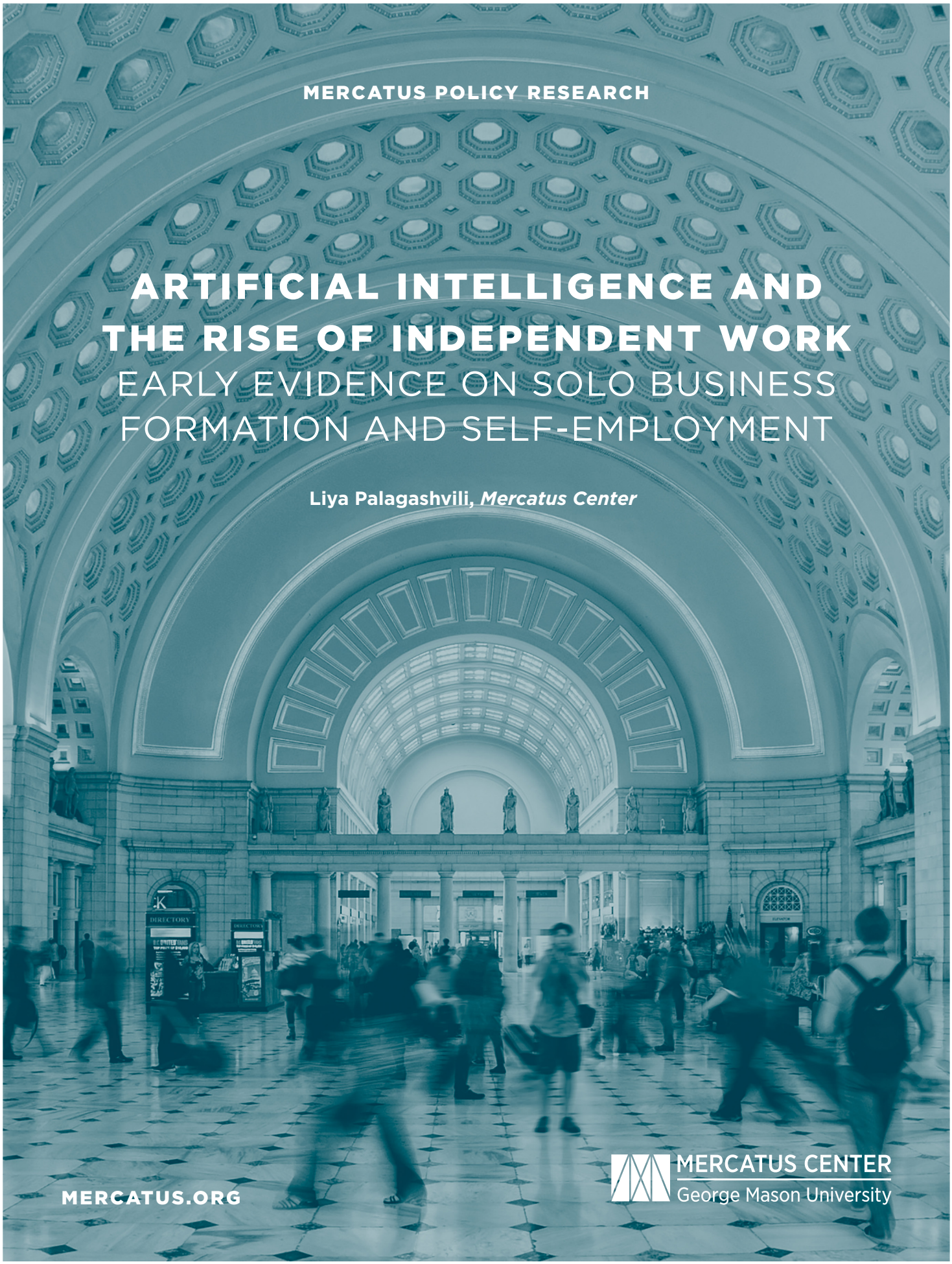


MERCATUS POLICY RESEARCH

ARTIFICIAL INTELLIGENCE AND THE RISE OF INDEPENDENT WORK

EARLY EVIDENCE ON SOLO BUSINESS FORMATION AND SELF-EMPLOYMENT

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Abstract

Most debates over artificial intelligence begin with the question of whether AI will replace human workers. This study asks a different question: whether AI is already changing how work is organized. In particular, AI may be lowering the cost of operating outside a traditional firm by allowing one worker to perform tasks that once required a team, support staff, or firm-based infrastructure.

The evidence is preliminary, descriptive, and not causal. But the pattern across two independent data sources is striking. Using US Census Bureau Business Formation Statistics, this study finds that business applications unlikely to become employer firms in AI-exposed sectors rose sharply after early 2024, while a comparison group remained essentially flat. Using Current Population Survey data, this study finds that self-employment and solo self-employment rose after 2024 in AI-exposed industries and occupations, while remaining flat or declining in comparison groups. A preliminary event study finds that in 2022 and 2023, applications from businesses unlikely to become employer firms moved similarly across AI-exposed and less exposed sectors.

This result does not mean that AI is replacing the firm or that traditional employment is disappearing. Rather, in some forms of knowledge work, AI may be reducing the advantages of being inside a firm and increasing the feasibility of independent work, solo self-employment, freelancing, and contract-based work. This means that institutions built around a single employer, such as benefits, will become increasingly mismatched to how people actually work. That result points toward portable benefits that travel with workers and modernized income-security systems, such as worker-owned portable accounts, built for workers whose earnings come from clients and contracts rather than a single employer.

JEL codes: D23, J23, L26

Keywords: artificial intelligence; independent work; self-employment; labor markets; transaction costs

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1. Introduction: Beyond Job Displacement

The public debate over artificial intelligence and work is still dominated by a substitution question: Which jobs will AI eliminate? That question matters, but it misses another important margin of change. AI may also be reshaping how work is organized, thereby making it easier for individuals to sell their skills directly to clients, customers, and organizations outside the boundaries of the firm.

For decades, firms have solved a basic organizational problem. Complex production often requires team production consisting of coordination, monitoring, complementary skills, and repeated contracting. A firm economizes on those costs by organizing workers internally, bundling capabilities, supervising effort, and providing shared infrastructure. When the transaction costs of using the market fall, however, the boundary between firm and market can shift.

Generative AI may be creating exactly this kind of transaction-cost shock for some knowledge workers. A consultant who once relied on junior analysts, designers, editors, and administrative staff can now use AI tools for research, drafting, data visualization, formatting, and client communication. A software developer can use AI to write tests, debug code, document changes, and produce prototypes. A researcher can analyze data and prepare polished written outputs with fewer institutional resources. The result is not necessarily unemployment. It may instead be a migration of some work away from firms.

This study provides early empirical evidence on the possibility of such migration. It examines whether the post-2024 rise of widely accessible generative AI tools coincided with disproportionate growth in independent work and solo-type business formation in AI-exposed sectors and occupations. The study combines two data sources: US Census Bureau Business Formation Statistics (BFS), which capture new EIN business applications, and Current Population Survey (CPS) microdata, which capture self-employment and solo self-employment among workers.

Findings show that solo-type business formation and solo self-employment rose disproportionately in AI-exposed sectors and occupations after early 2024:

- **Business formation evidence.** From Q1 2024 to Q1 2026, nonemployer-type applications in AI-exposed sectors rose 26.8 percent, while the construction-and-wholesale comparison group was essentially unchanged at −0.4 percent.
- **Composition evidence.** Employer-type applications in AI-exposed sectors fell 6.4 percent from Q1 2024 to Q1 2026, even as total applications rose. The growth came entirely from filings with no markers of employer intent.
- **Event-study evidence.** A preliminary business formation event study using seven sectors from 2022 to 2025 finds no statistically significant pre-treatment difference in 2022 relative to the 2023 base year. The 2024 coefficient is positive but not statistically significant; the 2025 coefficient is positive, large, and statistically significant.
- **Industry labor-market evidence.** In CPS data, solo self-employment in AI-exposed industries rose 7.9 percent from the 2022–2023 baseline to 2025, while the construction-and-wholesale comparison group declined 2.1 percent.
- **Occupation labor-market evidence.** The sharper CPS result appears by occupation: Solo self-employment in the 10 most AI-exposed occupations rose 20 percent from the 2022–2023 baseline to 2025, while solo self-employment in the 10 least AI-exposed occupations did not change.
- **Consulting evidence.** Among management analysts—a large, highly AI-exposed occupation and a useful proxy for independent consulting—overall employment grew from roughly 1.0 million workers in the 2022–2023 baseline to 1.12 million in Q1 2026. Solo self-employment grew more than twice as fast, with the share working independently rising from 5.6 percent to 7.0 percent, near its highest level in a decade. The shift is not toward fewer management analysts. It is toward more of them working for themselves.

Taken together, the evidence suggests that AI may be making independent knowledge work more feasible, though the results are descriptive and should not be interpreted as causal. If so, the first sign of AI's labor-market disruption may appear in EIN business applications before it appears in unemployment claims.

2. Theoretical Framework: AI as a Transaction-Cost Shock

The starting point is the Coasean framework—the body of research on transaction costs and firm boundaries that Ronald Coase initiated and that economists including Oliver Williamson, Harold Demsetz, and Armen Alchian developed across subsequent decades.[1] Firms exist in part because using markets is costly. It can be expensive to search for counterparties, negotiate contracts, monitor performance, evaluate output, coordinate across contributors, and enforce agreements. When these costs are high, production is more likely to be organized inside firms. When technology lowers these costs, more production can occur through markets, contracting, and independent work.

Earlier work on the gig economy has identified several transaction costs that digital platforms reduced: triangulation costs, transfer costs, trust costs, and measurement costs.[2] Digital platforms made it easier to match buyers and sellers, move payments, build trust through ratings, and measure discrete outputs. AI may be understood as a related transaction-cost shock, though one operating through a different mechanism. As I have argued elsewhere, generative AI may reduce several transaction costs that historically favored firm-based employment—including the need for complementary labor inputs, relationship-specific skill investments, and the difficulty of specifying and measuring knowledge work outputs.[3]

In many professional services, the minimum efficient scale of production historically required a team: analysis plus editing, design, presentation, document review, coding support, administrative scheduling, and client communications. AI tools increasingly provide some of those complements directly to the worker. That accessibility lowers the resource threshold for operating independently.

AI may also improve output measurability. If work products can be specified, drafted, tested, revised, and documented more clearly, clients can contract for outputs more easily. This increased feasibility does not eliminate the need for firms, and it will not apply uniformly across occupations. But it plausibly expands the set of tasks and occupations where independent work is feasible.

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1. Ronald H. Coase, "The Nature of the Firm," *Economica* 4, no. 16 (1937): 386–405; Armen A. Alchian and Harold Demsetz, "Production, Information Costs, and Economic Organization," *American Economic Review* 62, no. 5 (1972): 777–95; Oliver E. Williamson, "The Economics of Organization: The Transaction Cost Approach," *American Journal of Sociology* 87, no. 3 (1981): 548–77.
2. Seth Oranburg and Liya Palagashvili, "Transaction Cost Economics, Labor Law, and the Gig Economy," *Journal of Legal Studies* 50, no. S2 (2021): S219–S237; Michael Munger, *Tomorrow 3.0: Transaction Costs and the Sharing Economy* (Cambridge University Press, 2018).
3. See Liya Palagashvili, "AI, Transaction Costs, and a Quiet Shift Toward Self-Employment," *Labor Market Matters*, February 5, 2026.

Not all transaction-cost mechanisms point in one direction, however. Large firms may have advantages in proprietary data, compliance systems, internal AI infrastructure, and distribution. AI can also make input monitoring cheaper, which may strengthen employment relationships in some contexts. Some AI-augmented work may require more coordination rather than less.

The empirical question is therefore not whether AI will eliminate firms, but whether independent work is rising most where AI plausibly reduces the cost of working solo.

3. Data and Empirical Strategy

3.1 Business Formation Statistics

The Census Bureau's Business Formation Statistics (BFS) analysis uses monthly business application data based on applications for Employer Identification Numbers (EINs).[4] The key constructed measure is adjusted applications: total business applications minus high-propensity business applications. High-propensity applications are those the Census Bureau identifies as having characteristics—such as corporate entity structure, planned wages, hiring intent, or certain industry codes—historically associated with becoming employer businesses. Subtracting high-propensity applications from total business applications provides a proxy for applications unlikely to become employer firms.

This study refers to the constructed residual as nonemployer-type or solo-type business formation.[5] The interpretation is straightforward: These are new business filings that do not display the markers of near-term employer intent.

The AI-exposed sector group consists of Professional Services, Information, Education, and Finance and Insurance. These sectors are knowledge-intensive and less dependent than other sectors on physical capital, crews, or location-specific coordination. Additionally, these are sectors with the highest AI-adoption rates in the recent Census Bureau Business Trends and Outlook Survey (BTOS).[6] This sectoral grouping is also consistent with Anthropic's study

4. US Census Bureau, "Monthly Not-Seasonally-Adjusted Business Applications (BA) and High-Propensity Business Applications (HBA) by NAICS Sector," Business Formation Statistics, accessed April 7, 2026, https://www.census.gov/econ/bfs/index.html.
5. Note: This is not a published Census series; it is an author-constructed proxy.
6. Kathryn Bonney et al., "The Microstructure of AI Diffusion: Evidence from Firms, Business Functions, and Worker Tasks," CES Working Paper 26-25 (Center for Economic Studies, US Census Bureau, April 2026).

on the high-exposure side: Financial analysts, accountants, and management-related roles—occupations concentrated in these sectors—rank among the highest in observed AI exposure based on Claude usage data.[7] The comparison sectors, Construction and Wholesale Trade, appear among the lower-adoption industries in the BTOS.

Separately, the CPS occupation analysis uses the AI Occupational Exposure (AIOE) index, developed by Edward Felten and coauthors, to identify low-exposure occupations, many of which are physical, place-based, or construction-related.[8] Transportation and Warehousing is excluded from the main levels and index analysis because of its pandemic-era formation boom, though it is retained in the event-study panel, which begins in 2022 and uses sector fixed effects to absorb level differences. Real Estate, Manufacturing, and Retail Trade are excluded because interest-rate cycles and tariff-related shocks may confound interpretation. No comparison group is perfect, but Construction and Wholesale Trade are used because they have lower measured AI adoption in the BTOS data, relatively stable pre-2024 nonemployer-type application patterns, and fewer of the large pandemic-era or tariff-related distortions present in other candidate sectors.

3.2 Current Population Survey

The Current Population Survey (CPS) analysis uses IPUMS-CPS microdata and examines employed workers from Q1 2022 through Q1 2026.[9] Self-employment includes incorporated and unincorporated self-employed workers. Solo self-employment narrows the measure to self-employed workers with no paid employees. All estimates apply the CPS person weights, which account for the survey's sampling design and ensure that the estimates are representative of the US population.

The CPS analysis proceeds in three steps. First, it compares AI-exposed industries with construction and wholesale trade. Second, it uses the AIOE to

7. Maxim Massenkoff and Peter McCrory, *Labor Market Impacts of AI: A New Measure and Early Evidence* (Anthropic Economic Research, March 5, 2026).
8. Edward Felten et al., "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses," *Strategic Management Journal* 42, no. 12 (2021): 2195–217.
9. Sarah Flood et al., "IPUMS CPS: Version 13.0" (dataset), US Census Bureau, Current Population Survey, 2025, https://doi.org/10.18128/D030.V13.0.

compare the ten most AI-exposed occupations with the ten least AI-exposed occupations.[10]

Third, it zooms into management analysts as a specific occupation-level test case. Management analysts are selected for three reasons: The occupation is large enough to produce stable CPS estimates, it sits near the top of the AIOE distribution, and it closely proxies the kind of independent consulting and advisory work where the transaction-cost mechanisms outlined in the theoretical framework apply most directly—work that is knowledge-intensive, output-measurable, and not dependent on physical co-location or team production.

3.3 Event study

This event study uses the BFS adjusted applications series described in section 3.1 and is conducted at the sector-quarter level. The study treats Q1 2024 as a practical reference point, reflecting the period by which generative AI tools had become broadly accessible as business infrastructure. Because the model estimates annual differences, the 2024 estimate should be read as a transition-year estimate rather than a precise Q1 2024 effect. The 2024 estimate is positive but not statistically significant, consistent with a gradual rather than immediate break; the clearest divergence appears in 2025. The descriptive BFS series continues through Q1 2026, but Q1 2026 is reported separately from the 2022–2025 event-study sample.

The event study estimates year-by-treatment interaction coefficients from the specification:

$$log(Adj_Apps_{sqt}) = \alpha + \Sigma_t \beta_t (Year_t \times AI_s) + Sector\ FE + Year\ FE + Quarter\ FE + \varepsilon_{sqt}$$

where s indexes sectors, q indexes quarters, and t indexes years. The unit of observation is the sector-quarter. The coefficients of interest vary by year because the event-study indicators interact AI-exposed sector status with year indicators, while quarter fixed effects absorb seasonal variation across quarters. The omitted year is 2023, so the coefficients are interpreted relative to the 2023 baseline.

The sample covers 2022 through 2025 across seven sectors, including Transportation and Warehousing, which is excluded from the levels analysis but retained here with sector fixed effects absorbing its pandemic-era level differences. Standard errors are not clustered at the sector level; with only seven

10. Felten et al., "Occupational, Industry, and Geographic Exposure to Artificial Intelligence." Felten and his coauthors construct the AI Occupational Exposure index used here to classify occupations by AI exposure.

sector clusters, clustered standard errors would be unreliable, and the reported standard errors are likely understated. Results should be treated as preliminary and suggestive rather than definitive. The year-by-treatment interaction coefficients show whether AI-exposed sectors diverged from the comparison group after the reference point (2024), relative to the 2023 baseline.

4. Results from Business Formation Data

4.1 Main results

As shown in table 1, the BFS evidence shows a clear post-2024 divergence between AI-exposed sectors and the comparison group. In the pre-treatment period, the two groups move broadly together. In 2025, nonemployer-type applications in AI-exposed sectors rise sharply, whereas the comparison group remains broadly flat.

Figure 1 shows that nonemployer-type applications in AI-exposed sectors trended broadly alongside the comparison group through 2023, then diverged sharply in 2025. The comparison group remained flat throughout.

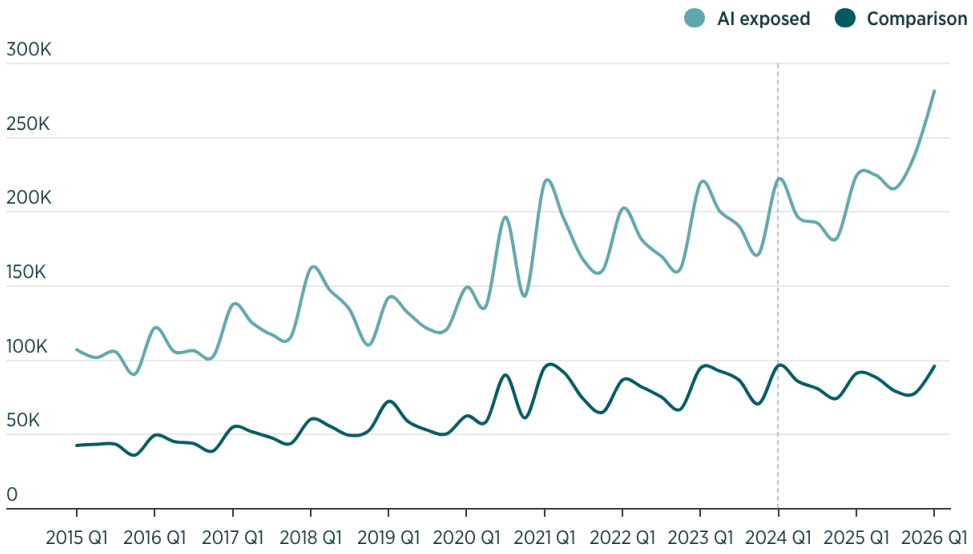
Figure 2 indexes both groups to Q1 2022 = 100, making the divergence in growth rates visible. By Q1 2026, AI-exposed sectors reached an index of 139.2 while the comparison group reached only 110.7, which is a gap of roughly 28 index points from the same starting baseline.

TABLE 1. Nonemployer-type business applications in AI-exposed and comparison sectors

Measure	AI-exposed sectors	Comparison group
Pre-treatment average, 2022-2023 (monthly)	62,416	27,338
2025 monthly average	75,293	28,065
Change from 2022-2023 average to 2025	+20.6%	+2.7%
Q1 2024 adjusted applications	221,996	96,427
Q1 2026 adjusted applications	281,480	96,071
Q1 2024 to Q1 2026 change	+26.8%	-0.4%
Index, Q1 2026 (Q1 2022 = 100)	139.2	110.7

Note: Pretreatment average uses monthly averages from 2022 and 2023. The 2025 figure uses monthly averages across all available 2025 months.
Source: Author's calculations using US Census Bureau, "Monthly Not-Seasonally-Adjusted Business Applications (BA) and High-Propensity Business Applications (HBA) by NAICS Sector," Business Formation Statistics, accessed April 7, 2026, https://www.census.gov/econ/bfs/index.html.

FIGURE 1. Quarterly nonemployer business applications, Q1 2015 to Q1 2026



Note: AI-exposed (Professional Services + Information + Education + Finance & Insurance) and comparison group (Construction + Wholesale Trade only). Vertical line at Q1 2024. Nonemployer applications = total business applications minus high-propensity business applications (author-constructed). Transportation & Warehousing excluded due to pandemic-era distortion.
Source: Author's calculations using US Census Bureau, "Monthly Not-Seasonally-Adjusted Business Applications (BA) and High-Propensity Business Applications (HBA) by NAICS Sector," Business Formation Statistics, accessed April 7, 2026, https://www.census.gov/econ/bfs/index.html.

4.2 The composition of applications matters

The sharpest result is not simply that applications rose in AI-exposed sectors. It is that the rise came entirely from applications that do not display employer intent. From Q1 2024 to Q1 2026, total applications in the AI-exposed group rose 18.0 percent. But high-propensity employer-type applications fell 6.4 percent, while nonemployer-type applications rose 26.8 percent, as table 2 shows.

In the comparison group over the same period, total applications fell 4.7 percent, high-propensity applications fell 9.3 percent, and nonemployer-type applications were essentially unchanged at −0.4 percent. There was no comparable divergence between employer-type and nonemployer-type filings in the comparison group.

The divergence between employer-type and nonemployer-type filings within the same sectors and time window is the strongest evidence in the BFS data that the growth is specifically in solo formation rather than in business formation broadly.

FIGURE 2. Nonemployer business applications indexed to Q1 2022



Note: Both groups indexed to 100 at Q1 2022. AI-exposed: Professional Services, Information, Education, Finance & Insurance. Comparison: Construction + Wholesale Trade only. Vertical line at Q1 2024. Nonemployer applications = total business applications minus high-propensity business applications (author-constructed).
Source: Author's calculations using US Census Bureau, "Monthly Not-Seasonally-Adjusted Business Applications (BA) and High-Propensity Business Applications (HBA) by NAICS Sector," Business Formation Statistics, accessed April 7, 2026, https://www.census.gov/econ/bfs/index.html.

TABLE 2. Decomposition of AI-exposed business application growth

AI-exposed sectors	Q1 2024	Q1 2026	Change
Total business applications	302,891	357,171	+18.0%
High-propensity applications	80,895	75,691	-6.4%
Non-employer-type applications	221,996	281,480	+26.8%

Source: Author's calculations using US Census Bureau, "Monthly Not-Seasonally-Adjusted Business Applications (BA) and High-Propensity Business Applications (HBA) by NAICS Sector," Business Formation Statistics, accessed April 7, 2026, https://www.census.gov/econ/bfs/index.html.

4.3 Preliminary event-study evidence

A before-and-after event study using a panel of seven sectors from 2022 to 2025 reinforces the timing. Relative to 2023, the 2022 pretreatment coefficient is statistically insignificant, the 2024 coefficient is positive but not statistically significant, and the 2025 coefficient is positive and statistically significant, as table 3 shows. The 2025 estimate implies approximately 16 percent more growth

TABLE 3. Year-by-AI-exposed interaction coefficients from BFS event study

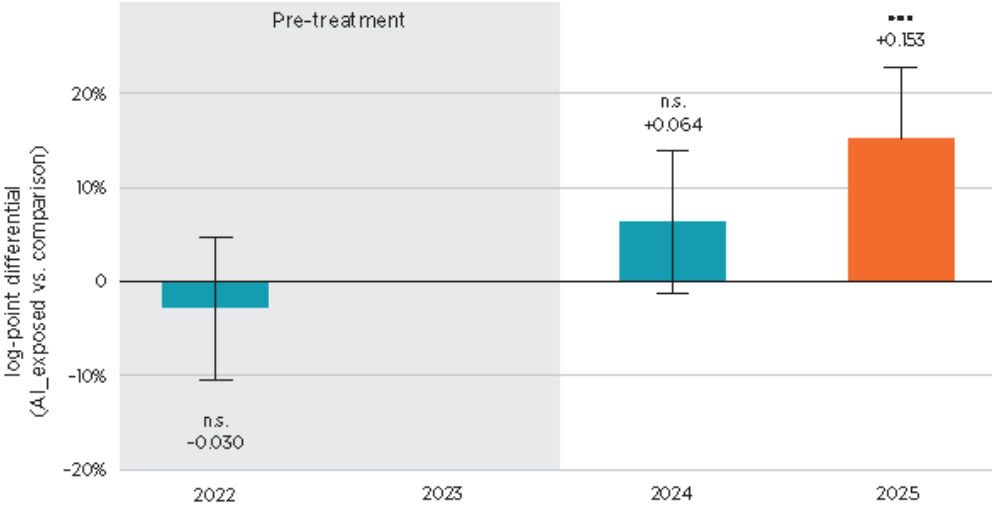
Year	Coefficient	p-value	Interpretation
2022	-0.030	0.44	Not significant; supports parallel pre-trends
2023	0.000	–	Base year
2024	+0.064	0.11	Positive but not significant

Source: Author's calculations using US Census Bureau, "Monthly Not-Seasonally-Adjusted Business Applications (BA) and High- Propensity Business Applications (HBA) by NAICS Sector," Business Formation Statistics, accessed April 7, 2026, https://www.census.gov/econ/bfs/index.html.

in solo-type business formation in AI-exposed sectors than in the comparison group, controlling for sector composition, common time trends, and seasonality.

The nonsignificance of the 2022 pretreatment coefficient provides no evidence of a differential pre-trend in the short pre-period, though the small number of sectors limits statistical precision. The 2024 coefficient is positive but not statistically significant, while the 2025 coefficient is positive and statistically significant, suggesting that the divergence emerges after the reference period and becomes clear in 2025, as figure 3 illustrates. With only seven sectors, these estimates should be treated as suggestive rather than definitive.

FIGURE 3. Solo business applications diverged in AI-exposed sectors after 2024



Note: Bars show year-by-AI-exposed interaction coefficients from sector-quarter event study of the log of adjusted applications. The omitted base year is 2023. Blue bar = statistically significant ($p < 0.05$); gray = not statistically significant (n.s.). Estimates include sector, year, and quarter fixed effects.
Source: Author's calculations using US Census Bureau, "Monthly Not-Seasonally-Adjusted Business Applications (BA) and High-Propensity Business Applications (HBA) by NAICS Sector," Business Formation Statistics, accessed April 7, 2026, https://www.census.gov/econ/bfs/index.html.

4.4 Interpretation

These results are consistent with AI lowering the threshold for one-person business formation. People appear to be filing for businesses in AI-exposed sectors at higher rates, but those filings increasingly do not look like near-term employer firms. This finding is what one would expect if it is true that AI lowers the minimum efficient scale for producing professional services, information products, educational content, financial analysis, and related knowledge work.

The pattern is consistent with the transaction-cost mechanism outlined in section 2: When AI reduces the need for complementary labor inputs, the resource threshold for operating independently falls, and the firm's bundling advantage shrinks. Section 5 examines whether the same pattern appears in labor-market data on actual self-employment.

5. Results from CPS Self-Employment Data

The CPS evidence points in the same direction. Across industries and occupations, and within one detailed occupation, self-employment and solo self-employment rise after 2024 in AI-exposed work while remaining flat or declining in comparison groups.

5.1 Industry-level self-employment

From the 2022–2023 baseline to 2025, total self-employment in AI-exposed industries rose 7.4 percent, compared with 1.8 percent in the comparison group, as shown in table 4. Solo self-employment rose 7.9 percent in AI-exposed

TABLE 4. CPS self-employment in AI-exposed and comparison industries

Measure	AI-exposed industries	Comparison group
All self-employment, 2022-2023 average	3,073k/month	2,750k/month
All self-employment, 2025	3,300k/month	2,800k/month
All self-employment change	+7.4%	+1.8%
Solo self-employment, 2022-2023 average	620k/month	505k/month
Solo self-employment, 2025	669k/month	494k/month
Solo self-employment change	+7.9%	-2.1%

Source: Author's calculations using Sarah Flood et al., "IPUMS CPS: Version 13.0" (dataset), US Census Bureau, Current Population Survey, 2025, https://doi.org/10.18128/D030.V13.0.

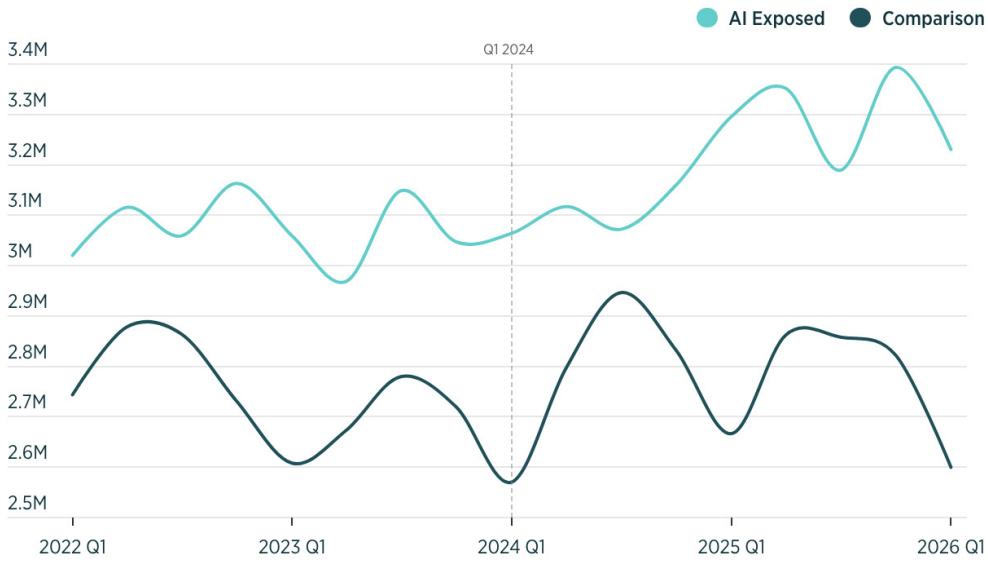
industries and declined 2.1 percent in the comparison group. Both groups were essentially flat through 2024, consistent with treating that year as a transition period; the divergence is concentrated in 2025.

The solo self-employment contrast is the more meaningful result. Total self-employment includes workers who employ others—a slightly different phenomenon from working independently. Solo self-employment, which excludes any worker with paid employees, is the more direct conception of independent work and test of the mechanism: AI lowering the cost of working entirely outside a firm.

Figure 4 shows self-employment in AI-exposed industries trending broadly flat through 2022–2024, then rising clearly in 2025. The comparison group remained broadly flat throughout.

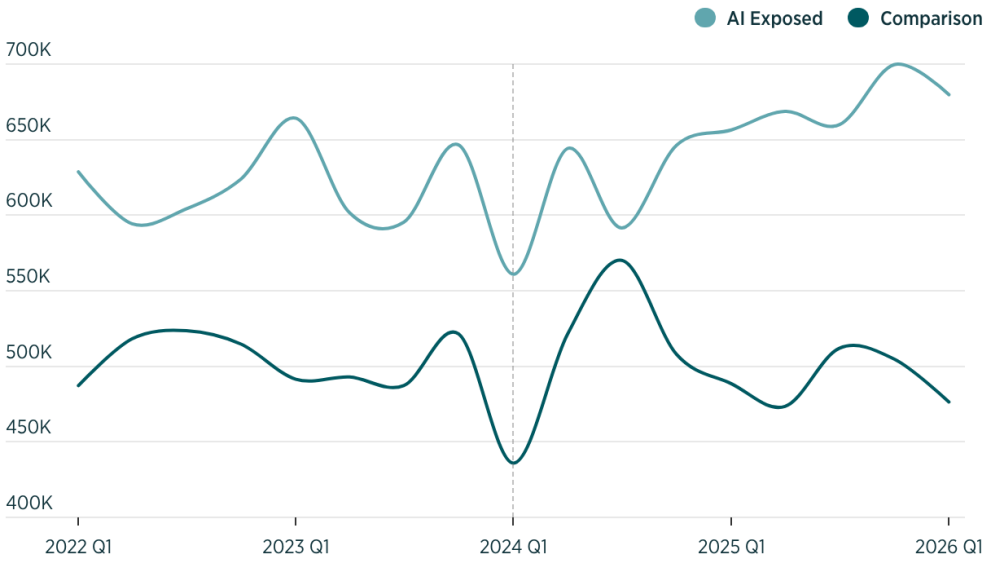
Figure 5 shows the same pattern for solo self-employment. The AI-exposed group rises clearly in 2025 while the comparison group declines slightly but shows no meaningful change.

FIGURE 4. Quarterly self-employment levels, Q1 2022 to Q1 2026



Note: Values represent average monthly self-employment within each quarter. AI-exposed group ranges roughly 3.0 to 3.16 million in 2022–2024 and rises clearly in 2025. Comparison group is broadly flat throughout. Vertical line at Q1 2024. Q1 values tend to be lower due to seasonal patterns. Q1 2026 reflects January–March only.
Source: Author's calculations using Sarah Flood et al., "IPUMS CPS: Version 13.0" (dataset), US Census Bureau, Current Population Survey, 2025, https://doi.org/10.18128/D030.V13.0.

FIGURE 5. Quarterly solo self-employment levels, Q1 2022 to Q1 2026



Note: Values represent average monthly solo self-employment within each quarter. AI-exposed group ranges roughly 560,000 to 665,000 in 2022–2024 and rises clearly in 2025. Comparison group is broadly flat throughout. Vertical line at Q1 2024. Q1 values tend to be lower due to seasonal patterns. Q1 2026 reflects January–March only.
Source: Author's calculations using Sarah Flood et al., "IPUMS CPS: Version 13.0" (dataset), US Census Bureau, Current Population Survey, 2025, https://doi.org/10.18128/D030.V13.0.

5.2 Occupation-level AI exposure

Using the AIOE creates a nonarbitrary grouping of occupations. The 10 most AI-exposed occupations include financial examiners, actuaries, budget analysts, accountants and auditors, compensation and benefits specialists, management analysts, market research analysts, economists, mathematicians and statisticians, and lawyers. The 10 least exposed occupations include dancers, fitness trainers, dining room attendants, landscaping workers, athletes, structural iron workers, cement masons, brickmasons, roofers, and construction laborers.

The contrast between the two groups is intuitive: The high-exposure occupations are knowledge-intensive, output-measurable, and not dependent on physical presence or team coordination, which are precisely the conditions under which AI plausibly lowers the cost of working independently.

The results, as seen in table 5, show that solo self-employment in the 10 most AI-exposed occupations rose 20 percent from the 2022–2023 baseline to 2025, while solo self-employment in the 10 least AI-exposed occupations was essentially unchanged.

TABLE 5. Solo self-employment among high- and low-AI-exposure occupations

Measure	High AI exposure	Low AI exposure
Solo self-employment, 2022-2023 average	129k/month	204k/month
Solo self-employment, 2025	155k/month	204k/month
Change	+20%	Flat (about 0%)
Solo self-employment share, 2022-2023 average	2.64%	4.12%
Solo self-employment share, 2025	2.98%	3.95%
Share change	+0.34 pp	-0.17 pp

Note: The abbreviation "pp" means percentage points.
Source: Author's calculations using Sarah Flood et al., "IPUMS CPS: Version 13.0" (dataset), US Census Bureau, Current Population Survey, 2025, https://doi.org/10.18128/D030.V13.0. Occupation groups based on Edward Felten et al., "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses," *Strategic Management Journal* 42, no. 12 (2021): 2195–217.

The levels contrast is worth noting: The low-exposure group starts larger in absolute terms and remains flat at about 204,000 per month. The high-exposure group starts smaller, at 129,000 per month, but grows to 155,000 by 2025, narrowing the gap by about 26,000 workers per month. The share data reinforce the direction: The solo self-employment share rose 0.34 percentage points in high-exposure occupations and fell 0.17 percentage points in low-exposure occupations over the same period.

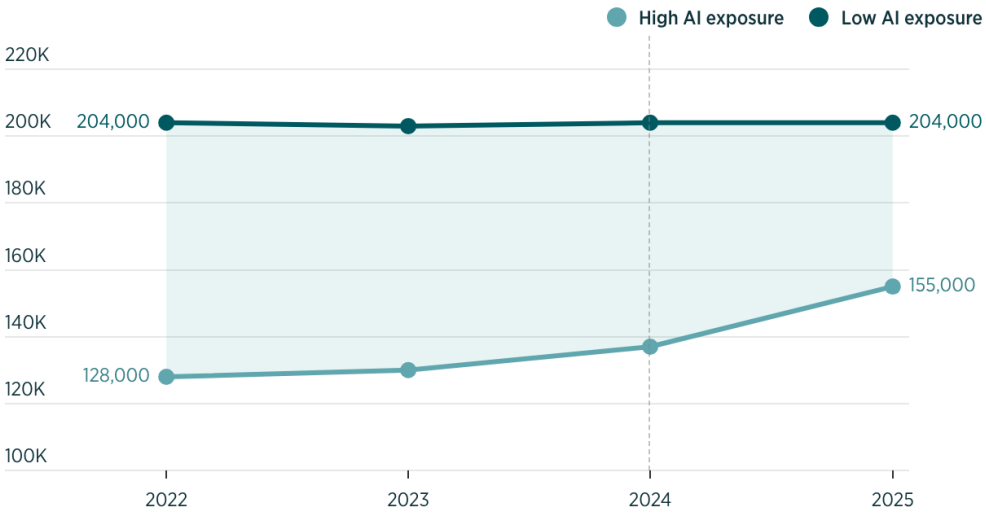
Figure 6 shows the divergence visually. The low-exposure group is flat across the full period. The high-exposure group rises steadily from 2022 through 2025, with the clearest acceleration after 2024.

5.3 Management analysts and independent consulting

Management analysts provide a particularly useful test case. The occupation is large enough to produce stable CPS estimates and is near the top of the AI exposure distribution. It is also the kind of knowledge work where AI can substitute for support functions such as research, drafting, analysis, presentation preparation, and document review.

The management analyst evidence shows a clear break in 2025. The solo self-employment share was roughly 5.6 percent in the 2022–2023 baseline, 5.3 percent in 2024, 6.8 percent in 2025, and over 7 percent in Q1 2026, as table 6 shows.

FIGURE 6. Annual solo self-employment levels, high- vs. low-AI-exposure occupations, 2022–2025



Note: High-AI-exposure group rose from 128,000 to 155,000 per month, whereas low-AI-exposure group stayed flat at roughly 204,000. Vertical line at 2024. Values represent average monthly solo self-employment.
Source: Author's calculations using Sarah Flood et al., "IPUMS CPS: Version 13.0" (dataset), US Census Bureau, Current Population Survey, 2025, https://doi.org/10.18128/D030.V13.0; Edward Felten et al., "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses," *Strategic Management Journal* 42, no. 12 (2021): 2195–217.

TABLE 6. Management analyst solo self-employment share and total employment

Period	Solo self-employment share	Total employed
2015 (peak)	7.2%	808k/month
2019 (pre-COVID)	5.4%	911k/month
2020 (COVID)	2.9%	958k/month
2022-2023 (average)	5.6%	1,008k/month
2024	5.3%	1,056k/month
2025	6.8%	1,033k/month
Q1 2026 (partial year)	7.0%	1,119k/month

Source: Author's calculations using Sarah Flood et al., "IPUMS CPS: Version 13.0" (dataset), US Census Bureau, Current Population Survey, 2025, https://doi.org/10.18128/D030.V13.0.

Overall employment in the occupation remained above the 2022–2023 baseline and rose further in Q1 2026; the occupation was not shrinking. Instead, more work appears to be reorganizing toward solo self-employment.

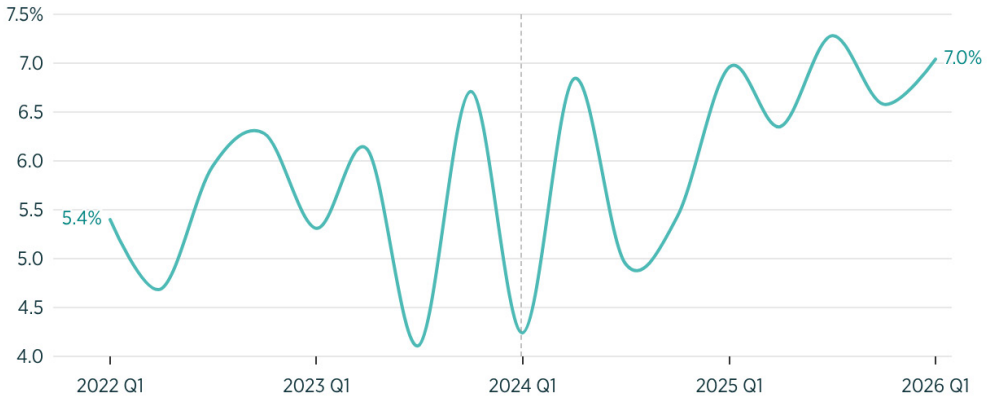
Two features of table 6 are worth emphasizing. First, the pandemic shock was severe: The solo share nearly halved from 5.4 percent in 2019 to 2.9 percent in 2020, even as total employment in the occupation rose slightly. These data suggest that independent consultants were disproportionately displaced while salaried analysts held their positions.

Second, the recovery through 2022–2023 brought the share back to roughly its prepandemic level, where it remained flat through 2024. The 2025 break therefore does not look like a simple continuation of pandemic recovery dynamics; it appears to be a departure from the postrecovery baseline.

The occupation-level finding also reinforces the "unbundling, not shrinking" interpretation. Solo self-employment grew more than twice as fast as overall employment in the occupation from 2022 to early 2026. The occupation as a whole is not contracting, but it is reorganizing, with a rising share of the work being performed outside traditional firm structures.

Figure 7 shows the quarterly series. The share was volatile but broadly flat from 2022 through 2024, then broke upward in 2025 with all four quarters coming in above 6.3 percent—elevated relative to most of the prior period. Q1 2026

FIGURE 7. Solo self-employment among management analysts, Q1 2022 to Q1 2026



Note: The share of management analysts working solo was flat through 2022–2024, then broke upward in 2025. All four quarters of 2025 remained elevated relative to most earlier quarters, though quarter-to-quarter noise remains substantial. Q1 2026 reached 7.0 percent. Q1 values tend to be lower due to seasonal patterns. Q1 2026 reflects January–March only.
Source: Author's calculations using Sarah Flood et al., "IPUMS CPS: Version 13.0" (dataset), US Census Bureau, Current Population Survey, 2025, https://doi.org/10.18128/D030.V13.0.

reached 7.0 percent, though this reflects January through March only and should be treated as a partial-year observation.

6. Interpretations and Limitations

Several recent surveys document rapid but uneven AI adoption across workers, firms, industries, and tasks.[11] The Census Bureau BTOS AI supplement is especially relevant for this study because it maps adoption to business sectors: It shows that AI use is concentrated in knowledge-intensive sectors such as Information, Professional Services, Finance and Insurance, and Education, and that AI's current effects inside firms are more often augmenting tasks than replacing jobs.[12] These data are consistent with the possibility that AI's early effects may operate through augmentation, scale, and work organization rather than immediate mass displacement.

Emerging firm-level evidence reinforces this organizational interpretation. Hyunjin Kim and coauthors study a field experiment with high-growth startups and find that helping firms identify how to map AI into production increased AI use cases, task completion, customer acquisition, and revenue, while reducing demand for external capital and leaving labor demand unchanged.[13] Hyunjin Kim and Rembrand Koning also find that AI-native startups are smaller, flatter, more technically concentrated, and more capital efficient than comparable non-AI startups, with similar valuations.[14] These studies examine startups and firm organization rather than independent work, but they reinforce the mechanism in this study: AI may allow production to scale with fewer complementary labor inputs, less hierarchy, and less firm-based infrastructure.

The most closely related study is by Guillermo Gallacher, who finds that sectors with greater AI exposure saw faster post-2022 growth in business applications, with a dynamic pattern that reemerges in 2024 and persists through March 2026.[15] The present study differs in three ways. First, it isolates the

11. Alexander Bick et al., "The Rapid Adoption of Generative AI," NBER Working Paper No. 32966 (National Bureau of Economic Research, September 2024); Jonathan Hartley et al., "The Labor Market Effects of Generative Artificial Intelligence" (SSRN, December 18, 2024), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5136877.
12. Bonney et al., "The Microstructure of AI Diffusion."
13. Hyunjin Kim et al., "Mapping AI into Production: A Field Experiment on Firm Performance," INSEAD Working Paper 2026/20/STR (INSEAD, March 30, 2026).
14. Hyunjin Kim and Rembrand Koning, "AI-Native Firms," Working Paper 26-090 (Harvard Business School, June 9, 2026).
15. Guillermo Gallacher, "Firm Entry and AI Exposure: Evidence from US Industries," working paper (April 24, 2026), https://guillgall.github.io/files/firm_entry_ai.pdf.

non-employer-type margin rather than total business applications—a distinction that matters because the growth in AI-exposed sectors is coming specifically from solo formation, not business formation broadly. Second, it pairs the business-formation evidence with CPS evidence on actual self-employment and solo self-employment. Third, it connects the independent worker trend to the policy institutions (e.g., unemployment insurance, employer-sponsored benefits) that were built for a different model of work and may be increasingly mismatched to how knowledge workers earn their incomes.

This study also extends prior work on transaction costs and the gig economy.[16] Digital platforms reduced frictions in terms of matching, payment, trust, and monitoring. AI may reduce a different set of frictions for knowledge work: the need for complementary labor inputs, the difficulty of measuring outputs, and the cost of producing polished deliverables without firm infrastructure.

The evidence is descriptive and preliminary, however, and does not prove that AI caused the observed divergence. Other sector-specific shocks could be operating simultaneously. The purpose of this study is to document a coherent pattern, connect it to a plausible economic mechanism, and identify a labor-market margin the AI debate has largely overlooked. Other limitations include the following:

- **BFS limitations:** The non-employer-type measure is constructed as total applications minus high-propensity applications; it is a proxy, not a direct Census measure of solo firms. BFS data are not seasonally adjusted, so the analysis relies on quarterly aggregation and same-quarter comparisons.
- **Event-study limitations:** The event study uses a small number of sector clusters. Standard errors should be interpreted cautiously.
- **CPS limitations:** Monthly estimates at detailed industry or occupation levels are noisy. The paid-employees question is asked only of a subset of self-employed respondents, limiting sample size for solo self-employment.
- **Exposure-index limitations:** The AIOE index predates the most recent generative AI capabilities and is used as a published, nonarbitrary classification device rather than a precise measure of generative AI exposure.
- **Timing limitations:** Q1 2026 reflects January through March only and should be treated as a partial-year observation.

16. Oranburg and Palagashvili, "Transaction Cost Economics, Labor Law, and the Gig Economy"; Munger, *Tomorrow* 3.0.

7. Policy Implications

If AI is making independent work more feasible in knowledge-intensive occupations, the central policy challenge is not only loss of traditional jobs, but also an erosion of the institutions that support those jobs. Much of the US labor-market safety net is still built around firms, and benefits such as health insurance, retirement savings, paid leave, unemployment insurance, and other protections are generally organized around W-2 employment. That model fits poorly with a labor market in which more workers may move across clients, contracts, platforms, solo businesses, and periods of self-employment.

The first implication is that benefits should become more portable. Workers who leave a firm to become independent consultants are still fully attached to the labor market, but they may lose access to employer-sponsored benefits. A freelancer or solo business owner may earn income from multiple clients without any one client serving as the institutional provider of benefits. If AI expands this kind of independent knowledge work, then benefits should increasingly attach to the worker rather than to a single firm.

Portable benefits would allow workers to maintain access to health benefits, retirement accounts, paid leave, and other forms of security across different work arrangements.[17] Contributions could come from multiple sources: the worker, firms, clients, platforms, customers, or government matches for lower-income workers. The goal is not to make independent work look exactly like traditional employment. It is to make sure that workers do not lose financial security simply because their income comes from contracts, clients, or a one-person business rather than from a firm.

The second implication concerns unemployment insurance and income disruption. Traditional unemployment insurance is built around a clean layoff from an employer. But AI-related disruption may not always appear that way. A consultant may lose clients. A software contractor may face fewer projects. A designer may see rates fall. A worker may move from a salaried job into solo self-employment, not because work disappeared entirely, but because the organization of work changed. In these cases, the relevant question is not only whether an employer laid someone off. It is whether the worker experienced a meaningful earnings shock or transition.

A more flexible system would provide worker-owned, portable accounts that follow individuals across employment, contracting, freelancing, platform

17. Liya Palagashvili, "Flexible Benefits for a Flexible Workforce: Unleashing Portable Benefits Solutions for Independent Workers and the Gig Economy" (Mercatus Policy Brief, Mercatus Center at George Mason University, February 2023).

work, and self-employment.[18] These accounts could provide first-line liquidity during unemployment, major earnings loss, reduced hours, the end of a contract, illness- or caregiving-related work interruptions, or other labor-market transitions. Because the account belongs to the worker, unused balances would remain with the worker and could eventually roll into long-term savings or retirement. That ownership feature preserves incentives to work, rebuild earnings, and avoid unnecessary withdrawals.

To provide additional security for more vulnerable workers, portable accounts should be paired with a limited pooled insurance backstop. Lower-income workers, new labor-market entrants, and workers hit by severe recessions or sector-wide AI shocks may not have enough time or income to build adequate balances. The individualized account would be the first layer; pooled insurance would be the second layer for workers with insufficient balances or unusually severe disruptions.

Together, these ideas point toward a broader principle: Labor-market security should travel with the worker rather than remain tied to a single firm. If AI expands independent work, policy should not force workers back into traditional employment relationships simply so they can access benefits or income security. Instead, institutions should become portable across employment, contracting, freelancing, platform work, and self-employment.

8. Conclusion

The first labor-market effects of AI may not appear primarily as mass unemployment. They may instead emerge through the growth of independent work and solo self-employment.

Across two independent data sources, the pattern points in the same direction. In business formation data, the entire post-2024 growth in AI-exposed sectors came from applications with no markers of employer intent, while employer-type applications fell. In labor-market data, solo self-employment rose in AI-exposed industries and occupations while holding flat or declining in comparison groups. Among management analysts, a large and highly AI-exposed occupation, solo self-employment grew more than twice as fast as overall

18. For related proposals for worker-owned security accounts, see: Jonathan Gruber, *Security Accounts as Short-Term Social Insurance and Long-Term Savings* (Aspen Institute Future of Work Initiative, 2026); Liya Palagashvili, "Portable Unemployment Security Accounts: Worker-Owned Accounts for Job Loss, Earnings Disruption, and AI-Era Labor Market Transitions," unpublished manuscript, 2026.

employment from 2022 to early 2026, reversing a decade-long decline in the share working independently. The occupation is not shrinking; it is reorganizing.

The evidence is descriptive, early, and concentrated in a short post-2024 window. But the pattern is coherent across data sources, consistent with the transaction-cost mechanisms outlined in this study, and concentrated precisely where it should be if AI is lowering the cost of working outside a firm.

The policy challenge this study raises is not primarily about unemployment. It is about institutional mismatch. The labor-market infrastructure, including unemployment insurance and employer-sponsored benefits, was built around a model of work that assumed one employer, W-2 wages, and a clean separation upon a worker's job change. If AI is expanding the population of workers who earn income outside that model, the mismatch will grow. The EIN business applications are already coming in. The question is whether labor policy will catch up.

Methodological Appendix

Business Formation Statistics

Data source: US Census Bureau Business Formation Statistics, monthly, by North American Industry Classification System (NAICS) sector. Monthly values are summed to quarterly totals. The author-constructed outcome is adjusted applications, defined as total business applications minus high-propensity business applications. The author's calculation isolates applications unlikely to become employer firms and is used as the proxy for nonemployer-type or solo-type business formation.

BFS event-study specification: log adjusted applications by sector and quarter is modeled with year-by-AI-exposed interactions, sector fixed effects, year fixed effects, and quarter fixed effects. The omitted year is 2023. The sample covers 2022 through 2025.

Current Population Survey

Data source: IPUMS-CPS microdata, January 2015 through March 2026. The 2025 CPS annual estimates use all available monthly observations in the extract; October 2025 is not included because it was unavailable in IPUMS-CPS during the federal government shutdown. Employment is restricted to workers currently at work (EMPSTAT = 10). *All self-employed workers* includes incorporated and unincorporated self-employed workers (CLASSWKR = 13 or 14). *Solo self-employed workers* are self-employed workers who report no paid employees on the first job (PAIDEMP1 = 1). Estimates use CPS final person weights (WTFINL) and are aggregated to monthly, quarterly, or annual averages as indicated.

CPS industry analysis compares professional services, information, and education with construction and wholesale trade. The occupation analysis uses the Felten, Raj, and Seamans AI Occupational Exposure index crosswalked to CPS OCC2010 codes. Management analysts are identified as OCC2010 = 710.

About the Author

Liya Palagashvili is a senior research fellow and director of the Labor Policy Project at the Mercatus Center at George Mason University, where her research focuses on labor markets, independent work, portable benefits, and the role of artificial intelligence in the changing nature of work. This research has been cited in congressional hearings and the *Federal Register* and has served as the basis of federal and state legislation on independent workers and portable benefits.