Democratizing Entrepreneurial Ecosystems: How Accessible AI Reshapes the Geography of Entrepreneurship

Abstract

Entrepreneurial activity is highly uneven across space, with a small number of high-volume ecosystems accounting for a disproportionate share of startups. This paper examines whether universally accessible artificial intelligence, specifically large language models (LLMs), alters this geography. We theorize LLMs as synthetic human capital that democratizes entrepreneurship through capability enhancement and task internalization in resource-scarce ecosystems. Using ChatGPT's November 2022 release as a quasi-experimental shock, we analyze 6.2 million new firm formations across 843 U.S. metropolitan and micropolitan areas. Entrepreneurial entry increases across all ecosystems following ChatGPT's release, with significantly larger proportional increases in low-volume ecosystems. These findings demonstrate that accessible AI can partially substitute for missing complementary resources, contributing to research on entrepreneurial ecosystems, AI in strategy and entrepreneurship, and task-based theories.

INTRODUCTION

"AI is the greatest technology equalizer we have ever seen."
- Jensen Huang, Co-founder & CEO of NVIDIA

Entrepreneurial activity is not evenly distributed across space. Research in economic geography, strategy, and entrepreneurship documents that new firm formation concentrates in a small number of entrepreneurial ecosystems such as Silicon Valley, Boston, and Seattle (Audretsch & Feldman, 1996; Delgado, Porter, & Stern, 2010; Saxenian, 1994; Stuart & Sorenson, 2003). These ecosystems are characterized as configurations of interdependent actors and factors that jointly enable productive entrepreneurship (Jacobides, Cennamo, & Gawer, 2018; Spigel, 2017). These ecosystems benefit from dense specialized talent, thick labor markets, and complementary institutions that create self-reinforcing entrepreneurial advantages through knowledge spillovers and resource channeling (DeCarolis & Deeds, 1999; Feldman, 2001; Feldman & Zoller, 2016; Glaeser, Kallal, Scheinkman, & Shleifer, 1992; Moretti, 2021; Sorenson & Audia, 2000).

Most regions, in contrast, exhibit lower rates of new firm formation, thinner markets for specialized labor, and weaker institutional support (Chatterji, Glaeser, & Kerr, 2014; Spigel, 2017). Founders in these ecosystems struggle to access mentors, cofounders, startup-specific expertise, and resources, creating what we term complementarity gaps—mismatches between the complements required to execute the venture-creation task bundle and the complements locally available to founders at acceptable cost and quality. The result is durable spatial inequality in entrepreneurial opportunity, shaping who becomes an entrepreneur, what kinds of ventures emerge, and where innovation-driven growth occurs (Decker, Haltiwanger, Jarmin, & Miranda, 2014; Echeverri-Carroll & Feldman, 2019; Guzman & Stern, 2020).

This persistent geographic inequality has motivated scholars to examine whether new technologies can mitigate such patterns in entrepreneurship, as technologies that reallocate capabilities and complements required for venture creation could reshape where entrepreneurship occurs and who can participate. For example, scholars have examined broadband internet, cloud computing, and other digital technologies and their role in shaping patterns of entrepreneurship. While these technologies have lowered some barriers to entry by enabling remote work, global market access, and reduced transaction costs (Autio, Nambisan, Thomas, & Wright, 2018; Nambisan, Wright, & Feldman, 2019), their entrepreneurial benefits have accrued disproportionately to regions where complementary capabilities were already strong. Broadband adoption increased wage growth primarily in wealthy, educated counties with IT-intensive industries (Forman, Goldfarb, & Greenstein, 2012), and e-commerce platforms enabled market access but could not substitute for local capabilities in digital marketing and logistics (Forman, Ghose, & Goldfarb, 2009). These technologies complemented existing assets rather than substantially substituting for them, amplifying rather than narrowing the advantages of entrepreneurial ecosystems with abundant complementarity (Akerman, Gaarder, & Mogstad, 2015).

The emergence of accessible artificial intelligence (AI), specifically large language models (LLMs), offers a distinctive opportunity to revisit this question. Unlike prior technologies requiring specialized technical skills, LLMs like ChatGPT—released publicly in November 2022—provide general-purpose cognitive capabilities through natural-language interfaces accessible to non-experts. They enable users to perform a wide range of cognitive tasks, from writing and analysis to code generation and document synthesis (Eloundou, Manning, Mishkin, & Rock, 2024). Experimental evidence shows these tools improve writing quality, accelerate analysis, and disproportionately benefit lower-skilled workers by compressing performance gaps (Brynjolfsson, Li, & Raymond, 2025; Dell'Acqua et al., 2023; Noy & Zhang, 2023). In parallel, strategy research documents how AI adoption changes competitive advantage sources and decision-making processes, highlighting both substitution and complementarity between human and machine capabilities (Doshi, Bell, Mirzayev, & Vanneste, 2025; Krakowski, Luger, & Raisch, 2023). These characteristics raise a fundamental question: can universally accessible AI reduce the capability thresholds for entrepreneurial entry, particularly in ecosystems with wide complementarity gaps?

We argue that LLMs, as a form of accessible AI, function as synthetic human capital—cognitive task capacity approximating specialist labor that is location-independent, scalable, available at near-zero marginal cost, and remains human-directed and human-validated—that can narrow complementarity gaps (Choudhury, Starr, & Agarwal, 2020). Drawing on task-based theories of technological change (Acemoglu & Restrepo, 2018, 2020; Autor, Levy, & Murnane, 2003), we hypothesize that LLMs will increase entrepreneurial entry more in low-volume ecosystems, those with lower baseline entrepreneurial activity and wider complementarity gaps, than in high-volume ecosystems where complementarities are abundant and accessible. We theorize two mechanisms underlying this effect: LLMs expand founders' feasible task sets through quality-equalizing effects that disproportionately benefit lower-capability users, and they enable founders to internalize tasks necessary for business launch that were traditionally contracted out, often at significant cost in low-volume ecosystems. Both mechanisms operate most significantly where complementarity gaps are widest, creating democratization effects.

We test the theory using a quasi-experimental difference-in-differences design that exploits ChatGPT's November 2022 release as a plausibly exogenous technological shock, analyzing approximately 6.2 million new firm formations across 843 U.S. Core-Based Statistical Areas (CBSA) from December 2021 through November 2023. We classify ecosystems by pre-period entry volume and estimate difference-in-differences models with CBSA and month fixed effects, controlling for CBSA-specific linear time trends. We also estimate event-study specifications to assess dynamic effects and pre-trends (Rambachan & Roth, 2023; Roth, Sant'Anna, Bilinski, & Poe, 2023). We find that

ChatGPT's release is associated with increased entrepreneurial entry across all ecosystems, with the largest relative increases in low-volume ecosystems compared to high-volume ecosystems, indicating a democratization effect of accessible AI. Event-study estimates and extensive robustness checks support these findings.

This study makes three contributions. First, we contribute to entrepreneurial ecosystem research by introducing the concept of complementarity gaps and demonstrating that such gaps are partially addressed through accessible technology. While existing work emphasizes that ecosystem advantages stem from bundled complementary assets that are largely path-dependent, we show that location-independent capabilities can partially substitute for missing local resources, altering ecosystems' role in filtering entrepreneurial entry. Second, we contribute to strategy and entrepreneurship research on artificial intelligence by conceptualizing large language models as synthetic human capital and documenting their effects on venture creation feasibility rather than established firm productivity. This shifts attention from how AI improves productivity within existing firms to how AI enables new individuals to become founders, revealing that AI's entrepreneurial impact depends critically on ecosystem context. Third, we extend task-based theories of technological change from labor markets to entrepreneurial ecosystems, demonstrating that technologies reducing task costs have heterogeneous spatial effects on entrepreneurial entry depending on local task bundles and resource availability.

THEORY AND HYPOTHESIS

Entrepreneurial ecosystems are territorially embedded configurations of complementary actors, resources, and institutions that jointly enable productive entrepreneurship (Adner, 2017; Jacobides et al., 2018; Wurth, Stam, & Spigel, 2022). These ecosystems differ systematically in the availability of specialized complements such as technical talent, startup-oriented service providers, venture capital, and institutional supports, creating fundamental variation in the costs founders face when assembling the capabilities needed to launch ventures (Delgado et al., 2010; Spigel, 2017; Stam & Van de Ven, 2021).

We capture these differences using ecosystem volume, the local intensity of entrepreneurial activity reflected in regional entry rates. Persistent differences in entry volume correlate with the thickness of specialist labor markets and the availability of venture-supporting complements (Chatterji et al., 2014; Glaeser & Kerr, 2009; Guzman & Stern, 2020). High-volume ecosystems such as Silicon Valley, Boston, and Seattle host thick labor markets for technical talent and dense networks of specialized service providers that allow founders to delegate complex tasks to readily available experts (Feldman, 2001; Feldman & Zoller, 2016; Kerr & Nanda, 2011; Spigel, 2017). Low-volume ecosystems feature thinner specialist markets and weaker institutional supports, imposing higher search, evaluation, and coordination costs on founders seeking to assemble capabilities (Chatterji et al., 2014; Spigel, 2017).

These structural differences create complementarity gaps, defined as mismatches between the complements required to execute the venture-creation task bundle and the complements locally available to founders at acceptable cost and quality. In high-volume ecosystems, complementarity gaps are small because founders can delegate specialist tasks, such as software development, legal incorporation, market research, and financial modeling, to local experts with relative ease and at competitive prices. In low-volume ecosystems, complementarity gaps are large because founders face three costly alternatives: self-perform specialist tasks despite limited expertise, contract with distant providers at premium prices and high coordination costs, or forego tasks entirely. These gaps raise both the capability requirements and financial costs of venture creation, suppressing entrepreneurial entry in low-volume regions.

Early-stage entrepreneurship involves a heterogeneous bundle of organizing tasks spanning technical, business planning, and administrative domains (Gartner, Carter, & Reynolds, 2010). Founders must draft business plans, build prototypes or write code, conduct market research, develop financial models, prepare pitch decks, handle incorporation and basic legal documents, and produce branding materials. The feasibility and cost of completing this task bundle varies systematically with ecosystem volume: in high-volume ecosystems, founders can distribute tasks across teams and local specialists; in low-volume ecosystems, founders must self-perform a larger share or incur high costs to access distant expertise.

LLMs as Synthetic Human Capital

Until recently, few technologies had meaningfully addressed these complementarity gaps. Prior digital technologies—from enterprise software to cloud computing—typically required specialized technical skills or complementary organizational investments that amplified rather than reduced regional advantages (Forman et al., 2012). Large language models, such as ChatGPT, represent a qualitatively different intervention as they are accessible to all founders with no geographic limitations. Moreover, they require no specialized technical skills and face effectively no capacity constraints. Given these properties, we conceptualize LLMs as synthetic human capital: cognitive task capacity approximating specialist labor that is location-independent, scalable and available at near-zero marginal cost, and remains human-directed and human-validated. We label this capability "synthetic" because it remains human-directed and human-validated—founders provide objectives, domain context, and judgment while task-execution capacity is generated by a scalable nonhuman input rather than locally hired labor. LLMs enable founders to execute many venture-creation tasks directly such as drafting business plans and marketing copy, generating functional code, designing customer surveys, synthesizing research documents, and preparing investor materials (Brynjolfsson et al., 2025; Eloundou et al., 2024). By expanding the set of knowledge-intensive tasks founders can feasibly complete in-house, LLMs reduce dependence on locally available specialist complements, particularly at the earliest stages of venture formation.

One might suggest that high-volume ecosystems would benefit most from LLMs by combining synthetic human capital with superior local resources, thereby realizing larger productivity gains through complementarity (Forman et al., 2012). Under this logic, LLMs would amplify existing advantages, encouraging even more new venture creation in already resource-rich regions and further concentrating entrepreneurial activity in high-volume ecosystems. However, we draw on task-based theories of technological change (Autor et al., 2003; Acemoglu & Restrepo, 2018, 2020) to propose the opposite. Task-based theories argue that technologies reshape production by changing the feasibility and cost of specific tasks. We extend this perspective to entrepreneurial ecosystems, theorizing that LLMs will affect venture creation unevenly across ecosystems because they reshape the set of venture-creation tasks founders can execute, effects that should be strongest where complementarity gaps are wider.

We propose two underlying mechanisms through which LLMs can mitigate complementarity gaps—particularly in low-volume ecosystems. First, LLMs enable capability enhancement. Experimental evidence shows that LLMs improve professional task performance by roughly 20–40 percent on average, with disproportionately large gains for lower-skilled workers—a skill-equalizing pattern that compresses capability disparities (Brynjolfsson et al., 2025; Dell'Acqua et al., 2023; Noy & Zhang, 2023). In entrepreneurial ecosystems, this implies that founders in ecosystems with wide complementarity gaps can increasingly generate specialist-quality intermediate outputs in tasks they must perform themselves. When a founder in a low-volume ecosystem cannot hire an experienced developer or marketer, LLMs expand the feasible set of tasks they can execute credibly—often enough to reach early milestones such as a functional prototype, testable positioning, or a fundable pitch. In contrast, founders in high-volume ecosystems with narrow complementarity gaps already access specialized talent; for them, LLMs primarily augment existing expertise by accelerating iteration rather than substituting for missing capabilities at the margin.

Second, LLMs enable task internalization. Recent evidence shows that the release of generative AI coincided with sharp declines in demand for freelance writing, translation, and basic software services—consistent with organizations bringing some of these activities in-house (Demirci, Hannane, & Zhu, 2024; Hui, Reshef, & Zhou, 2024). We argue a parallel shift can occur in entrepreneurial ecosystems: LLMs expand the range of venture-creation tasks founders can complete without relying on external specialists. This matters because ecosystems differ in the availability and accessibility of complementary service providers. In high-volume ecosystems, dense networks and thick markets make it easier to source specialized inputs; in low-volume ecosystems, founders more often face limited local options, higher effective costs, and slower progress when key services must be obtained externally. By allowing founders to generate credible first-pass outputs themselves (e.g., workable code, customer-facing materials, synthesized market information), LLMs reduce dependence on ecosystem-provided complements and lower the minimum bundle of external inputs required to reach early venture milestones.

We posit that these two mechanisms generate larger effects in low-volume ecosystems where LLMs substitute for scarce resources rather than augment abundant ones. This substitution effect lowers the capability and financial thresholds required for venture creation, enabling marginal founders—those previously unable to assemble necessary capabilities—to enter entrepreneurship.

We therefore hypothesize that entrepreneurial entry will increase across all ecosystems following ChatGPT's public release, as founders everywhere gain access to synthetic human capital that improves execution speed and quality. However, consistent with task-based theories predicting that technologies altering task costs will have larger effects where those tasks are most costly to access, the relative increase should be largest in low-volume ecosystems where LLMs most powerfully substitute for missing complementary resources. While we expect effects in medium-volume ecosystems to fall between those in low- and high-volume ecosystems, our formal hypothesis focuses on the core theoretical contrast between ecosystems with wider versus narrower complementarity gaps.

> *Hypothesis: The release of ChatGPT increases entrepreneurial entry more in low-volume ecosystems than in high-volume ecosystems.*

METHODS

We examine whether LLMs affected entrepreneurial entry across U.S. entrepreneurial ecosystems using a quasi-experimental difference-in-differences design with monthly CBSA-level data on new firm formations from December 2021 through November 2023. Our main data source is Dun & Bradstreet (D&B), which maintains one of the most comprehensive longitudinal databases of U.S. business establishments. D&B compiles establishment records from telephone surveys, public filings, trade directories, and government registries and assigns each establishment a unique D-U-N-S identifier, enabling consistent tracking over time. Prior research shows that D&B (and closely related NETS data) reliably captures entrepreneurial dynamics and has been widely used in entrepreneurship, strategy, and regional studies (Decker et al., 2014; Echeverri-Carroll & Feldman, 2019; Eesley & Lee, 2021; McDougall, Covin, Robinson, & Herron, 1994; Walls & Associates, 2013).

We obtain records on new firm formations between December 2021 and November 2023, yielding a balanced twelve-month pre-period (December 2021 to November 2022) and twelve-month post-period (December 2022 to November 2023). The treatment is the public release of ChatGPT on November 30, 2022, which made a powerful large language model free and easily accessible worldwide via a natural-language interface. This timing provides a clean fixed treatment date and helps balance statistical power against exposure to unrelated macroeconomic shocks (Bertrand, Duflo, & Mullainathan, 2004). Each D&B record includes the firm's start date, primary four-digit SIC industry, and geographic location. We map establishments to U.S. CBSAs using standard county-CBSA crosswalks and aggregate firm formations to the CBSA-month level. Our main analytic sample comprises approximately 6.2 million new firm formations across 843 CBSAs, yielding 18,500 CBSA-month observations.

Variables

Our primary dependent variable is the log of entrepreneurial entry ln(Total Entries$_{it}$ + 1), which indicates the number of new firms founded in CBSA$_i$ during month t. The log transformation mitigates skewness and allows coefficients to be interpreted as approximate percentage changes, while retaining observations with zero entries. In robustness analyses, we also estimate models using the level of entries as the dependent variable and alternative functional forms that better accommodate count outcomes. Note that we focus on entrepreneurial entry as our outcome because we assume that LLMs primarily affect the feasibility of launching ventures through synthetic human capital rather than subsequent venture performance, which depends on additional factors such as market conditions, competition, and growth capital access.

Our key independent variables capture ecosystem type and exposure to the ChatGPT shock. To characterize ecosystem conditions, we classify CBSAs into low-, medium-, and high-volume entrepreneurial ecosystems based on pre-treatment entry. For each CBSA, we sum new firm formations across the pre-period (December 2021 to November 2022) and rank CBSAs by this total. CBSAs in the bottom third of the distribution are labeled low-volume ecosystems, those in the middle third medium-volume ecosystems, and those in the top third high-volume ecosystems. This classification operationalizes our theoretical concept of ecosystem volume—the local intensity of entrepreneurial activity that reflects the thickness of specialist labor markets and availability of complementary resources (Feldman, 2001; Guzman & Stern, 2020). High-volume ecosystems include large, globally recognized hubs such as the San Francisco Bay Area, Boston–Cambridge, New York–Newark, and Austin–Round Rock, which typically host dense stocks of specialized human capital, investor networks, and support organizations. Medium-volume ecosystems include diversified mid-sized metropolitan areas such as Denver, Raleigh–Durham, Pittsburgh, and Salt Lake City, where entrepreneurial activity is meaningful but less concentrated than in leading hubs. Low-volume ecosystems encompass smaller metropolitan and micropolitan regions—for example, places such as Beckley, WV, Pine Bluff, AR, Grand Island, NE, and El Centro, CA—where complementarity gaps are largest due to thinner markets for specialist talent and fewer startup-oriented intermediaries. We construct indicators for low- and medium-volume ecosystems, Low_i and Med_i, with high-volume ecosystems serving as the omitted reference category. Categorical classification is theoretically motivated by non-linear complementarity dynamics and methodologically appropriate for estimating heterogeneous treatment effects without imposing restrictive functional form assumptions on the ecosystem volume-treatment effect relationship.

We define a post-treatment indicator, $Post_t$, equal to 1 for months December 2022–November 2023 (post–ChatGPT release) and 0 for months December 2021–November 2022 (pre-period). The central parameters of interest are the interaction terms $Low_i \times Post_t$ and $Med_i \times Post_t$, which identify whether entrepreneurial entry in low- and medium-volume ecosystems changed differentially relative to high-volume ecosystems after ChatGPT became widely available.

Difference-in-Differences Specification

Our identification strategy treats ChatGPT's release as a quasi-experimental shock—a fixed-timing technological event that arrives simultaneously across all regions, enabling causal inference through comparison of differential responses across ecosystem types. Our empirical strategy uses a difference-in-differences design that compares changes in entrepreneurial entry across low-, medium-, and high-volume ecosystems before and after the release of ChatGPT.

Our specification includes CBSA fixed effects to control for time-invariant regional characteristics and month-of-year fixed effects to capture recurring seasonal patterns in entrepreneurial entry. In addition, we include CBSA-specific linear time trends to accommodate heterogeneous pre-existing trajectories across CBSAs. These areas exhibit substantial heterogeneity in their entrepreneurial dynamics due to factors including differential exposure to industrial decline or growth (Autor & Dorn, 2013), varying local policy environments, demographic shifts, and divergent technology adoption rates (Glaeser & Kerr, 2009). For instance, low-volume ecosystems include both declining industrial cities facing negative secular trends (e.g., Youngstown, OH) and smaller emerging tech hubs with positive trends (e.g., Boulder, CO). These CBSA-specific trends enable us to identify treatment effects from discrete breaks in trajectories at ChatGPT's release rather than continuation of pre-existing patterns. We estimate,

$$\mathrm{Y_{it}} = \alpha_\mathrm{i} + \gamma_\mathrm{t} + \lambda_\mathrm{i}\mathrm{t} + \beta_\mathrm{L}(\mathrm{Low_i} \times \mathrm{Post_t}) + \beta_\mathrm{M}(\mathrm{Med_i} \times \mathrm{Post_t}) + \varepsilon_\mathrm{it}$$

where Y_{it} denote the log of one plus the number of new firms founded in CBSA_i during month t. α_i are CBSA fixed effects, γ_t are month-of-year fixed effects, $\lambda_i t$ is a CBSA-specific linear time trend, and ε_{it} is an idiosyncratic error term. $\mathrm{Post_t}$ is an indicator equal to one for December 2022 and subsequent months (following ChatGPT's release on November 30, 2022) and zero otherwise. The coefficients of interest are β_L and β_M, which capture differential changes in entrepreneurial entry in low- and medium-volume ecosystems relative to high-volume ecosystems after ChatGPT became widely available. Under the assumption that, conditional on CBSA fixed effects, month-of-year fixed effects, and CBSA-specific trends, low-, medium-, and high-volume ecosystems would have continued to follow parallel trends in the absence of ChatGPT, these coefficients recover the causal effect of the ChatGPT shock on entrepreneurial entry by ecosystem type (Angrist & Pischke, 2009). All reported standard errors are heteroskedasticity-robust and clustered at the CBSA level, allowing for arbitrary heteroskedasticity and serial correlation within ecosystems (Bertrand et al., 2004; Cameron & Miller, 2015).

Event-Study Specification

We also estimate an event-study specification to examine the dynamic pattern of effects and to assess the plausibility of the identifying assumptions. Months are indexed relative to the ChatGPT release: τ = 0 corresponds to November 2022, τ = –1 to October 2022, τ = 1 to December 2022, and so forth. For each relative month τ, we define an indicator $D_{\tau,t}$ that equals 1 if calendar month t corresponds to relative time τ, and 0 otherwise. Using the month immediately preceding the release (τ = –1) as the omitted reference period, we estimate,

$$Y_{it} = \alpha_i + \gamma_t + \sum_{\tau \neq -1} \delta_{L\tau} \left(Low_i \, D_{\tau,t} \right) + \sum_{\tau \neq -1} \delta_{M\tau} \left(Med_i \, D_{\tau,t} \right) + \epsilon_{it}$$

where α_i are CBSA fixed effects and γ_t are month-of-year fixed effects. The coefficients $\delta_{L\tau}$ and $\delta_{M\tau}$ trace the evolution of differences in log entry between low- and high-volume ecosystems and between medium- and high-volume ecosystems before and after the ChatGPT release, relative to October 2022. Following recent recommendations that emphasize the size and shape of pre-treatment coefficients rather than simple significance tests (Kahn-Lang & Lang, 2020; Bilinski & Hatfield, 2018; Rambachan & Roth, 2023; Roth et al., 2023), we view small and statistically indistinguishable pre-treatment coefficients (τ < 0) relative to the post-treatment estimates (τ ≥ 0) as evidence consistent with the identifying assumptions. Because ChatGPT's release represents a fixed-timing technological shock that arrived simultaneously for all regions, our setting avoids the complications that arise with staggered treatment adoption (Goodman-Bacon, 2021; Callaway & Sant'Anna, 2021). Following methodological guidance on pre-trends assessment (Roth et al., 2023; Rambachan & Roth, 2023), our primary validation strategy focuses on examination of event-study coefficients, which allows readers to directly assess whether low-, medium-, and high-volume ecosystems were on parallel trajectories prior to treatment. While placebo tests that arbitrarily reassign treatment dates could provide additional validation, such tests offer limited leverage in our setting where treatment timing is determined by an external technological event rather than endogenous adoption decisions (Freyaldenhoven, Hansen, & Shapiro, 2019).

We further assess the stability of our estimates using robustness checks that vary functional forms, address outlier treatment, test temporal specifications, examine alternative volume categorizations, and restrict the sample to AI-exposed industries where task-substitution mechanisms should operate most directly (Felten, Raj, & Seamans, 2021). We discuss these robustness checks in detail below.

RESULTS

We begin by examining descriptive patterns in entrepreneurial entry across ecosystems. Table 1 reports CBSA-month descriptive statistics. Consistent with our classification, high-volume ecosystems exhibit substantially higher average monthly entry (730.35 firms in the pre-period, 1013.01 in the post-period) than medium-volume ecosystems (37.15 and 52.96, respectively) and low-volume ecosystems (12.82 and 32.09). The overall mean number of entries per CBSA-month is 281.60, with considerable dispersion (standard deviation of 1476.05), reflecting the highly skewed distribution of entrepreneurial activity across CBSAs.

INSERT FIGURE 1 AND TABLE 1 & 2 ABOUT HERE

Figure 1 summarizes absolute percentage changes in total entrepreneurial entries between the pre-period (December 2021–November 2022) and the post-period (December 2022–November 2023) for each ecosystem category. Entry increases in all ecosystems: low-volume ecosystems experience a 169.5 percent increase in total entries, medium-volume ecosystems a 46.7 percent increase, and high-volume ecosystems a 40.6 percent increase. The figure illustrates both a common upward shift in entrepreneurial activity and a disproportionately large increase for low-volume ecosystems, consistent with our hypothesis that synthetic human capital reduces complementarity gaps most powerfully in resource-scarce ecosystems.

Table 2 presents the main difference-in-differences estimates. Column (1) shows the baseline specification with CBSA and month-of-year fixed effects, but without CBSA-specific trends, yielding a coefficient of 0.431 ($p < 0.001$). Column (2), our main specification, includes CBSA fixed effects, month-of-year fixed effects, and CBSA-specific linear time trends to accommodate differential pre-period trajectories across ecosystems. In this model, the coefficient on Low Volume × Post is 0.438 ($p < 0.001$), indicating that low-volume ecosystems experienced a 55 percent larger proportional increase in entry relative to high-volume ecosystems after ChatGPT's release, conditional on CBSA fixed effects, month-of-year fixed effects, and CBSA-specific linear trends. The modest increase in the coefficient when adding CBSA-specific trends (from 0.431 to 0.438) suggests that low-volume ecosystems were, on average, on slightly less favorable pre-treatment trajectories than high-volume ecosystems. The substantial improvement in model fit (R^2 increases from 0.673 to 0.704) confirms that CBSAs exhibit meaningful heterogeneity in their baseline entrepreneurial dynamics. Controlling for these CBSA-specific trends is essential for isolating the discrete break in entry patterns attributable to ChatGPT's release rather than continuation of pre-existing trajectories.

To interpret the economic magnitude, we calculate predicted values from our main specification and construct counterfactuals that remove the differential ChatGPT effects. The model predicts an average of 18.11 new firm entries per CBSA-month for low-volume ecosystems in the post-period. If low-volume ecosystems had experienced only the common effects captured by month-of-year fixed effects and their own pre-existing trends, the counterfactual entry would be 11.97 firms per CBSA-month. The difference of 6.14 additional firms per CBSA-month represents the differential ChatGPT effect.

On an annual basis, this translates to approximately 74 additional startups per low-volume CBSA per year beyond the high-volume baseline. With 281 low-volume CBSAs in our sample, the differential ChatGPT effect accounts for roughly 20,800 additional startups per year in low-volume ecosystems. This substantial democratization effect suggests that generative AI technology disproportionately benefits entrepreneurial ecosystems with thinner resource bases, consistent with our theoretical prediction that synthetic human capital generates larger marginal returns where complementarity gaps are widest.

The coefficient for medium-volume ecosystems, Med Volume × Post, is not statistically significant ($\beta = 0.155$, $p = 0.140$), indicating that in our tercile specification, medium-volume ecosystems experienced ChatGPT effects statistically indistinguishable from high-volume ecosystems. This pattern is consistent with our theoretical prediction that synthetic human capital generates the largest marginal benefits where it substitutes for missing resources rather than augmenting abundant ones: the significant differential effects concentrate in low-volume ecosystems where complementary resources are scarcest. We examine the gradient across ecosystem volume more granularly using alternative specifications below and find evidence of a broader democratization pattern extending into medium-volume ecosystems when we increase distributional granularity.

The event-study results in Figure 2 further support a causal interpretation. In the year preceding the ChatGPT release, estimated differences in entry between low- and high-volume ecosystems fluctuate around zero and are small relative to the post-treatment effects; for pre-period months, the confidence intervals repeatedly include zero. This pattern of flat pre-trends is consistent with our quasi-experimental identifying assumption that ecosystem types would have continued on parallel trajectories absent the ChatGPT shock. After the release ($\tau = 0$ for November 2022), the coefficients for low-volume ecosystems turn positive and remain predominantly elevated. The immediate post-release period shows some volatility, potentially going through a short adjustment period in which founders may be experimenting with ChatGPT before integrating it into founding workflows, in line with adoption patterns for general-purpose technologies (Bresnahan & Trajtenberg, 1995). The pronounced spikes around month +11 likely reflect a combination of heightened media attention and seasonal patterns (e.g., Q4 shopping season) in business registration. The core pattern, flat pre-trends followed by a sustained post-treatment elevation for low-volume ecosystems, persists when we exclude the spike months in robustness analyses, indicating that our conclusions are not driven by late-sample fluctuations. Medium-volume ecosystems also exhibit positive but generally smaller post-treatment deviations. Overall, the pattern is consistent with a discrete and persistent upward shift in entry for low-, and to a lesser extent medium-, volume ecosystems relative to high-volume ecosystems once ChatGPT becomes available, rather than a continuation of pre-existing trends.

INSERT TABLE 3 & 4 AND FIGURE 2 ABOUT HERE

Robustness Checks

We assess the robustness of our main findings to alternative specifications, sample restrictions, and volume classifications. Tables 3 and 4 report these analyses. All specifications use heteroskedasticity-robust standard errors clustered at the CBSA level.

In Table 3, we first examine sensitivity to functional form assumptions, outlier treatment, and sample restrictions. Column (1) adds CBSA-specific quadratic time trends to allow for non-linear pre-treatment trajectories, yielding nearly identical results (Low Volume × Post = 0.418, $p < 0.001$). Column (2) restricts analysis to AI-exposed industries where tasks are intensive in text processing and analytical reasoning (AIIE > 0; Felten et al., 2021). The democratizing effect persists in this subsample ($\beta = 0.348$,

$p < 0.001$), confirming that ChatGPT's impact operates powerfully in domains where its capabilities directly substitute for human cognitive labor.

Column (3) excludes December 2022 to ensure results are not driven by transition-period anomalies ($\beta = 0.658$, $p < 0.001$). Columns (4)-(5) winsorize the dependent variable at the 1st/99th and 5th/95th percentiles to address outliers ($\beta = 0.395$ and 0.347, both $p < 0.001$). Column (6) uses ln(Y) without the +1 transformation, restricting to positive entries ($\beta = 0.398$, $p < 0.001$). Column (7) estimates levels rather than logs, confirming the positive direction ($\beta = 615.065$, $p < 0.001$), though interpretation is challenging given the 56-fold baseline difference between high- and low-volume ecosystems. Columns (8)-(10) examine temporal robustness by excluding the first two months ($\beta = 0.411$, $p < 0.001$), last two months ($\beta = 0.464$, $p < 0.001$), and shifting treatment to January 2023 ($\beta = 0.753$ $p < 0.001$). Low Volume × Post remains positive and significant across all specifications.

We also examine whether our findings are sensitive to how we categorize ecosystem volume in Table 4. Column (1) reports our main tercile specification. Column (2) uses quartiles, revealing a monotonic gradient: bottom quartile ($\beta = 0.573$, $p < 0.001$), second quartile ($\beta = 0.388$, $p < 0.001$), and third quartile ($\beta = 0.252$, $p = 0.040$) all significantly exceed the top quartile. This pattern confirms that democratization intensifies as ecosystem volume decreases and extends significantly beyond the bottom tercile. Column (3) compares the bottom 10 percent ($\beta = 0.524$, $p = 0.010$) and middle 80 percent ($\beta = 0.245$, $p = 0.138$) to the top 10 percent, showing the strongest effects in the most resource-constrained ecosystems. Column (4) treats volume as a continuous variable (rather than categories), finding a negative and marginally significant interaction ($\beta = -0.084$, $p = 0.064$). This negative coefficient confirms that democratizing effects decrease monotonically as ecosystem volume increases, with the continuous specification corroborating the gradient patterns observed in our categorical analyses. The marginal significance ($p = 0.064$) reflects the expected loss of statistical power from treating volume as a continuous variable, which assumes linear effects, rather than exploiting sharp contrasts across categories, but the direction, magnitude, and consistency across specifications provide strong evidence for a monotonic relationship between ecosystem volume and ChatGPT's democratizing impact.

Across these robustness specifications, we also observe evidence that medium-volume ecosystems experience positive differential effects relative to high-volume ecosystems, though smaller in magnitude than low-volume. While the Medium Volume × Post coefficient does not reach conventional significance in our main tercile specification ($\beta = 0.155$, $p = 0.140$), the quartile analysis reveals significant effects for both the second quartile ($\beta = 0.388$, $p = 0.001$) and third quartile ($\beta = 0.252$, $p = 0.040$), indicating that the tercile aggregation masks heterogeneity within the medium-volume category. This pattern demonstrates that ChatGPT's democratizing effects operate along a gradient, with marginal benefits diminishing as local resource availability increases, consistent with our theoretical prediction.

Together, these analyses demonstrate that our core finding that larger relative entry increases in low-volume ecosystems is robust to alternative functional forms, sample restrictions, outlier treatment, and volume measurement approaches, strengthening confidence that we are capturing a genuine structural relationship between complementarity gaps and the marginal value of synthetic human capital.

DISCUSSION

This paper has examined whether a universally accessible large language model—ChatGPT—reshapes the geography of entrepreneurial entry within the United States. Exploiting the fixed-timing release of ChatGPT in November 2022 as a quasi-experimental shock, we showed that new firm formation increases in all entrepreneurial ecosystems but rises disproportionately in low-volume ecosystems, with medium-volume ecosystems marginally occupying an intermediate position. Event-study estimates display parallel pre-trends and persistent post-treatment divergence, and the extensive robustness analyses support the interpretation that these patterns are consistent with a democratizing effect of accessible AI on entry.

Theoretical Contributions

We contribute to several literatures. Our first contribution advances entrepreneurial ecosystem theory by introducing complementarity gaps as a lens for understanding spatial inequality and demonstrating that ecosystem constraints are partially malleable through accessible technology. Existing research emphasizes that entrepreneurial ecosystems bundle together human capital, finance, institutions, and culture in configurations that strongly condition entrepreneurial processes (Jacobides et al., 2018; Spigel, 2017; Wurth et al., 2022). These configurations exhibit path dependence and self-reinforcing dynamics, leading to the view that spatial inequality in entrepreneurship largely reflects immutable differences in accumulated complementary assets across regions (Feldman, 2001; Sorenson & Audia, 2000). We challenge this structural determinism by showing that the functional role of ecosystems in filtering who can plausibly attempt to start a venture can be altered by accessible, location-independent capabilities.

We introduce complementarity gaps—the extent to which founders' required task bundles exceed locally accessible complementary resources—which vary systematically across ecosystems and shape the marginal value of new capabilities. Our finding that ChatGPT's release generates a 55 percent larger proportional increase in entrepreneurial entry in low-volume ecosystems demonstrates that synthetic human capital can partially substitute for missing local resources, thereby narrowing complementarity gaps. This does not eliminate ecosystem effects. High-volume regions still generate substantially more startups in absolute terms, but our findings reveal that ecosystem advantages are not purely structural. Technologies that decouple capability access from geographic proximity can partially offset complementarity gaps, suggesting that ecosystem evolution may increasingly be shaped by general-purpose technologies that alter the effective bundle of local resources available to founders. The same technology can have fundamentally different implications depending on ecosystem context: acting primarily as augmentation in resource-rich environments where complementarity gaps are small, but as substitution in resource-scarce ones where complementarity gaps are large.

We also contribute to strategy and entrepreneurship research on AI by conceptualizing large language models as synthetic human capital and documenting how accessible AI reshapes venture creation feasibility. Much of the strategy literature on AI examines how these tools affect competitive advantage, decision-making, and organizational capabilities in existing firms (Brynjolfsson & McAfee, 2017; Krakowski et al., 2023). Recent work documents productivity gains for knowledge workers using generative AI (Brynjolfsson et al., 2025; Dell'Acqua et al., 2023; Noy & Zhang, 2023). We shift the empirical focus to the earliest stage of entrepreneurship and introduce synthetic human capital as a construct to understand AI's role at this stage. Synthetic human capital differs from traditional human capital in three ways: it is location-independent, infinitely scalable, and accessible at near-zero marginal cost while remaining human-directed and human-validated through natural-language interfaces. These properties enable LLMs to approximate certain specialist capabilities such as business planning, market research, basic coding, without requiring founders to hire employees or contract with service providers.

Our findings demonstrate that synthetic human capital affects who can credibly consider founding a venture. The disproportionate entry increase in low-volume ecosystems following ChatGPT's release indicates that founders in these regions translate AI capabilities into ventures despite lacking access to thick specialist labor markets. This operates through two mechanisms: LLMs enhance founder capabilities through quality-equalizing effects (Brynjolfsson et al., 2025), and they enable task internalization to substitute costly external contracting especially in low-volume ecosystems. Importantly, our results reveal that AI's entrepreneurial impact depends critically on ecosystem context.

The monotonic gradient we observe in the robustness analyses demonstrates that the same technology generates heterogeneous outcomes based on local complementarity gaps, with implications for how we theorize about AI and competitive advantage in entrepreneurship.

Our third contribution extends task-based theories of technological change from labor markets to entrepreneurial ecosystems, demonstrating that technologies reducing task costs have heterogeneous spatial effects on entrepreneurial entry. Task-based theories emphasize that technologies have differential impacts because they alter the cost and feasibility of performing particular tasks (Acemoglu & Restrepo, 2018, 2020; Autor et al., 2003). However, this framework has primarily been applied to labor demand and occupational employment rather than entrepreneurial entry across geographic contexts. We demonstrate that task-based logic extends to entrepreneurial entry by recognizing that founders in different ecosystems face systematically different task bundles. Early-stage entrepreneurship involves executing heterogeneous knowledge-intensive tasks. In high-volume ecosystems, thick specialist markets allow founders to delegate tasks at competitive prices. In low-volume ecosystems, thin specialist markets force founders to self-perform specialist tasks, contract with distant providers at premium prices, or forego tasks entirely.

When LLMs reduce the marginal cost of executing knowledge-intensive tasks, the benefit is largest where complementarity gaps are widest. Our finding that ChatGPT's release generates the largest proportional increases in low-volume ecosystems—with a monotonic gradient and particularly strong effects in AI-exposed industries—demonstrates that task-cost reductions have heterogeneous spatial effects on entrepreneurial entry. This extension has several implications. First, it shows that task-based frameworks apply not only to labor allocation within existing structures but also to new venture creation across geographic contexts. Second, it suggests we should conceptualize ecosystems in terms of both available resources and the task bundles founders must complete. Complementarity gaps reflect mismatches between required tasks and locally accessible task-execution capabilities. Third, general-purpose technologies with broad task applicability may have particularly strong democratizing effects precisely because they reduce costs across the wide range of heterogeneous tasks required for venture creation.

Practical and Policy Implications

The results also carry implications for ecosystem builders, policymakers, and practitioners. For regional policymakers in low-volume ecosystems, the findings suggest that investments that complement accessible AI may be particularly effective levers for stimulating entrepreneurial entry. Rather than trying to replicate the full suite of resources found in major hubs, regions could focus on ensuring reliable digital infrastructure, broad AI literacy, and targeted founder-facing support that helps entrepreneurs integrate AI tools into core early-stage tasks such as market research, prototyping, and fundraising. Such interventions may be relatively low cost compared to large-scale physical infrastructure investments and could yield disproportionately large returns in ecosystems where traditional entrepreneurial support structures are thin.

Ecosystem intermediaries, such as universities, accelerators, incubators, and public–private partnerships, can design programs that help founders effectively leverage accessible AI. In ecosystems with wide complementarity gaps, programs might focus on teaching founders to use LLMs as substitutes for scarce local expertise—executing tasks like business planning, market research, and basic coding that would otherwise require hiring specialists. Training modules could showcase concrete workflows in which AI handles first-draft or exploratory tasks, enabling founders to self-perform work previously requiring costly external contracting. Such programs should also help founders discern which tasks can be effectively delegated to LLMs and which still require human judgment, local knowledge, or specialized legal and regulatory expertise.

Our findings highlight both opportunities and challenges for entrepreneurs. Entrepreneurs in low-volume ecosystems may now find it more feasible to launch ventures without relocating to major hubs or assembling large in-person teams. At the same time, they will still face constraints in later stages of venture development, where access to growth capital, sophisticated customers, and scale-up partners remains uneven across regions. Our results thus point to the importance of viewing AI not as a complete solution to geographic disadvantage but as a powerful tool that can help founders overcome some early-stage capability gaps while leaving other structural constraints intact.

More broadly, these implications align with research on ecosystem architects and the strategies they can use to shape ecosystem emergence and evolution (Daymond, Knight, Rumyantseva, & Maguire, 2023).

Limitations and Future Research

Like any empirical study, this work has limitations that suggest avenues for future research. First, while our findings demonstrate democratization across both AI-exposed and general industries, the specific mechanisms through which LLMs expand entry in non-AI-intensive sectors remain incompletely understood. Our robustness analyses show significant effects in AI-exposed industries, consistent with direct task-substitution mechanisms, but comparable effects across all industries suggest LLMs narrow complementarity gaps through additional channels. These could include overhead task support (e.g., marketing, business planning, administrative documentation) or general equilibrium effects such as heightened entrepreneurial confidence in resource-constrained ecosystems. Examining these mechanisms through surveys or digital trace evidence on founders' AI usage patterns, or through longitudinal designs tracking how usage evolves from venture ideation through scaling, would clarify the scope and persistence of democratization effects.

Second, we study the short-run effects of ChatGPT over a two-year window, which creates several interrelated limitations. The short period cannot fully rule out confounding from concurrent macroeconomic or technological developments. Our design emphasizes supply-side mechanisms—LLMs lowering founders' task burdens—while demand-side channels, such as customers substituting AI for human services, may require longer horizons to manifest (Acemoglu & Restrepo, 2018; Felten et al., 2021). Longitudinal work following cohorts across multiple AI waves would help assess the persistence of entry gains, rule out alternative explanations, and clarify how supply- and demand-side forces interact over time.

Third, our outcome measure is entry, not post-entry performance. We cannot observe whether the additional firms founded in low-volume ecosystems ultimately grow, innovate, or survive at different rates than those in other ecosystems. If accessible AI primarily enables the launch of marginal or less viable ventures, democratization at the entry stage might not translate into reduced inequality in realized entrepreneurial outcomes. Linking firm-level outcomes—such as revenue growth, patenting, funding, or job creation—to founders' locations and AI adoption patterns would assess whether accessible AI narrows or widens performance disparities among ecosystems with varying resource endowments.

Lastly, our analysis is conducted at the CBSA-month level within the United States. This design choice creates two limitations. First, aggregation masks individual founders' characteristics, motivations, and actual AI usage patterns. Second, our U.S.-only sample limits generalizability to other institutional contexts. Micro-level studies combining survey or digital trace data on founders' AI practices with administrative data on venture outcomes would illuminate the mechanisms linking ecosystem shocks to entry patterns. Comparative work between countries or institutional regimes—for example, comparing European, North American, and emerging-market ecosystems—would assess external validity and reveal how accessible AI interacts with different institutional architectures and complementarity structures.

CONCLUSION

This paper demonstrates that universally accessible artificial intelligence can reshape the geography of entrepreneurial entry. We find that ChatGPT's release increased new firm formation across all U.S. ecosystems, with 55 percent larger proportional gains in low-volume ecosystems where complementarity gaps are widest. This pattern is consistent with our theorization of LLMs as synthetic human capital that substitutes for missing local expertise, lowering entry thresholds in resource-constrained regions. However, AI is a partial equalizer: high-volume ecosystems retain absolute advantages, and many scale-up resources remain spatially concentrated. Key questions remain whether entry gains persist over time, extend to venture growth and survival, and translate into sustained regional prosperity—ultimately determining whether accessible AI reshapes, not just enlarges, the geography of entrepreneurial opportunity.

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Table 1. Descriptive Statistics: CBSA-Month Panel

	Pre-period				Post-period			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Total entries (count)	281.60	1476.05	1	75642	387.07	2006.41	1	61846
Low-volume total entries (count)	12.82	17.35	1	169	32.09	99.03	1	3546
Medium-volume entries (count)	37.15	39.24	1	507	52.96	106.12	1	3215
High-volume entries (count)	730.35	2384.46	1	75642	1013.01	3275.18	1	61846

Table 2. Main Results

	(1) Baseline	(2) CBSA Trends
Low Volume × Post	0.431	0.438
	(0.044)	(0.096)
	[0.0000]	[0.0000]
Med Volume × Post	0.072	0.155
	(0.044)	(0.105)
	[0.1003]	[0.1399]
Observations	18,500	18,500
Number of CBSAs	843	843
Adj. R-squared	0.673	0.704

Reference category: High-volume ecosystems / Standard errors in parentheses, p-values in brackets

Table 3. Robustness Checks: Functional Forms and Outliers

	(1) Quadratic	(2) AI-exposed	(3) Excl Dec	(4) Wins 1%	(5) Wins 5%	(6) ln(Y)	(7) Levels	(8) Excl Early	(9) Excl Late	(10) Jan 2023
Low Volume × Post	0.418	0.348	0.658	0.395	0.347	0.398	615.065	0.411	0.464	0.753
	(0.100)	(0.032)	(0.126)	(0.097)	(0.093)	(0.105)	(124.721)	(0.093)	(0.093)	(0.085)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0002]	[0.0002]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Med Volume × Post	0.140	0.228	0.187	0.128	0.061	0.093	614.027	0.150	0.175	0.276
	(0.108)	(0.025)	(0.133)	(0.105)	(0.101)	(0.113)	(127.139)	(0.100)	(0.102)	(0.088)
	[0.1945]	[0.0000]	[0.1603]	[0.2236]	[0.5458]	[0.4106]	[0.0000]	[0.1329]	[0.0867]	[0.0019]
Observations	18,500	16,307	17,666	18,500	18,500	18,500	18,500	17,222	16,823	18,500
Number of CBSAs	843	843	843	843	843	843	843	843	843	843
R-squared	0.722	0.732	0.699	0.737	0.681	0.690	0.533	0.718	0.723	0.706

All specifications include CBSA and month-of-year fixed effects and CBSA-specific linear time trends
Reference category: High-volume ecosystems / Standard errors in parentheses, p-values in brackets

Table 4. Robustness Checks: Alternative Ecosystem Volume Classifications

	(1) Terciles (Main)	(2) Quartiles	(3) Extremes (10%)	(4) Continuous
Low Volume × Post	0.438			
	(0.096)			
	[0.0000]			
Medium Volume × Post	0.155			
	(0.105)			
	[0.1399]			
Quartile 1 (Bottom 25%) × Post		0.573		
		(0.113)		
		[0.0000]		
Quartile 2 × Post		0.388		
		(0.119)		
		[0.0011]		
Quartile 3 × Post		0.252		
		(0.123)		
		[0.0404]		
Bottom 10% × Post			0.524	
			(0.204)	
			[0.0104]	
Middle 80% × Post			0.245	
			(0.165)	
			[0.1376]	
Volume × Post				-0.084
				(0.046)
				[0.0640]
Observations	18,500	18,500	18,500	18,500
Number of CBSAs	843	843	843	843
R-squared	0.704	0.705	0.704	0.704

All specifications include CBSA and month-of-year fixed effects and CBSA-specific linear time trends
Reference category: High-volume ecosystems / Standard errors clustered at the CBSA level

Figure 1. Absolute Percent Changes in Total Entrepreneurial Entry by Ecosystem Volume Category

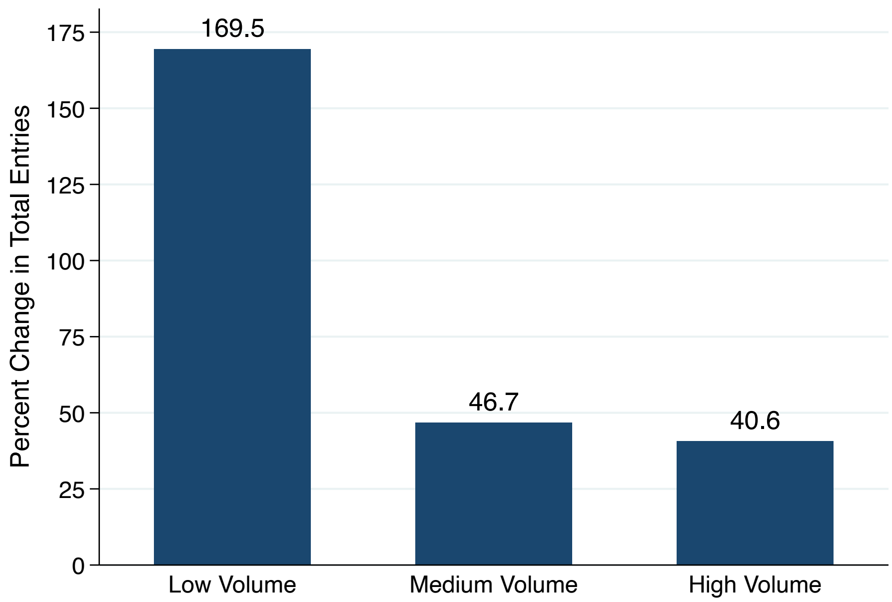

Figure 2. Event-Study Estimates of Low- and Medium-Volume Ecosystems Relative to High-Volume Ecosystems