adoption take-up is moderately spatially autocorrelated (January–March I = .137, p = .057; May–August I = .149, p = .046) and so is the local component (I = .173, p = .028).

The residuals of the full model show no remaining spatial autocorrelation ($I = .036$, $p = .27$). In the spatial lag model, the spatial autoregressive parameter is small and not significant ($\rho = .076$, $p = .63$). The measured covariates therefore account for the geographic clustering of AI adoption: neighbouring states resemble each other because they share infrastructure and economic structure, not because adoption spills across state borders.

The disadvantage indicators co-locate strongly (Table 7). The mean inter-indicator correlation is .50, the first principal component explains 61.3% of the variance, and Cronbach's α is .83 (.79 without DC). Low-adoption industry mix correlates with low density at .76 and with low tertiary attainment at .79. Small establishment scale correlates with low density at .70. The one weak link is between broadband and establishment scale ($r = .06$).

The composite fracture index correlates $-.55$ with AI adoption ($p < .001$; $-.51$ without DC; Figure 3). The states with the highest index values (Wyoming, Mississippi, Montana, Alaska, South Dakota and North Dakota) are predominantly rural and lie in the Great Plains, Mountain West and Deep South. Those with the lowest values (DC, Massachusetts, New Jersey, Maryland and Connecticut) are dense, highly educated and connected. H5 is supported: the disadvantages measured in separate federal data programmes form a single, internally consistent dimension.

Table 7. Correlations among indicators of digital disadvantage (N = 51)

	(1)	(2)	(3)	(4)	(5)
(1) Low broadband	—				
(2) Low tertiary attainment	0.61	—			
(3) Small establishments	0.06	0.27	—		
(4) Low-adoption industry mix	0.43	0.79	0.53	—	
(5) Low density (rurality)	0.26	0.56	0.70	0.76	—

Authors' Computation, (2026) Note. All indicators are coded so that higher values mean greater disadvantage. Mean inter-item $r = .50$; first principal component explains 61.3% of variance; Cronbach's $\alpha = .83$ (excluding DC: $\alpha = .79$, PC1 = 56.4%). Correlation of the composite fracture index with AI adoption: $r = -.55$ ($p < .001$; excluding DC: $r = -.51$).

Table 7 demonstrates that there is enough correlation between the five disadvantage measures to justify combining them into a single composite measure. Plotting this composite fracture indicator versus business AI adoption by state in Figure 3 pushes this research even further. The majority of the mostly rural states in the Great Plains, Mountain West, and Deep South are at the high-index, low-adoption end of the range, and the negative trend ($r = -.55$) shows that places that face several disadvantages at once typically have the lowest adoption rates.

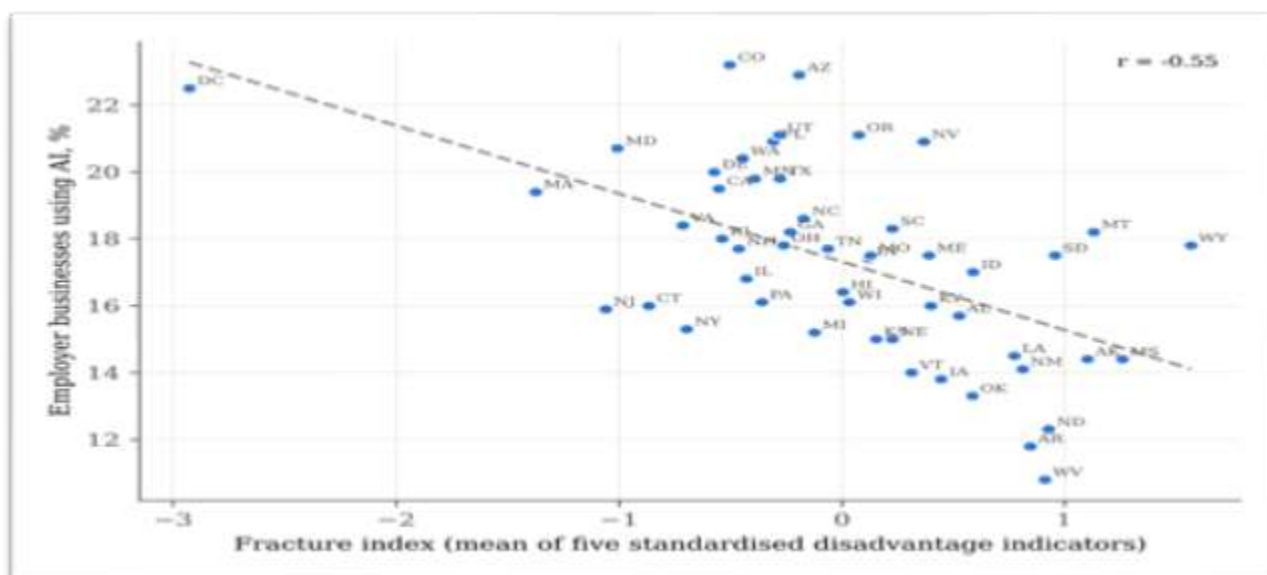


Figure 3. Composite fracture index and business AI adoption across states. Higher index values indicate greater co-located disadvantage.

Overall, the evidence in Sections 4.2 to 4.5 provides a coherent explanation of when and why the diffusion of AI stagnates across states. Table 8 summarizes the results by restating the verdict on each hypothesis with its main pieces of supporting evidence from the national size-class contrasts, the shift-share decomposition, the nested and robustness regressions, and the spatial and co-location analyses.

Table 8. Summary of hypothesis tests

Hypothesis	Prediction	Verdict	Key evidence
H1	Firm-size threshold in AI adoption	Supported (national); not detected across states	Flat 1–19 ($p = .35$); slope change +4.47 ($p = .002$); state establishment size n.s.
H2	Industry mix predicts adoption	Partly supported	M1 $\beta = 1.36^{**}$; mix explains 12% (19% with covariance); knowledge share robust
H3a	Broadband positive	Supported	$\beta = 1.7\text{--}3.3$ in all 9 specifications, all $p < .05$
H3b	Human capital positive	Not supported independently	Bivariate $r = .51$; n.s. net of broadband
H4a / H4b	Ownership composition negative / null	H4b supported	Ownership n.s. in M3–M4; bivariate sign positive
H5	Disadvantages co-locate; spatial clustering	Supported	$\alpha = .83$; index $r = -.55$; Moran's I local = .17*

Authors' Compilation, (2026)

V. DISCUSSION

5.1 Theoretical implications

The findings refine the Technology Organisation Environment (TOE account of AI adoption in three ways.

First, the organisational dimension is better described as a *threshold* than as a continuous effect of size. Earlier ABS and BTOS work documents that AI use rises with firm size (Zolas et al., 2020; McElheran et al., 2024; Bonney et al., 2024). In the most recent BTOS AI Supplement, however, adoption among firms with 1–19 employees is statistically flat and rises sharply only from 20 employees. This shape fits fixed-cost and complementarity explanations (Bloom et al., 2012; Brynjolfsson et al., 2021). Below a certain scale, firms lack the specialised roles, data assets and slack resources needed to make AI integration worthwhile. Once they have them, adoption climbs quickly. The non-adoption responses in the same supplement support this reading. “Not applicable to this business” is the most common reason for not planning to adopt in *every* size class, falling from 63.3% among the smallest firms to 42.2% among the largest. “Lack of a skilled workforce” never exceeds 9.2%. Most micro-firm non-adopters do not believe they lack the skills to use AI; they do not yet see what AI would do for them. In diffusion terms (Rogers, 2003), this is a barrier of perceived relative advantage, not complexity.

Second, the environmental dimension is dominated by digital access. Among the place-level conditions that federal data measure, household broadband subscription is the most robust correlate of business AI adoption. The association holds conditional on industry mix, human capital, income, ownership and density; across two non-overlapping measurement windows; and in a spatial lag model. This extends the digital-divide literature from households to firms. The “first-level” access divide (van Deursen & van Dijk, 2019), long treated as largely closed for businesses, appears to persist as a *place-level* condition that limits the next wave of technology adoption. It matches earlier evidence that internet diffusion in the 1990s and 2000s followed local infrastructure and complementary inputs (Forman et al., 2005). It also matches evidence that rural broadband supports local economic activity (Whitacre et al., 2014).

Household broadband is best read as a marker of a place's overall digital readiness, covering local networks, digitally fluent owners and workers, and vendor ecosystems, rather than as a measure of firms' own connectivity. The current design cannot separate these channels.

Third, the results indicate that the disadvantages of ownership is not increased at the state level. States with higher concentrations of women-owned and minority-owned enterprises are not less likely to adopt AI; on the contrary, there is a positive unconditional association. The association is not statistically different from zero when industry, scale, and infrastructure are taken into account. In addition to being consistent with findings on sector concentration that minority and women-owned businesses are disproportionately represented in low-adoption sectors (construction; lodging and food services) and high-adoption sectors (healthcare; professional services), that interpretation of the “double divide” is compositional rather than constraint-based. This is an ecological finding, it does it preclude within-state owner disadvantage, which the ABS technology module would enable researchers to test directly (Zolas et al. 2020).

Finally, the metaphor of the “fracture line” is empirically supported by the disadvantage indicators' strong internal consistency ($\alpha = .83$). The drawbacks of limited bandwidth, low attainment, small establishment size, poorer industry mix, and low density are all present in the group of rural states. They all group together, and the index accounts for roughly 30% of the difference in AI

adoption between states. Because each index somewhat proxies the others, the clustering also contributes to the explanation of why crude bivariate comparisons overstate any one element.

5.2 Policy implications

Four implications follow, each stated as conditional on the evidence above.

1. Focus on the threshold rather than micro-firms as a whole. The majority of micro-firm non-adopters claim that AI is irrelevant rather than that they lack AI expertise, and the size gradient starts at roughly 20 employees. Therefore, small-business programs have a higher chance of success when they present micro-firms with sector-specific use cases (such as those provided by Small Business Development Centers or Manufacturing Extension Partnership centers) and assist firms that are just over the 20 employee threshold with implementation. Training in more general AI skills is unlikely to be effective for all small businesses.
2. Treat broadband as a foundation for AI readiness. State broadband deployment plans, including the federal Broadband Equity, Access, and Deployment (BEAD) funds, should be evaluated for the downstream effects on household connectivity and corporate technology uptake, according to the robust broadband association. Deploy concurrently with business-facing adoption support.
3. Focus on differences within industries. Roughly 80% of the geographic variation occurs among businesses in the same industries. States such as West Virginia, Arkansas, North Dakota, Oklahoma, and New Mexico are therefore not falling behind primarily because of their mix of industries. Targeted support for local adoption could make a meaningful difference, and the local component of the shift-share analysis in Table 4 provides a straightforward guide for setting state priorities.
4. Never use ownership composition as a targeting criterion for the purchase of AI funding. At state level, ownership composition provides nothing additional about uptake beyond sector and scale and infrastructure. Any programmes to close owner-level gaps should be based on firm-level data, which is provided by the ABS technology module.

5.3 Recommendations and Implementing Agencies

These policy implications are translated into seven clear recommendations, each signposted to the lead implementing agency and the supporting partners that should act on it, in view of their statutory role and programme portfolios.

Recommendation 1: Assist companies with fewer than 20 workers in implementing AI in ways that suit their requirements. Through its network of Small Business Development Centers, the Office of Entrepreneurial Development of the U.S. Small Business Administration should spearhead this endeavor. Additional assistance is available from state economic development departments and centers in the Manufacturing Extension Partnership of the National Institute of Standards and Technology.

This recommendation is informed by the threshold effect observed in Table 3 showing little variation in adoption for firms with less than 20 employees and a strong jump for those above this threshold. Companies nearing or just surpassing that size, then, would stand to gain the most from focused implementation support. If passed, the Small Business Artificial Intelligence Training Act of 2026 would potentially create another avenue for the Department of Commerce and SBA to engage in a joint AI training effort.

Recommendation 2: Create sector-specific AI demonstration programmes for micro-firms in low-adoption industries. Lead agencies: SBA, through SBDCs, Women's Business Centers, and SCORE; and, in rural communities, the U.S. Department of Agriculture National Institute of Food and Agriculture (USDA NIFA), through the Cooperative Extension System. Supporting

partners: Relevant industry associations, community colleges and technical institutions.

Assistance in AI for micro-firms should focus on showing what can be done, rather than generic awareness or training. 63.3% of non-adopting micro-firms believe AI is "not applicable" to their businesses, while just 6.4% cite a shortage of skilled personnel as the reason for non-adoption, indicating that relevance of AI is perceived as a higher barrier compared to that of human capital. Therefore, industry specific demos should highlight off-the-shelf solutions for things like scheduling, cost estimation, inventory management, customer communication, and admin automation. Trusted local intermediaries to deliver would enhance accessibility and contextual relevance.

Recommendation 3: Programs for broadband deployment should incorporate business technology adoption. Lead agencies: USDA Rural Development through the ReConnect Program in rural areas and the National Telecommunications and Information Administration (NTIA) through the Broadband Equity, Access, and Deployment (BEAD) Program in collaboration with state broadband offices. Supporting agency: Federal Communications Commission (FCC), with the National Broadband Map.

In Tables 5 and 6, broadband subscription is the most robust and consistent predictor of state-level AI adoption. As a result, broadband policy must address businesses' efficient use of digital infrastructure in addition to providing physical infrastructure. NTIA should think about permitting certain portions of the non-deployment money to be utilized for business digital adoption, AI

readiness, and technical support for places that have successfully attained connectivity as BEAD is implemented. In a similar vein, the state broadband offices should incorporate business technology adoption metrics into their program monitoring frameworks so that the return on a broadband investment is determined by both its use in a productive sector of the economy and its connectivity.

Recommendation 4: Introduce localized AI adoption programs in states where companies fall behind their industry competitors. Lead agency: U.S. Economic Development Administration (EDA), Department of Commerce. Support agencies: Federal–state regional commissions and state economic development agencies in designated lagging states, such as the Appalachian Regional Commission, Delta Regional Authority and Northern Great Plains Regional Authority.

Table 4 demonstrates that variations within industries account for approximately four-fifths of the cross-state variation in AI adoption. West Virginia, Arkansas, North Dakota, Oklahoma, New York, and New Mexico had the biggest negative within-industry disparities. Therefore, the shift-share local component should be considered by EDA and pertinent regional commissions as a diagnostic screening tool for funds that support adoption, digital capacity building, and technical assistance. This approach would improve the spatial targeting of public initiatives by distinguishing states with genuinely low industry-adjusted adoption from those whose low adoption rates are mostly a result of their industry mix.

Recommendation 5: Build on federal statistics of the application of AI in business. Lead agencies: the Economic Directorate of the U.S. Census Bureau, via the Annual Business Survey (ABS) and Business Trends and Outlook Survey (BTOS). Support agency: NSF National Center for Science and Engineering Statistics.

Census Bureau should improve the measurement infrastructure of business AI adoption by: (a) administering the BTOS AI Supplement at regular intervals to create a time series; (b) releasing state-level estimates of AI adoption by firm size and industry with corresponding estimates of sampling uncertainty; (c) adding new technology-use tables to the ABS that include AI adoption by owner sex, ethnicity, race, and veteran status for the most recent reference year; and (d) improving access for researchers to appropriate linked micro-data through the Federal Statistical Research Data Centers. Such efforts would directly address the measurement gaps discussed in Section 6 and enable firm-level analyses of relationships that cannot be adequately explored using only state-level data.

Recommendation 6: AI interventions aimed at ownership should be based on firm-level data. Lead agency: SBA Office of Advocacy. Supporting agencies: U.S. Census Bureau, NSF NCSES, and, if not prohibited by institutional regulations, the Minority Business Development Agency (MBDA).

Ownership characteristics should not constitute the main criteria for targeting AI adoption interventions in the absence of evidence of within-sector and within-size disparities. That ownership structure does not offer a statistically significant independent account of state-level AI adoption when industry, firm size and infrastructure are controlled for, implies that aggregate ownership differences may mask significant heterogeneity at the firm level. Consequently, the SBA Office of Advocacy should conduct firm-level studies using the ABS technology module to assess whether meaningful gaps in AI adoption do exist among ownership groups – once sector, firm size, and other relevant variables are controlled for. Such a demonstration effect may serve as a better basis for establishing fair and properly targeted AI support schemes.

Recommendation 7: Increase provision of AI-related training for existing employees employed in already adopting firms. Lead agency: Department of Labor, Employment and Training Administration (DOL ETA) in collaboration with State and local workforce development boards under the Workforce Innovation and Opportunity Act (WIOA). Alternative Name: Community and Technical College(s) and SBDC(s) in partner support.

Workforce development around AI should target firms with 20–249 workers, as nearly one-quarter (23–25%) of non-adopters in this size group cite limited skills and knowledge of what AI can do as a barrier to adoption. WIOA incumbent-worker and customized-training resources should therefore enable workers to build the specific skills needed for AI adoption in small and medium-sized enterprises. Training should focus on capabilities that may facilitate effective human–AI collaboration, such as the ability to understand how and where to use AI to add value, manage data, work effectively with data and AI, understand the costs and risks of AI, and adapt current business processes accordingly.

Overall, these suggestions prioritize focused, evidence-based, location-sensitive interventions above widespread AI subsidies or general training initiatives. Evidence suggests that factors other than ownership structure alone are more important for policy design, including business size, industry characteristics, broadband connectivity, regional variance, and understanding of the advantages of AI. As a result, treatments ought to be tested, their effects impartially evaluated, and scaled up if they prove effective.

VI. LIMITATIONS AND RESEARCH

1. This study has several limitations.
2. The dependent variable is a second-level compilation. It is a six-release average of published BTOS state estimates from a third-party source and does not come with any published standard errors. The replication window (May–August 2026), compiled independently, gives similar results. Even so, re-extracting state estimates and standard errors directly from the Census Bureau's BTOS downloads, and weighting by precision, is a priority for the final analysis.
3. The industry-implied measure is an approximation. It maps national two-digit sector rates onto BLS supersectors and weights them by employment, whereas BTOS rates are firm-weighted. The assumption-free knowledge-share measure gives consistent conclusions, but exact sector-by-state AI rates would sharpen the decomposition.
4. The design is ecological and cross-sectional ($N = 51$). Associations are not measures of causality. The models' ability to distinguish broadband from wealth and human capital is limited by a number of highly collinear factors. Owner-level behavior is not reflected in ownership results (Robinson, 1950).
5. Reference periods differ. The ACS (2020–2024), ABS and CBP (2023) and BLS (August 2026) measures describe slowly changing structural conditions, but they are not synchronized with the 2026 adoption measures.
6. The size threshold is based on an estimate derived from national statistics that is not particularly reliable. The percentage of businesses with more than 20 employees is not well approximated by the state establishment-size average.

To get over these limitations, three extensions would be helpful. The first would be a county- or metro-area study utilizing BTOS metropolitan estimates, which would allow for quasi-experimental designs based on the timing of broadband deployment and increase the number of observations. The second would be a Federal Statistical Research Data Center investigation of the ABS technology module at the business level, broken down by owner characteristics. In order to determine whether the threshold and the broadband association are resilient as AI spreads, the third would be a panel built from subsequent BTOS waves.

VII. CONCLUSION

When considered individually, federal data on business ownership, broadband access, workforce skills, and AI adoption each reveal a partial digital divide. When analyzed together and examined systematically, they indicate a single dividing line. The same rural, lower-density states tend to have less robust broadband, lower levels of educational attainment, smaller businesses, and industries that use less AI, and these states adopt AI at significantly lower rates. Three aspects of this dividing line are most important for policy:

- It runs through a firm-size *threshold* at about 20 employees, not along a smooth gradient.
- It is mainly a *within-industry* phenomenon, not a by-product of industrial structure.
- Among the measured place-level conditions, it follows digital access most closely, not business-ownership composition.
- Closing it will require treating broadband, adoption support at the size threshold and place-specific diagnosis as parts of one integrated strategy.

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