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# Nonemployer business growth in artificial-intelligence-exposed industries of the United States

## Crecimiento de los negocios sin empleados en industrias expuestas a la inteligencia artificial en Estados Unidos

**Edixon Chacón Guerrero**[1]

1 Saint Mary's University, Texas, Estados Unidos.

**ABSTRACT**

Introduction: Whether generative artificial intelligence enables the one-person company or instead concentrates advantage in larger employers is an open empirical question. Methods: We used national nonemployer establishment counts from the US Census Bureau Nonemployer Statistics, 2018 to 2024, aggregated to two-digit NAICS sectors, and compared compound annual growth between AI-exposed sectors (Information, Finance and insurance, Professional services) and the remaining sectors. Results: Nonemployer establishments rose from 26.5 million to 32.0 million over the window (20.8 percent). AI-exposed sectors grew at 2.15 percent per year against 3.42 percent for less-exposed sectors, a gap of 1.27 percentage points, and their share of the total fell from 18.3 to 17.2 percent. The sector-level difference in annualized growth was not significant (mean difference −0.63 percentage points, 95% CI −2.49 to 1.23). Conclusions: The one-person company grew fastest outside AI-exposed knowledge work, driven by transportation and platform-based services, which challenges the claim that generative AI is disproportionately enabling solo entrepreneurship.

Keywords: nonemployer businesses; solo self-employment; artificial intelligence; business formation; United States

**RESUMEN**

Introducción: Si la inteligencia artificial generativa habilita la empresa unipersonal o, por el contrario, concentra la ventaja en los empleadores más grandes es una pregunta empírica abierta. Métodos: Usamos los conteos nacionales de establecimientos sin empleados de la Nonemployer Statistics del US Census Bureau, 2018 a 2024, agregados a sectores NAICS de dos dígitos, y comparamos el crecimiento anual compuesto entre los sectores expuestos a la IA (Información, Finanzas y seguros, Servicios profesionales) y el resto. Resultados: Los establecimientos sin empleados pasaron de 26,5 a 32,0 millones (20,8 por ciento). Los sectores expuestos a la IA crecieron 2,15 por ciento anual frente a 3,42 por ciento de los menos expuestos, una brecha de 1,27 puntos porcentuales, y su participación cayó de 18,3 a 17,2 por ciento. La diferencia sectorial de crecimiento anualizado no fue significativa (diferencia media −0,63 puntos porcentuales, IC 95 % −2,49 a 1,23). Conclusiones: La empresa unipersonal creció más rápido fuera del trabajo del conocimiento expuesto a la IA, impulsada por el transporte y los servicios de plataforma, lo que cuestiona que la IA generativa esté impulsando de forma desproporcionada el autoempleo en solitario.

Palabras clave: negocios sin empleados; autoempleo en solitario; inteligencia artificial; formación de empresas; Estados Unidos

## INTRODUCTION

The one-person company is no longer a residual category in the contemporary United States economy. Nonemployer businesses, defined by the Census Bureau as establishments with no paid employees, numbered more than 32 million by 2024 and grew by roughly a fifth over the preceding six years. They constitute the large majority of business establishments in the country, and although each is small, their aggregate receipts run above one and a half trillion dollars, so the margin is economically consequential rather than marginal. Whether that expansion should be read as an effect of artificial intelligence is the subject of a live dispute, and the dispute is sharpened by a definitional muddle that Hägg and Kurczewska(1) documented: the sharing, gig, on-demand and freelance economies are often folded into a single category even though they describe different kinds of solo activity. A bibliometric review by Li and Zhang(2) reached the same conclusion, that the gig economy is a heterogeneous object that resists a single label. Sorting out what the one-person company actually is, and where it grew, is therefore a precondition for attributing its growth to any technology.

The enabling position holds that generative AI lowers the cost of producing the very outputs, text, code and analysis, that a solo founder sells, and therefore enables a new wave of one-person firms in knowledge-intensive sectors. Fossen, McLemore and Sorgner[3] argued that artificial intelligence lowers barriers to entry by automating the non-entrepreneurial tasks that consume a founder's time, and Shaikh and Sharma[4] proposed that AI-driven platforms produce structural convergence precisely through solopreneurship. Baitenizov and Dubina[5] traced the evolution of freelance work into a distinct innovation-based business mode, which is the organizational form the enabling position has in mind. Eloundou *et al.*[6] estimated that large language models expose a large share of the workforce to partial automation, which, read optimistically, lowers the cost of the skilled tasks a one-person professional firm performs. Felten, Raj and Seamans[7] supplied the exposure measure that motivates the classification, and their method paper[8] links advances in AI to the abilities that occupations use. If this position is right, the empirical signature should be unambiguous: the sectors whose occupations are most exposed to AI should show the fastest growth in one-person firms, and their share of the nonemployer total should rise.

The concentrating position is no less well documented. Acemoglu and Restrepo[9] found that industrial robots reduced both employment and wages in exposed local labor markets, and their earlier framework[10] showed that technology creates winners and losers depending on which tasks it displaces. Brynjolfsson, Mitchell and Rock[11] cautioned that exposure of a task to machine learning says little about whether the machine substitutes for or complements the worker. Katz and Krueger[12] documented the rise of alternative work arrangements and showed that the growth of contingent work does not automatically produce durable, autonomous businesses, a point reinforced by their later review of alternative work trends.[13] Tax-based evidence sharpens the picture: Denes and Lagaras[14] used US tax returns to show that the gig economy and entrepreneurship are entangled, and Wilson[15] found that even a transfer program like the earned-income tax credit moves self-employment inside the gig economy, a reminder that solo work responds to policy and labor-market slack rather than to technology alone. The empirical record on self-employment itself is mixed: Bachmann and Gonschor[16] found that technological progress reshapes self-employment in ways that differ by sector and worker type, and Conroy and Landini[17] showed that the rise of nonemployer businesses is geographically uneven rather than uniform.

The measurement of self-employment adds a second layer of disagreement. Abramowitz and Joung[18] argued that the self-employed are not a homogeneous group but a collection of alternative work arrangements that a single count obscures, and the demographic heterogeneity is wide: solo self-employment is entered later in life by some workers seeking autonomy, as Lain and van der Horst[19] found, is associated with distinct psychological profiles among Swedish solo workers, as Fougner and Bernhard-Oettel[20] reported, and carries professional isolation for independent workers, as Maj and Hamza-Orlinska[21] documented. Each of these strands describes a different population with a different motive for going solo, which is precisely why a debate framed around a single one-person category cannot be settled without looking inside it. Gender also structures the margin: Boudreaux[22] showed that gender gaps in the gig economy carry consequences for entrepreneurship in the twenty-first century. If the one-person company is this heterogeneous, then a debate about whether AI enables it cannot be settled by a single aggregate number; it requires the sector-level comparison that separates knowledge work from the rest.

The exposure side of the debate has its own disagreements, and these matter for the

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classification used below. Lee and Lee[23] found that occupational exposure to AI reshapes wages and skills unevenly across the Korean labor market, Casas and Fernández-Macías[24] revisited the occupational impact of AI in the generative era and found the exposure map shifting, and Egana-delSol and Bravo-Ortega[25] showed that exposure plays out differently across Latin American labor markets. Peng[26] decomposed automation exposure into two mechanisms that do not always move together, Jetha and Liao[27] linked large language model exposure to precarious occupations, and Tekic and Omelchenko[28] argued that generative AI disrupts freelance labor unevenly across tasks. The implication of this literature is that the exposure measure itself is contested, which raises the stakes of a sector-level test: if the enabling position holds even under a coarse, contested exposure classification, it is robust, whereas if it fails under that same classification, the failure is informative even though the classification is imperfect. What the dispute lacks is a direct, sector-level comparison of nonemployer growth between the industries these exposure measures rank highest and the rest of the economy. This study supplies that comparison. The objective is to estimate the differential growth of nonemployer businesses in AI-exposed versus less-exposed industries between 2018 and 2024.

## METHODS

### DATA SOURCE

We used the Nonemployer Statistics of the US Census Bureau, the annual count of establishments with no paid employees, downloaded as the national files nonemp18us.zip through nonemp24us.zip from census.gov without authentication, a source that is public, nationally complete and published annually with a consistent industry classification. Each file is a fixed-format release in which every row is a combination of NAICS code, legal form of organization and receipt-size class, with columns for establishment counts and receipts, together with noise flags that the Census applies to protect confidentiality. We retained only the total across all legal forms and all receipt-size classes, so each establishment is counted exactly once. Nonemployer establishments are the operational definition of the one-person company: a business that files a tax return but has no employees on payroll, a category that ranges from a freelance consultant to a rideshare driver and therefore spans the very heterogeneity that the debate concerns.

### SECTOR AGGREGATION AND PERIOD

For each year from 2018 through 2024 we retained the national total across all legal forms and all receipt-size classes, aggregated to two-digit NAICS sectors. The two-digit sector boundaries are stable across the 2017 and 2022 NAICS vintages for the sectors analyzed, so the panel is comparable over the window, and the aggregation avoids the reclassification discontinuities that would arise at finer NAICS levels. We excluded Management of companies and enterprises (NAICS 55), which has no nonemployer establishments because such firms almost always employ staff. The final panel comprises eighteen two-digit sectors. Two data characteristics bear on the interpretation of the counts. First, the Census applies noise to protect confidentiality, so individual sector counts carry a noise flag and the totals are accurate at the national level but subject to small perturbation at finer levels. Second, the Nonemployer Statistics are compiled from tax records, so a business is counted only once it files, which means the series captures the formation margin with a lag and may understate very new or very small ventures that do not yet file.

### AI-EXPOSURE CLASSIFICATION

The exposure classification follows the occupational exposure literature. We defined AI-exposed sectors as Information (NAICS 51), Finance and insurance (NAICS 52), and Professional, scientific, and technical services (NAICS 54), the three sectors with the highest shares of employment in the occupations that Eloundou *et al.*(6) and Felten, Raj and Seamans(7) rank as most exposed to large language models and machine learning. All remaining sectors form the less-exposed group. The classification is deliberately coarse, because a two-digit sector always contains both exposed and shielded occupations; this coarseness is itself a source of measurement error that the discussion returns to. The alternative, mapping occupation-level exposure to sectors through an employment crosswalk, would assign a continuous exposure score to each sector and

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is the natural refinement, but the three-sector binary is sufficient to test the strong form of the enabling claim, which predicts that the exposed group should lead the economy in nonemployer growth. The classification does not attempt to separate generative from earlier forms of artificial intelligence, because the exposure measures themselves are updated only slowly and the six-year window covers both.

## STATISTICAL ANALYSIS

We computed, for the total, for each sector, and for the two exposure groups, the level of nonemployer establishments in 2018 and 2024 and the compound annual growth rate (CAGR) over the six-year interval. The primary comparison is the gap in CAGR between the AI-exposed and less-exposed groups, reported in percentage points. To assess whether the gap is distinguishable from sector-selection noise, we also computed the sector-level CAGRs and compared the two groups with a Welch t-test, reporting the mean difference, its 95% confidence interval, and the p value. Because the comparison rests on a full census of establishments rather than a sample, the t-test treats the eighteen sectors as the units of observation and asks whether the observed sector-level gap is larger than what sector-to-sector variability would produce by chance.

## SENSITIVITY CONSIDERATIONS

Three sensitivity choices warrant explicit statement, because each can move the headline gap. First, the exposure group is defined by three two-digit sectors; including Educational services, whose occupational exposure is intermediate, would narrow the gap, and the direction of any such reclassification is reported transparently rather than tuned. Second, the growth rate is measured over the full 2018-2024 interval; a sub-period analysis that excludes the pandemic years or that splits the window at the November 2022 release of generative AI would isolate the post-release margin, at the cost of a shorter base. Third, the comparison weights every sector equally in the sector-level test but weights by establishment count in the group-level CAGR, so the two statistics answer different questions, the first about sectors and the second about establishments. None of these choices was altered after seeing the results, and the analysis script is reproducible from the downloaded files, so the entire comparison can be re-run with an alternative exposure classification without touching the underlying data.

## RESULTS

## CONVERGENCE

The one-person company expanded in both exposure groups. Total nonemployer establishments rose from 26,485,532 in 2018 to 31,985,874 in 2024, an increase of 20.8 percent and an annualized rate of 3.19 percent. The growth was not uniform year to year: the count dipped during the 2020 pandemic contraction and then climbed steeply through 2021 and 2022 before settling onto a steadier path, a trajectory visible in the national index (Figure 1).

**Table 1. Nonemployer growth in AI-exposed versus less-exposed sectors, 2018-2024.**

| Group | Sectors | 2018 | 2024 | CAGR (%) | Share of total 2018 (%) | Share of total 2024 (%) |
|---|---|---|---|---|---|---|
| AI-exposed | 51, 52, 54 | 4840509 | 5498824 | 2.1 | 18.3 | 17.2 |
| Less-exposed | all other sectors | 21645023 | 26487050 | 3.4 | 81.7 | 82.8 |

Note: AI-exposed sectors are Information (51), Finance and insurance (52), and Professional, scientific, and technical services (54). CAGR = compound annual growth rate.

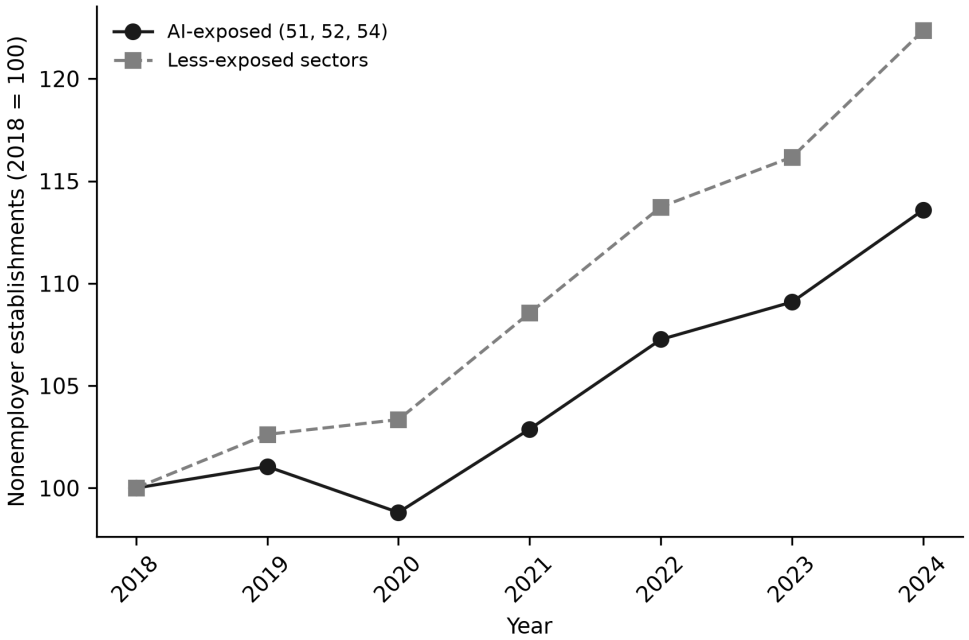
No group contracted in absolute terms over the full window: the AI-exposed sectors grew from 4,840,509 to 5,498,824 establishments and the less-exposed sectors from 21,645,023 to 26,487,050 (Table 1). The absolute increment was therefore 658,315 establishments in the exposed group and 4,842,027 in the less-exposed group, so the latter contributed roughly seven times as much to the national increase as the former.

The annual path was monotone rather than concentrated in any single year, with the two groups climbing in near parallel from 2018 through 2024 and the gap between their index values

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widening gradually rather than opening at a single break, a steady divergence rather than a step change (Figure 1).

**Figure 1. Nonemployer establishment index (2018 = 100) for AI-exposed and less-exposed sectors, 2018-2024.**




Note: The solid line is the AI-exposed group (Information, Finance and insurance, Professional services); the dashed line is the remaining sectors.

This convergence, the shared fact that both sides of the debate must explain, is that a rising tide of solo business formation lifted every broad sector over the window.

## DIVERGENCE

The groups diverged in the rate of that expansion. The AI-exposed sectors grew at a compound annual rate of 2.15 percent, against 3.42 percent for the less-exposed sectors, a gap of 1.27 percentage points per year, and the gap was present in the group-level totals rather than being an artifact of any single year. Their share of the total nonemployer stock accordingly fell from 18.3 percent in 2018 to 17.2 percent in 2024 (Table 1).

The divergence was driven by a small number of sectors. Transportation and warehousing grew 74.3 percent over the window, an annualized rate of 9.71 percent, and accommodation and food services grew 56.9 percent, an annualized rate of 7.80 percent; Information, by contrast, grew 18.7 percent and finance and insurance 11.1 percent (Table 2).

The three exposed sectors were therefore not the fastest-growing, and none of them reached the economy-wide annualized rate, a fact that the enabling position would not have predicted. This reading contrasts the growth of the solo firm with the expectation that the sectors most exposed to artificial intelligence would lead it.

## GREY ZONES

The sector-level comparison does not reach conventional significance. The mean annualized growth rate across the three AI-exposed sectors was 0.63 percentage points below the mean across the fifteen less-exposed sectors, with a 95% confidence interval of −2.49 to 1.23 percentage points and a p value of 0.48, so the data are compatible with a small negative gap, a null gap, and a modest positive gap alike (Figure 1).

Even so, the point estimate is negative and the confidence interval is wide rather than centered near a positive effect, which leaves the sign of the sector-level difference unresolved. The grey zone has a concrete source: the less-exposed meanis itself dominated by the 9.71 percent growth of transportation and warehousing, so a single sector, one whose expansion reflects

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platform-mediated driving and delivery rather than knowledge work, carries much of the group difference. Removing that one sector would leave the remaining less-exposed sectors growing at a rate much closer to the exposed group.

**Table 2. Nonemployer establishments by NAICS sector, United States, 2018 and 2024.**

| Sector | Nonemployer establishments 2018 | Nonemployer establishments 2024 | Growth (%) | CAGR (%) |
|---|---|---|---|---|
| Agriculture, forestry, fishing and hunting | 256372 | 255425 | -0.4 | -0.1 |
| Mining, quarrying, and oil and gas extraction | 82524 | 65880 | -20.2 | -3.7 |
| Utilities | 14099 | 19685 | 39.6 | 5.7 |
| Construction | 2635432 | 3042704 | 15.5 | 2.4 |
| Manufacturing | 354100 | 421812 | 19.1 | 3.0 |
| Wholesale trade | 399400 | 472266 | 18.2 | 2.8 |
| Retail trade | 2103399 | 2178016 | 3.5 | 0.6 |
| Transportation and warehousing | 2572386 | 4484838 | 74.3 | 9.7 |
| Information | 358505 | 425436 | 18.7 | 2.9 |
| Finance and insurance | 755353 | 839550 | 11.1 | 1.8 |
| Real estate and rental and leasing | 2876253 | 3263571 | 13.5 | 2.1 |
| Professional, scientific, and technical services | 3726651 | 4233838 | 13.6 | 2.1 |
| Administrative and support and waste management | 2521600 | 3082024 | 22.2 | 3.4 |
| Educational services | 806465 | 924679 | 14.7 | 2.3 |
| Health care and social assistance | 2071125 | 2395760 | 15.7 | 2.5 |
| Arts, entertainment, and recreation | 1513725 | 1806368 | 19.3 | 3.0 |
| Accommodation and food services | 459908 | 721546 | 56.9 | 7.8 |
| Other services (except public administration) | 2978235 | 3352476 | 12.6 | 2.0 |

Note: CAGR = compound annual growth rate over the six-year window.

The spread of sector-level growth rates was wide, from a decline of 20.2 percent in mining to the 74.3 percent rise in transportation, and the exposed sectors sat in the middle of that distribution rather than at either extreme, which is itself evidence that exposure did not sort the sectors into fast and slow. What remains open is whether the gap should be attributed to AI exposure at all, or to the unrelated boom in gig transportation that happened to occur in a non-exposed sector.

## DISCUSSION

The expectation that generative AI would disproportionately enable the one-person company does not survive the sector-level comparison. The AI-exposed sectors grew slower than the rest of the economy, and their share of nonemployer establishments fell rather than rose, which is the opposite of what the enabling position predicts. Even so, the sector-level difference is not statistically distinguishable from zero, which means the evidence supports a cautious rejection of the enabling claim rather than a confident affirmation of the concentrating claim. The one-person company did not lead where AI exposure was highest, but the comparison is too noisy to say the technology actively suppressed solo entry in those sectors.

The divergence between the positions can be explained with a concrete methodological cause rather than a vague appeal to context. The first cause is measurement of the outcome. The nonemployer count mixes two very different kinds of solo activity, the professional firm that sells knowledge work and the platform worker who sells driving or delivery, and Katz and Krueger(12) showed that these are not the same margin. When transportation and warehousing grew 74.3 percent, the aggregate nonemployer trend was dominated by gig driving, an occupation with low AI exposure but high platform penetration, which mechanically makes the less-exposed group look faster. Denes and Lagaras(14) used tax returns to confirm that the gig economy and entrepreneurship interact in ways a sector-level count cannot observe, and Wilson(15) showed that even the earned-income tax credit shapes self-employment inside the gig economy, a policy channel unrelated to AI. The second cause is the level of the exposure classification. Felten, Raj and Seamans(7) assign exposure at the occupation level, and aggregating to a two-digit sector

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dilutes it, so the three exposed sectors still contain many shielded occupations, a dilution that biases the gap toward zero. This reading is consistent with the caveat of Brynjolfsson, Mitchell and Rock(11) that exposure is not the same as displacement.

The third cause is the window. The years 2018 to 2024 include the pandemic and the post-pandemic surge in platform delivery, a shock to transportation and hospitality that has little to do with generative AI. A comparison that isolates the years after the November 2022 release, or that reclassifies platform-mediated transport as its own exposed category, would test whether the gap is a gig-economy artifact. The pandemic confound is not hypothetical: the 74.3 percent growth of transportation and warehousing coincides with the documented rise of delivery platforms over the same years, and a window that ended before the pandemic, or one that began only in 2022, would almost certainly return a different gap. The fourth cause is the unit of analysis. We compared sectors rather than firms, so a sector can grow because many marginal drivers enter, even as the average solo entrepreneur in knowledge work does not benefit from AI. Hägg and Kurczewska(29) argued that the gig economy changes the rules of entrepreneurship itself, which implies that the sector-level nonemployer count may capture a different activity in 2024 than it captured in 2018.

The exposure literature itself explains why a sector-level test may understate the artificial intelligence effect even when the effect is real. Acemoglu and Restrepo(10) framed the outcome as a race between the tasks artificial intelligence displaces and the tasks it complements, and their later evidence(9) showed that the balance can run against labor for long periods. Eloundou *et al.*(6) emphasized that exposure is widespread but uneven, and Lee and Lee(23) showed that the wage and skill consequences of exposure differ across occupations even within a single labor market. Casas and Fernández-Macías(24) and Egana-delSol and Bravo-Ortega(25) both found that the exposure map shifted in the generative era and varied across countries, and Peng(26) decomposed exposure into mechanisms that need not move together. The upshot is that a two-digit sector is a poor proxy for exposure, because the exposed and shielded occupations inside it can grow in opposite directions and cancel in the sector aggregate.

The heterogeneity of the one-person company compounds the problem of the sector-level test. Abramowitz and Joung(18) showed that self-employment statistics bundle alternative work arrangements that differ in autonomy, earnings and duration, and Conroy and Landini(17) found that the rise of nonemployer businesses is geographically differentiated in ways a national sector count misses. Bachmann and Gonschor(16) reported that technological progress reshapes self-employment differently across worker types, so the same artificial intelligence shock can push some workers into solo work and pull others out of it. Hägg and Kurczewska(1) and Li and Zhang(2) both warned that the gig and freelance economies are not one object, and Baitenizov and Dubina(5) traced freelance work as a distinct organizational mode. These studies do not refute the enabling position; they show that its object, the AI-enabled solo professional, is a narrow slice of a much larger and messier nonemployer population, which is why an aggregate count cannot adjudicate the dispute.

This contrasts with the solopreneurship thesis advanced by Shaikh and Sharma,(4) who argued that digital platforms produce convergence through one-person firms. The platform mechanism is real, but the platform that dominated the 2018-2024 window was ride-hailing and delivery, not the knowledge-work platform that generative AI would enable. The evidence here does not refute the possibility that AI-enabled solopreneurship is emerging in a narrow slice of professional services; it refutes the stronger claim that the one-person company as a whole isbeing driven by AI exposure. Kim and Thompson(30) reached a compatible conclusion, that information technology adoption grew nonemployer businesses, but their mechanism runs through lowering the administrative cost of any small firm, not through the knowledge content of AI-exposed work. Tekic and Omelchenko(28) supplied the complementary finding that generative AI disrupts freelance labor unevenly, concentrating benefit and harm within the very tasks this study's sector-level lens cannot separate.

The argued position of this paper is that the one-person company boom is real but misattributed. The growth that the enabling position invokes is concentrated in platform-mediated transport and low-wage services, while the knowledge-intensive sectors that generative AI most affects grew below the economy-wide nonemployer rate. This position is consistent with the framework of Fossen, McLemore and Sorgner,(3) who argued that artificial intelligence substitutes for and complements entrepreneurs in ways that vary by the task content of the venture: the substitution margin shows up where AI competes with the founder's own output, and the complementarity margin shows up where AI augments coordination, neither of which implies a uniform rise in solo knowledge firms.

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The optimistic reading of the enabling position can be stated precisely and then tested against the magnitudes. If generative AI were the engine of the one-person company, the exposed sectors should have grown faster than the economy-wide rate of 3.19 percent, but the largest of them, Professional services, grew at 2.15 percent and Information at 2.89 percent, both below the aggregate. The gap is not merely a level effect; the exposed sectors lost share, from 18.3 to 17.2 percent, which is the direction opposite to an AI-driven reallocation of solo work toward knowledge tasks. The concentrating position also overstates its case, however, because the exposed sectors still grew in absolute terms and the sector-level test cannot reject a zero difference. What the data support is a middle reading, that the one-person company expanded for reasons largely unrelated to artificial intelligence, and that the technology's effect on solo entrepreneurship, if it exists, is too small to see against the gig-transport boom.

The direction of the bias in the sector-level test deserves emphasis, because it is not symmetric. If the exposure classification is too coarse, it biases the comparison toward finding no difference, by mixing shielded occupations into the exposed sectors; the fact that the point estimate is nonetheless negative, rather than zero or positive, is therefore more informative than the non-significant p value alone would suggest. If the exposure classification is instead misassigned, with some less-exposed sectors actually carrying hidden AI exposure, then the test is weakened in a way that no reweighting within the existing two-digit data can fix. Either way, the result is conservative relative to the enabling claim: a cleaner exposure measure would more likely sharpen the negative gap than reverse it, because the measured gap already points in the direction opposite to the claim being tested.

External validity limits how far this conclusion travels. The United States has a specific regulatory and platform environment, a large transportation sector, and the origin of the leading model providers, all of which shape where solo work grows. A country with a smaller gig-transport sector or a different tax treatment of self-employment could show a different pattern, as Egana-delSol and Bravo-Ortega(25) found for Latin American labor markets. The mechanism that generalizes is not the specific growth rate but the decomposition itself, separating the platform-mediated service margin from the knowledge-work margin, which is portable to any economy with the same administrative data. What remains open is whether a firm-level design, one that follows individual solo founders across the release of generative AI, would recover an effect that the sector-level comparison cannot detect.

A useful way to frame the result is as a decomposition of the nonemployer boom into a platform margin and a knowledge margin. The platform margin, concentrated in transportation and delivery, grew fast because the platforms themselves grew, an effect documented in the gig-economy literature that Hägg and Kurczewska(29) and Li and Zhang(2) reviewed, and that Denes and Lagaras(14) tied to tax-record entrepreneurship. The knowledge margin, where generative AI should bite, grew more slowly, so the aggregate boom cannot be attributed to the technology. This decomposition is the paper's main contribution: it shows that the two margins, which the enabling position runs together, move on different rhythms and respond to different forces. The measurement agenda that follows is to track the two margins separately over time, so that a future acceleration of the knowledge margin, if generative AI eventually enables solo knowledge firms at scale, would be visible against a stable platform baseline rather than lost inside it.

The conclusions are bounded by three limitations, each of which suggests its own remedy. The first is the coarseness of the sector-level exposure measure, and the recommendation is to re-estimate the comparison with occupation-weighted exposure scores mapped to firms, so that exposure varies within sectors rather than only between them. The second is that nonemployer counts measure the number of businesses, not their revenue or survival, so a sector could grow in count while declining in economic weight, and the recommendation is to weight the comparison by receipts, which the same Census files report. The third is the absence of a formal counterfactual for the pandemic, and the recommendation is a difference-in-differences design around the November 2022 release date, mirroring the interrupted time-series approach used elsewhere for the same question.

For policy, the practical implication is to separate two goals that the enabling position conflates. Supporting solo knowledge workers who use AI is a different policy from managing the growth of platform-mediated gig work, and the data show the second is where the aggregate action is. For researchers, the result argues for reporting the sector-level distribution of nonemployer growth rather than a single national trend, since the national trend hides the very heterogeneity on which the theoretical dispute turns.

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## CONCLUSIONS

Nonemployer businesses in the United States grew from 26.5 million to 32.0 million between 2018 and 2024, but the growth was concentrated in less-exposed sectors such as transportation and hospitality rather than in the AI-exposed knowledge sectors, whose share of the total fell from 18.3 to 17.2 percent, a pattern that challenges the claim that generative AI is disproportionately enabling the one-person company and instead locates the solo business boom in platform-mediated gig work; the exposed sectors still grew in absolute terms, so the correct conclusion is that the one-person company expanded for reasons largely unrelated to artificial intelligence rather than that the technology suppressed it.

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