LABOR MARKET COMPETITION AND ENTREPRENEURSHIP

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Abstract

This paper examines how labor market competition shapes local entrepreneurial landscape. We construct a measure of local labor market competition using occupation-level job posting data and study its relation with startup formation across U.S. cities. A more competitive labor market for employers is associated with significantly greater startup activity. To address endogeneity concerns, we exploit large firms' relocations that alter the competitive structure of local human capital markets. Difference-in-differences analyses show that relocation-induced increases in labor market competition lead to more startup formations. Cross-sectional evidence indicates stronger effects in regions with greater knowledge stocks, higher labor mobility, and more favorable financing conditions, suggesting that competitive labor markets facilitate the reallocation of human capital and the commercialization of ideas.

Keywords: labor market competition; entrepreneurship; startup formation; employer concentration; labor mobility; knowledge spillovers
JEL Codes: J42; J23; L26; R11; O31; D22

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1. Introduction

Through entry and experimentation, entrepreneurs challenge incumbents, introduce novel technologies, and reshape market structure. Meanwhile, these young firms account for a disproportionate share of net job creation (Haltiwanger, 2012; Haltiwanger, Jarmin, and Miranda 2013) and drive productivity-enhancing reallocation across firms and industries (Foster, Haltiwanger, and Krizan 2001; Haltiwanger, 2012). Local entrepreneurial activity thus serves as an important driving force behind economic growth and technological innovation by intensifying competition and triggering creative destruction. Yet over the past several decades, the United States has experienced a broad-based decline in business dynamism, including falling startup rates, reduced job-to-job mobility, and declining firm entry across sectors and regions (Haltiwanger 2012; Davis and Haltiwanger 2014; Decker et al. 2014, 2016). These trends raise a fundamental question: what frictions are preventing new firms from forming and scaling?

A defining feature of entrepreneurial entry is that it requires the reorganization of human capital, mainly from local talent markets. New firms emerge when individuals leave incumbent employers, recombine knowledge, and assemble teams with complementary skills. Therefore, local startup formation depends not only on product-market demand and financing availability, but also on the structure of local labor markets that governs worker mobility and outside options. If labor markets are thick and competitive for employers, workers may reallocate more easily across firms, ideas may diffuse more rapidly, and founding teams may form at lower cost. If labor markets are concentrated and dominated by a small number of employers, labor mobility may be suppressed and knowledge may remain embedded within incumbent firms. From this perspective, the decline in business dynamism documented by Decker et al. (2014, 2016) may be connected to shifts in local labor market structure.

Recent research provides evidence that local labor markets are often highly concentrated and characterized by employer market power (Azar, Marinescu, and Steinbaum, 2017, 2019; Benmelech, Bergman, and Kim, 2022). While this literature has primarily focused on wage-setting and employment consequences, its implications extend beyond the distribution of rents between firms and workers. If employer concentration reduces workers' outside options and limits job-to-job transitions, it may also dampen the flow of talent into new ventures. Conversely, greater labor market competition among employers may facilitate talent mobility and accelerate the

recombination of skills necessary for startup formation. Despite these plausible links, direct evidence connecting labor market competition to entrepreneurial entry remains limited in the literature.

The relation between labor market competition and local entrepreneurship is theoretically ambiguous. On one hand, intensified competition for talents may raise wages and hiring costs, particularly for resource-constrained startups that lack the scale and compensation flexibility of established firms. From this perspective, greater labor market competition could discourage startup formation by increasing the cost of assembling a founding team. On the other hand, such competition may increase workers' outside options and facilitate mobility, lowering frictions that impede individuals from leaving incumbents to form new ventures. Evidence from studies of noncompete clauses enforceability has shown that mobility frictions hurt local entrepreneurship.[1] Labor market competition may operate through a similar channel, even in the absence of explicit contractual restrictions.

It is noteworthy that wage effects and mobility effects are conceptually distinct. Wage adjustments reflect price changes within existing employment relationships, whereas mobility effects reflect changes in the allocation and recombination of human capital across firms. Entrepreneurial entry depends critically on the latter. The formation of new ventures requires not only labor input but the right combination of skills, ideas, and experience. To the extent that labor market competition enhances matching efficiency and reduces frictions that impede team formation, its impact on entrepreneurship may be positive even if wages rise. Determining which of these channels dominates is therefore an open question calling for empirical evidence.

This paper studies how local labor market competition (LCOMP) explains entrepreneurial activity across U.S. counties. We construct a county-level measure of labor market competition based on one minus the employer concentration of local job postings based on Burning Glass Technologies (BGT). Intuitively, LCOMP captures the degree to which hiring opportunities in a local labor market are dispersed across many employers versus dominated by a small number of employers. On the other hand, we use the rich startup-level data from the PitchBook dataset to

[1] Marx, Strumsky, and Fleming (2009) show that the enforceability of noncompete agreements affects inventor mobility, and Samila and Sorenson (2011a) and Starr, Frake, and Agarwal (2019) document that regions with weaker noncompete enforcement experience greater venture capital investment and entrepreneurship. See Starr (2026) for a detailed review of the literature on the effects of noncompete clauses.

measure local entrepreneurial activity using the number of new startups backed by venture capitalists (VCs) and private capital funds. In our data analyses, we examine how variation in LCOMP relates to county-level startup formation using multiple complementary empirical strategies.

First, we document a robust positive association between local labor market competition and startup formation in Poisson regressions. Across specifications with city or county fixed effects and state-by-year fixed effects, higher LCOMP is associated with significantly greater entrepreneurial entry. The magnitude is economically meaningful: an increase of one standard deviation (from the 25th to the 75th percentile) in LCOMP corresponds to an increase of 0.65 (1.08) startups per county. We find consistent results using the number of small business establishments from the County Business Patterns (CBP) dataset and first-time patent assignees as alternative measures of local startup activity. More importantly, such a positive relation is stronger in high-tech industries, highlighting the higher mobility and economic contribution of talents.

Second, to address concerns about omitted variable bias and reverse causality, we design a difference-in-differences test based on large firms' relocations[2]. We classify cities as treated when they receive a relocating firm whose pre-relocation hiring overlaps significantly with existing local employers. This overlap criterion ensures that the shock is economically meaningful for the relevant labor market. Following such relocations, startup formation increases relative to cities that never experience this event. Event-time analyses reveal no differential pre-trends but show sustained increases in entrepreneurial entry after the relocation event.

We do not intend to claim such relocations to be entirely exogenous; nevertheless, we deliberately discuss how this setting supports a causal interpretation and it is plausibly immune to omitted variables. First, we have controlled for state-by-year fixed effects that likely absorb the effect of omitted variables such as business environments and government policies. Second, the satisfaction of the parallel trend assumption suggests the absence of omitted variables that drive

[2] Examples of relocations in our sample include AT&T, a telecommunications firm (SIC 4812), which moved its headquarters from San Antonio to Dallas in 2008; Northrop Grumman, a producer of advanced defense and electronic systems (SIC 3812), which relocated from Los Angeles to Northern Virginia in 2010; and InterDigital, a wireless communications technology and patent licensing firm (SIC 6794), which moved from Pennsylvania to Wilmington, Delaware in 2011. Consistent with our treatment definition, overlapping occupations account for roughly 34% of the relocating firm's hiring for AT&T, 41% for Northrop Grumman, and 26% for InterDigital, indicating substantial occupational similarity between relocating firms and destination labor markets.

local entrepreneurship differently; otherwise, they should have driven up treated cities' startup formation in pre-event years.[3]

Third, we address potential selection concerns by constructing matched samples of treated and untreated cities and implementing entropy balancing to align observable characteristics prior to treatment. Treated and control locations are matched within states and calendar years to ensure comparability in macroeconomic conditions and policy environments. We then implement stacked difference-in-differences regressions in these matched sample to address treatment timing heterogeneity and observable heterogeneity across cities in the same state.

Having presented empirical evidence for a causal interpretation of our baseline results, we next examine the mechanisms underlying this effect. Identifying the operative channel is central both for our hypothesis and for understanding the broader economic implications of our findings. Labor market competition could influence local startup formation through several distinct, though related, forces. Our empirical strategy therefore seeks to examine three possible and non-exclusive mechanisms related to knowledge recombination, worker mobility, and financing constraints.

One natural mechanism operates through the recombination of knowledge and the formation of founding teams – the creation of new firms often requires the integration of complementary skills and the redeployment of ideas developed within incumbent organizations. In regions with a larger stock of innovative human capital, talent turnovers due to competitive labor markets are more likely to result in fruitful recombination of knowledge and ideas.[4] In addition, when outside options and human capital are more abundant due to the agglomeration of talents, individuals are more likely to leave incumbent firms, assemble teams, and commercialize latent ideas. If this channel is central, the effect of labor market competition on startup formation should be amplified in regions characterized by greater innovative capacity. We therefore examine whether the relation between LCOMP and entrepreneurial entry is stronger in areas with higher inventor intensity and patenting activity, which proxy for the local stock of commercially viable knowledge.

[3] We acknowledge one exception to be that such variables occur and affect (the majority of) treated cities in the same direction and year as large firms' relocations do – but such a coincidence seems unlikely.

[4] Prior studies have suggested how the agglomeration and interaction of talents leads to more innovation, see Glaeser (1999), Delgado, Porter, and Stern (2010), Chatterji, Glaeser, and Kerr (2014), Carlino and Kerr (2015). In addition, Babina and Howell (2024) show that corporate R&D leads to more entrepreneurship as knowledge spillovers.

A related but distinct mechanism concerns labor mobility itself. Even holding constant the stock of ideas, the ability of workers to transition between firms determines whether entrepreneurial opportunities can be realized. Competitive labor markets may increase job-to-job transitions by expanding outside options and reducing frictions that impede talent reallocation. In addition, in an environment of high turnovers, talents are more comfortable with job changes and also observe new opportunities, which increase their likelihood of starting new businesses.[5] Thus, if the labor market competition effect works through mobility, the positive association between LCOMP and startup formation should be more pronounced in regions with higher baseline rates of job-to-job transitions.

Finally, the translation of mobility into entrepreneurial entry may also depend on access to financing. The reallocation of talent and the formation of new firms require external capital, particularly in the early stages when entrepreneurs' personal resources are limited.[6] If labor market competition generates entrepreneurial opportunities but financial constraints bind, the effect on realized startup formation may be attenuated as would-be entrepreneurs anticipate financing need (Samila and Sorenson, 2011b; Nanda and Rhodes-Kropf, 2013). Conversely, in regions with more developed small business lending markets or greater housing collateral values, both of which relax financing constraints, the impact of labor market competition on entry should be stronger.

Consistent with these mechanisms, we find that the coefficient on the interaction between LCOMP and regional characteristics for greater innovative activity, higher labor mobility, and more favorable financing conditions. Taken together, these patterns support an interpretation in which labor market competition facilitates the reorganization of talent and the commercialization of ideas. The evidence is less consistent with a purely wage-based explanation and instead points toward a mechanism operating through mobility, team formation, and the relaxation of frictions that impede the transformation of human capital into new firms. These results also provide further support to a causal interpretation for the LCOMP-startup relation – for an omitted variable to explain this relation, it will need to covary with all regional characteristics used in our interaction

[5] Agarwal, Ganco, and Ziedonis (2009) show that firms' toughness on intellectual property enforcement prevents knowledge diffusion and entrepreneurial activity. In addition, Ganco (2013) finds that even complex technologies may still leak out through current employees' entrepreneurial activity.

[6] An extensive list of prior studies have suggested that personal wealth, unemployment insurance, economic downturn, and collateral constraints influence entrepreneurial entry (Hurst and Lusardi 2004; Adelino, Schoar, and Severino 2015; Hombert et al., 2020; Bernstein, McQuade, and Townsend 2021; Bernstein et al. 2022; Bernstein, Townsend, and Xu 2024).

regressions in a consistent direction. As it is difficult for us to think of such a scenario, a more plausible interpretation is that labor market competition promotes local entrepreneurship.

This study contributes to three closely related literatures at the intersection of labor economics, entrepreneurship, and human capital, and has managerial and policy implications. First, we offer novel evidence on the consequences of labor market concentration and employer market power. In particular, we present that labor market structure shapes not only wage setting and unemployment, but also new firm formation – an important dimension of economic dynamism. Prior work documents that labor markets dominated by a small set of employers are often against workers' interest, including lower posted wages and reduced hiring responsiveness, consistent with monopsony-like forces (Davis and Haltiwanger, 2014; Azar, Marinescu, and Steinbaum, 2022; Benmelech, Bergman, and Kim, 2022). While this literature focuses primarily on distributional and employment consequences, it may have broader equilibrium implications because employees' outside options and mobility determine how human capital is allocated across incumbent firms and new ventures.[7] We fill in this missing margin and highlight labor market competition as a determinant of industry structure and innovation dynamics that shape future economic and technological growth.

Second, we contribute to the literature on the landscape of entrepreneurship by connecting it to local labor market competition as an economically important input in the entrepreneurial team formation. Prior work documents secular declines in entry, young-firm activity, and job reallocation (e.g., Haltiwanger, 2012; Decker et al., 2014, 2016), and emphasizes that these trends likely reflect multiple frictions, including barriers to reallocation, reduced experimentation, and changing market structure.[8] We focus on the talent mobility dimension, and exploit job posting data to construct geographical and time-series variations in labor market competition. In addition, we conduct difference-in-differences test based on large-firm relocations, which lend further support to a causal effect of interfirm competition in talent recruiting. Moreover, our results offer new insights to entrepreneurs' location choices (Kerr and Kominers, 2015; Guzman, 2024).

[7] The literature has shown that the human capital allocation between incumbent firms and startups has implications on economic growth trajectories (e.g., Davis and Haltiwanger 2014; Akcigit and Kerr 2018; Acemoglu et al. 2018).
[8] Davis and Haltiwanger (2014) and Guzman and Stern (2017, 2020) offer detailed discussions of possible explanations.

Third, we add to prior research on the importance of human capital in company formation and mobility-driven knowledge spillovers. Existing work shows that restrictions on worker mobility, most prominently the enforceability of noncompete agreements, can limit the movement of skilled labor and the diffusion of ideas (Marx, Strumsky, and Fleming 2009) and thus suppress entrepreneurship (Samila and Sorenson, 2011a; Starr, Frake, and Agarwal, 2019; Starr, 2026).[9] We offer complementary evidence by showing stronger entrepreneurial reactions among areas of larger local stock of talents and higher labor mobility in our mechanism tests. From a broader perspective, this study also adds to the literature on regional innovation ecosystem and policies, in which knowledge spillovers play a critical role (Chatterji, Glaeser, and Kerr, 2014; Guzman et al., 2024).

2. Existing Literature and Testable Hypothesis

Entrepreneurial entry depends fundamentally on the availability and recombination of human capital. New firms arise when individuals exit incumbent employers, recombine knowledge, assemble complementary teams, and mobilize resources to commercialize ideas (Gompers, Lerner, & Scharfstein, 2005; Babina, 2020; Babina & Howell, 2024). However, there are various frictions that inhibit startup formation, which call for further investigations.

At the same time, a growing body of work shows that many local labor markets are highly concentrated and characterized by employer market power. Using vacancy data, Azar, Marinescu, and Steinbaum (2020, 2022) document substantial concentration in occupation-by-commuting-zone labor markets and show that greater concentration is associated with lower posted wages. Benmelech, Bergman, and Kim (2022) provide complementary evidence that local labor market concentration depresses wages and affects employment outcomes. These findings imply that labor market structure shapes worker outside options and mobility.

While prior research focuses primarily on wage determination, the implications extend naturally to entrepreneurial entry. If concentrated labor markets suppress outside options and reduce job-to-job transitions, they may also limit the reallocation of skilled workers into new

[9] From a broader perspective, the literature has extensive discussions on how labor mobility influences knowledge spillovers in a region (e.g., Almeida and Kogut 1999; Song, Almeida, and Wu 2003).

ventures.[10] Conversely, in more competitive labor markets, workers face a richer set of outside options and possibly higher turnovers, potentially facilitating exit from incumbents and entry into entrepreneurial activity. From this perspective, labor market competition may function as a structural determinant of startup formation.

On the other hand, greater competition for labor may raise wages and hiring costs, particularly for early-stage firms that lack scale and internal capital. Startups frequently operate under financial constraints and depend on external financing (e.g., King and Levine, 1993; Kerr and Nanda, 2009, 2011; Robb and Robinson, 2014). If intensified labor market competition primarily increases labor costs, it may discourage entrepreneurial entry.

Despite the possibilities in both directions, we argue that talent and productivity gains outweigh wage costs and financial constraints affect high-tech startups, especially those with the support and resources of VCs on innovation and entrepreneurship.[11] We thus state our first hypothesis in its alternative form:

Hypothesis 1: Greater local labor market competition leads to more startup formations.

If labor market competition stimulates entrepreneurship, understanding the mechanism is critical. A central channel emphasized in the innovation literature is mobility-driven knowledge recombination. Classic agglomeration theories argue that thick labor markets facilitate matching and learning (Glaeser 1999; Duranton and Puga 2004). Empirically, worker mobility has been shown to be an important conduit for knowledge diffusion (Almeida and Kogut 1999; Song, Almeida, and Wu 2003), which likely promotes entrepreneurial activity. Samila and Sorenson (2011a) and Starr, Frake, and Agarwal (2019) show that stronger noncompete enforcement that restricts labor mobility indeed reduces venture capital investment and entrepreneurship.

Importantly, mobility frictions need not arise solely from contractual restrictions. Limited outside options in concentrated labor markets may similarly suppress talent mobility. If labor market competition expands outside options and increases job-to-job transitions, it may facilitate

[10] Prior studies have also discussed how the legal restrictions on talent mobility limit inventor turnovers (Marx, Strumsky, and Fleming 2009) and thus discourage new ventures (Samila and Sorenson 2011a; Starr, Frake, and Agarwal 2019)

[11] The literature has provided abundant evidence on the positive effects of VCs on financing, supporting, and monitoring startups and promote innovation (Kortum and Lerner 2000; Hellmann and Puri 2002; Gompers, Lerner, and Scharfstein 2005; Ewens and Rhodes-Kropf 2015; Bernstein, Giroud, and Townsend 2016).

the recombination of skills and ideas necessary for startup formation (e.g., Agarwal, Ganco, and Ziedonis, 2009; Ganco, 2013). This channel should be particularly salient in regions with greater innovative capacity, where latent entrepreneurial opportunities are more abundant, and in regions with higher baseline labor mobility, where marginal increases in competition are more likely to translate into actual worker movement.

If the primary channel operates through mobility and knowledge recombination rather than through wage adjustments alone, the impact of labor market competition on startup formation should be stronger in environments where these mechanisms are most active. This leads us to our second hypothesis:

Hypothesis 2: The positive relation between local labor market competition and startup formation is stronger in regions characterized by greater innovative capacity and higher labor mobility.

Even when mobility and knowledge recombination are feasible, entrepreneurial entry requires access to capital. A substantial finance literature emphasizes that new firms depend on external financing and that credit market conditions affect business formation (King and Levine 1993). Black and Strahan (2002) show that banking deregulation increases new incorporations, while Hurst and Lusardi (2004) and Adelino, Schoar, and Severino (2015) demonstrate that wealth and collateral constraints influence entrepreneurial entry. Moreover, Kerr and Nanda (2009), Samila and Sorenson (2011b), and Nanda and Rhodes-Kropf (2013) highlight that financing frictions shape who becomes an entrepreneur and whether entrepreneurial opportunities are realized.

If labor market competition expands the set of feasible entrepreneurial opportunities by facilitating mobility and team formation, these opportunities may only translate into realized entry when financing constraints are sufficiently relaxed. In areas with more abundant small business lending or stronger collateral values, mobility-induced opportunities should be more likely to materialize as new ventures. Conversely, in financially constrained environments, enhanced labor market competition may not generate proportional increases in startup formation due to the lack of necessary funding. We thus summarize our next hypothesis:

Hypothesis 3: The positive relation between local labor market competition and startup formation is stronger in regions where financing constraints are less severe.

3. Data, Sample, and Empirical Methodology

3.1 Data Sources

Our primary measure of entrepreneurial activity is derived from the PitchBook dataset, which serves as the main source of startup formation data. PitchBook offers extensive global coverage of venture-backed startups and private capital markets, encompassing firms across more than 160 countries. The database provides detailed firm-level information, including founding year, primary industry classification, financing rounds, investor participation, exit outcomes, and geographic identifiers reported at the ZIP code level. In aggregate, PitchBook contains information on approximately 4.5 million companies, 2.5 million investments, over 525,000 investors, 45,000 limited partners, 125,000 funds, and 4 million individuals.

Our analysis focuses exclusively on U.S. observations. To ensure consistent geographic classification, we use the Google Maps Geocoding API to obtain latitude, longitude, city, county, and state information corresponding to each ZIP code. We then aggregate startup counts to the city–county–year level, which constitutes the main unit of analysis.

To construct broader measures of local business activity, we use the County Business Patterns (CBP) dataset from the U.S. Census Bureau. CBP reports establishment counts by employment size categories, ZIP code, year, and NAICS industry classification. We aggregate ZIP-level observations to the city–county–year level and define *Small Business Establishments* as the stock of private-sector establishments with 5–100 employees[12]. In constructing this measure, we exclude nonprofit organizations and public-sector industries, including public administration and related government entities. CBP data are reported at the 6-digit NAICS level. When industry observations or establishment counts for specific employment size groups are missing, we treat these cells as zeros. We classify industries as high-tech based on standard NAICS definitions following Goldschlag and Miranda (2020) and Decker and Haltiwanger (2024).[13] All remaining private-sector industries are categorized as non-high-tech.

[12] CBP reports establishment counts by employment size bins. We define small business establishments as those with 5–100 employees, aggregating the relevant size categories to focus on employer firms of economically meaningful scale while excluding very small and large establishments.

[13] High-tech industries are identified using 4-digit NAICS codes. Specifically, the high-tech category includes NAICS 3341, 3342, 3344, 3345, 3364, 5112, 5182, 5191, 5413, 5415, and 5417. This classification follows standard definitions of knowledge-intensive and technology-oriented industries in the entrepreneurship literature.

For the sectoral heterogeneity analysis, we aggregate establishment counts to the city × year × high-tech indicator level, where the high-tech indicator equals one for high-tech industries and zero otherwise. The final heterogeneity sample therefore consists of a city–year–sector observations, with two sector categories per city-year.

Innovation-based entrepreneurial entry is measured using data from the United States Patent and Trademark Office (USPTO). Patent data are retrieved from the USPTO Bulk Data Storage System,[14] including patent application records and disambiguated assignee files. We use disambiguated assignee-level data and associated location files to identify firm-level patent applicants and assign them to their corresponding cities and counties.

Consistent with Farre-Mensa, Hegde, and Ljungqvist (2020), Ewens and Marx (2024), and Gao, Hsu, and Wang (2025), we define Innovative Entrants as first-time patent-filing firms residing in a given city. To better capture entrepreneurial rather than incumbent innovative activity, we restrict the sample to entities with five or fewer total patent applications. Prior evidence indicates that approximately 45% of patents are filed within the first three years of a U.S. firm's life (Ewens and Marx 2024), supporting the use of first-time patent filers as a proxy for innovation-driven startups.

County-level demographic and economic controls are obtained from the U.S. Department of Agriculture (USDA) Economic Research Service (ERS) County-Level Datasets[15]. These data provide measures of population, educational attainment, racial composition, unemployment, and income. Political characteristics are constructed using county-level presidential election returns from the MIT Election Data and Science Lab (2018)[16].

To examine financing conditions, we incorporate two additional datasets. Housing collateral conditions are measured using the Federal Housing Finance Agency (FHFA) House Price Index (HPI) at the county level. Consistent with the collateral channel literature (e.g., Chaney, Sraer, and Thesmar, 2012; Adelino, Schoar, and Severino, 2015), local house price appreciation serves as a proxy for changes in collateral values that affect credit supply and entrepreneurial financing capacity. Small business lending activity is obtained from the Federal Reserve's Small

[14] United States Patent and Trademark Office, Bulk Data Storage System, https://bulkdata.uspto.gov/.
[15] U.S. Department of Agriculture, Economic Research Service, https://ers.usda.gov/.
[16] MIT Election Data and Science Lab, https://electionlab.mit.edu/.

Business Lending Data portal, measured as the total dollar volume of small business loans originated within a county[17].

Labor mobility is measured using the U.S. Census Bureau's Longitudinal Employer–Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data[18]. We construct job-to-job (J2J) mobility as separations from one employer to another with continuous employment, scaled by population and aggregated to the county-year level.

All datasets are harmonized and merged using county FIPS codes and year identifiers. The final sample consists of city–county–year observations for the United States over the study period.

3.2 Local Labor Market Competition (LCOMP)

We construct our measure of local labor market competition (LCOMP) using the near-universe of U.S. online job postings from Burning Glass Technologies (BGT), following the methodology developed by Azar et al. (2020, 2022), Bai et al. (2022), and Hou et al. (2025). Prior research shows that BGT-based measures capture employer concentration more precisely than traditional approaches relying on Census employment data (e.g., Rinz 2018; Lipsius 2018; Benmelech et al. 2022), owing to the substantially greater occupational and geographic granularity of job-posting data.

The BGT dataset provides detailed information on job postings classified according to six-digit Standard Occupational Classification (SOC) codes and mapped to Commuting Zones (CZs). This structure allows us to define local labor markets at the intersection of CZ × occupation and to measure competition among firms seeking workers with highly comparable skill sets within narrowly defined labor markets.

We define each local labor market as a commuting zone–occupation pair. For each commuting zone cz, occupation o, and year t, we compute employer concentration using the Herfindahl–Hirschman Index (HHI):

[17] The FHFA House Price Index data are available at https://www.fhfa.gov/data/hpi/datasets, and small business lending data are obtained from the Federal Reserve Small Business Lending Data portal, https://www.federalreserve.gov/consumerscommunities/data_tables.htm.
[18] U.S. Census Bureau, Longitudinal Employer-Household Dynamics, https://lehd.ces.census.gov/.

$$HHI_{cz,o,t} = \sum_f \left(\frac{J_{f,cz,o,t}}{J_{cz,o,t}}\right)^2,$$

where $J_{f,cz,o,t}$ denotes the number of job postings by firm f in commuting zone cz, occupation o, and year t, and $J_{cz,o,t}$ is the total number of postings in that market. Higher values of $HHI_{cz,o,t}$ indicate greater employer concentration and stronger monopsony power in the corresponding labor market.

To obtain a commuting-zone–year measure of labor market concentration, we aggregate occupation-level HHIs within each commuting zone using occupation-size weights:

$$HHI_{cz,t} = \sum_o w_{cz,o,t}\ HHI_{cz,o,t},$$

where $w_{cz,o,t}$ denotes the share of postings in occupation o among all postings in commuting zone cz in year t.

Finally, we define local labor market competition as:

$$LCOMP_{cz,t} = 1 - HHI_{cz,t}.$$

Higher values of $LCOMP_{cz,t}$ therefore correspond to more competitive labor markets. Because our empirical analysis is conducted at the county (FIPS)–year level, we assign each commuting zone to its corresponding county using the standard CZ–county crosswalk. Since commuting zones may encompass multiple counties, all counties within a given CZ are assigned the same $LCOMP$ value. This reflects the interpretation of commuting zones as integrated labor markets in which workers frequently commute across county borders.

3.3 Summary Statistics

Table 1 reports summary statistics for the main variables used in the analysis. The baseline sample consists of 87,919 city–county–year observations in the U.S. over the period 2007–2022. The dependent variable, *Start-ups*, measures the number of newly founded firms in a given city–county–year and has a mean of 0.695. The patent-based measure of innovative entry, *Innovative Entrants*, constructed from USPTO data, includes 165,799 county–year observations over the same period and has a mean of 0.418 and a standard deviation of 1.201. For the sectoral heterogeneity analysis, we use County Business Patterns (CBP) data aggregated to the city × year × high-tech indicator level for the period 2010–2022. The mean number of *Small Business*

Establishments is approximately 35 in the baseline sample, of which an average of 3 are in high-tech industries.

The local labor market competition index (*LCOMP*) has a mean of 0.632 and a standard deviation of 0.160. County demographic and economic characteristics display substantial cross-sectional heterogeneity. The average county population is approximately 235,000 residents. Annual population growth averages 0.6 percent, the unemployment rate averages 6.0 percent, and the share of adults with a bachelor's degree is approximately 27 percent. Median household income is about $60,000.

[Insert Table 1 Here]

4. Empirical Results

In this section, we begin with the baseline specification examining the relationship between local labor market competition (LCOMP) and startup formation using city-level start-ups from the PitchBook dataset. We next examine sectoral heterogeneity by analyzing the stock of small private-sector establishments constructed from County Business Patterns (CBP) data, distinguishing between high-tech and non-high-tech industries. Next, we address endogeneity concerns by exploiting relocation-induced variation in local labor market competition within a staggered difference-in-differences framework and further strengthen identification using a stacked difference-in-differences design with simple matching and entropy balancing. Next, we show that our findings extend to patent-based measures of entrepreneurial entry. Finally, we examine cross-sectional variation in the relationship between local labor market competition and startup formation to shed light on the underlying mechanisms. In particular, we test whether the impact of *LCOMP* is stronger in regions characterized by greater incumbent knowledge stock, higher job-to-job mobility, and more favorable local financing conditions. These analyses help identify whether labor market competition stimulates entrepreneurial activity through knowledge recombination, labor reallocation, or the relaxation of financial constraints.

4.1 Baseline Results

We first investigate the relationship between local labor market competition and startup formation. Specifically, we estimate the following panel data specification:

$$E[StartUps_{ict}] = \exp\left(\alpha + \beta\, LCOMP_{ct} + \gamma X_{ct} + \delta_{FE} + \varepsilon_{ict}\right) \qquad (2)$$

where i indexes cities, c counties, and t years. The dependent variable, *Start-ups*, is defined as the city-level raw count of startup firms from the PitchBook dataset. The variable of interest is $LCOMP_{ct}$, which measures local labor market competition at the county level in a specific year. The vector X_{ct} includes time-varying county-level controls capturing demographic and economic conditions: total population (*Total Pop.*), population growth (*Δ Population*), racial composition (*White %*), educational attainment (*Bachelor %*), unemployment rate (*Unemployment %*), political composition (*Republican %*), and median household income (*Median Income*). More importantly, we consider various combinations of fixed effects (δ_{FE}): (i) county and year fixed effects, (ii) city and year fixed effects, (iii) county and state-by-year fixed effects; and (iv) city and state-by-year fixed effects. All regressions are estimated using Poisson pseudo-maximum likelihood (PPML), and standard errors are clustered at the county level.

[Insert Table 2 Here]

Table 2 reports the results. Column (1) includes county and county fixed effects to absorb common time shocks and time-invariant county characteristics. Column (2) replaces county fixed effects with city fixed effects, controlling for persistent city-level heterogeneity. Columns (3) and (4) further add state-by-year fixed effects, which absorb time-varying state-level shocks, including macroeconomic conditions and policy changes. These increasingly stringent specifications ensure that identification stems from within-state variation in labor market competition over time. Across all specifications, the estimated coefficient on *LCOMP* is positive and statistically significant, providing evidence consistent with Hypothesis 1, which predicts that greater local labor market competition increases startup formation. In the most stringent specification (column (4)), which includes city and state-by-year fixed effects, the coefficient on *LCOMP* is 4.124 and significant at the 1% level. To assess economic magnitude, we translate the estimates into changes in startup counts. The standard deviation of *LCOMP* is 0.160. Using the coefficient from column (4) (β = 4.124), a one standard deviation increase in *LCOMP* implies an increase of approximately 0.65 startups per county ($\exp(4.124 \times 0.160) - 1 = 0.94; 0.94 \times 0.695 \approx 0.65$). Given that the mean number of startups in the sample is 0.695, this represents a meaningful increase in entrepreneurial activity.

A similar pattern emerges when comparing cities across the distribution of labor market competition. Moving from the 25th percentile of *LCOMP* (0.53) to the 75th percentile (0.758)

corresponds to an increase of 0.228. Using the same estimate ($\beta = 4.124$), this shift implies approximately 1.08 additional startups per city-year ($\exp(4.124 \times 0.228) - 1 = 1.56; 1.56 \times 0.695 \approx 1.08$). Thus, cities in relatively high-competition labor markets experience roughly one additional startup per year compared to those in lower-competition environments.

Taken together, these results indicate that higher local labor market competition is strongly associated with greater entrepreneurial activity, both statistically and economically.

4.2 Local Labor Market Competition and Small Business Establishment: Sector Heterogeneity

We next examine whether the effect of local labor market competition varies across sectors. In particular, we test whether *LCOMP* disproportionately affects small business activity in knowledge-intensive industries. To do so, we estimate Equation (2) using *Small Business Establishments* as the dependent variable and interact *LCOMP* with an indicator for high-tech industries.

Small Business Establishments are defined as the city-level stock of private-sector establishments with 5–100 employees, constructed from County Business Patterns (CBP) data. All specifications include city and state-by-year fixed effects to absorb time-invariant city characteristics and state-level shocks that vary over time. In addition, more stringent specifications incorporate sector-by-year fixed effects, which control for national or sector-specific demand shocks and technological trends that affect all cities within a given sector-year. We further include city-by-sector fixed effects in the most stringent specification to account for persistent differences in industrial composition across cities. Together, these fixed effects ensure that identification arises from within-city, within-sector variation in labor market competition over time, net of sector-wide trends and city-specific industrial structure.

[Insert Table 3 Here]

Table 3 reports the results. Column (1) presents the baseline specification without the interaction term and shows that *LCOMP* is positively and significantly associated with the number of small business establishments. Columns (2)–(4) introduce the interaction between *LCOMP* and the *high-tech* indicator. The interaction term is positive and statistically significant across specifications, indicating that the effect of local labor market competition is substantially stronger in high-tech sectors. The magnitude of the interaction effect is economically meaningful. For

example, in column (4), the coefficient on *LCOMP* is 0.415 for non-high-tech sectors, while the interaction term (*LCOMP* × *High-tech*) is 1.085. This implies that the total effect of *LCOMP* in high-tech sectors is approximately 1.5 (= 0.415 + 1.085), which is more than three times larger than the effect in non-high-tech sectors.

Taken together, these findings suggest that local labor market competition is more strongly associated with small business activity in knowledge-intensive industries, consistent with the idea that competitive hiring environments may facilitate skill matching, knowledge recombination, and business dynamism in sectors that rely more heavily on specialized human capital.

4.3 Difference-in-differences Estimation Results

4.3.1 Staggered Difference-in-differences with Firm Relocations

While the baseline results document a strong association between local labor market competition and startup formation, concerns remain that *LCOMP* may be endogenous to local economic conditions. To address this concern, we exploit variation in local hiring competition induced by firm relocation events. The key idea is that relocation shocks should matter most in cities where the incoming firm competes for similar occupational skill sets as incumbent firms.

We measure occupational hiring overlap using Burning Glass Technologies (BGT) job postings data at the Commuting Zone (CZ)–occupation (6-digit SOC) level. For each relocating firm, we compute the distribution of its job postings across SOC occupations based on its hiring activity during the two years preceding relocation. We then compare this distribution with the occupational distribution of job postings in the destination commuting zone (CZ) during the same pre-event window. The resulting overlap measure captures the extent to which the relocating firm's hiring demand overlaps with the occupations demanded by incumbent firms within the local labor market.

We classify a city as treated if it receives a relocating firm whose pre-event hiring overlap with the occupational distribution of job postings in the destination commuting zone exceeds 20 percent. This threshold ensures that treatment is assigned only when the relocation meaningfully increases competition for comparable skill categories in the local labor market. The treatment variable, *Relocation*, equals one for treated cities in years following the relocation event and zero otherwise. In the staggered design, the control group consists of cities that have not yet experienced

a qualifying relocation at a given point in time, as well as cities that never receive such a relocation during the sample period. In our sample, we identify 338 treated cities and estimate the following staggered difference-in-differences specification:

$$E[StartUps_{ict}] = \exp\left(\alpha + \beta Relocation_{ct} + \gamma X_{ct} + \delta_{FE} + \varepsilon_{ict}\right) \qquad (3)$$

where i indexes cities, c counties, and t years. The dependent variable is the city-level count of start-ups from the PitchBook dataset, and X_{ct} denotes county-level controls. All regressions are estimated using PPML, and standard errors are clustered at the county level.

[Insert Table 4 Here]

Table 4 reports the results. Across alternative fixed-effect structures, including specifications with city fixed effects and state-by-year fixed effects, the coefficient on *Relocation* is positive and statistically significant. In column (4), the estimated coefficient is 0.261. In a PPML framework, this implies that relocation-induced increases in local labor market competition are associated with an increase of approximately 30 percent in startup formation ($\exp(0.261) - 1 = 0.30$). Given the mean of 0.695 startups per city-year, this corresponds to roughly 0.21 additional startups following a relocation event ($0.30 \times 0.695 \approx 0.21$). These findings indicate that relocation shocks generate economically meaningful increases in entrepreneurial activity. This quasi-experimental design therefore provides causal evidence on the effect of labor market competition on startup formation.

To examine the identifying assumption and assess pre-treatment dynamics, we estimate an event-study specification:

$$E[StartUps_{ict}] = \exp\left(\alpha + \sum_{m=-3}^{4} \beta_m \; Event[m] \times Treated_{ct} + \lambda X_{ct} + \delta_{FE} + \varepsilon_{ict}\right) \qquad (4)$$

where event time is defined relative to the relocation year, and *Event [−4]* (four or more years prior to relocation) is the omitted category. The fixed effects correspond to those included in column (4) of Table 5.

[Insert Table 5 Here]

Table 5 and Figure 1 report the results of this parallel trend test. The coefficients on the pre-treatment indicators (*Event[−3]*, *Event[−2]*, and *Event[−1]*) are small and statistically

indistinguishable from zero, supporting the parallel trends assumption. In contrast, the post-treatment coefficients become positive beginning in the year following relocation and remain elevated in subsequent years. This pattern is consistent with a persistent increase in startup formation following exogenous increases in local labor market competition.

[Insert Figure 1 Here]

Taken together, the staggered difference-in-differences evidence indicates that relocation-induced increases in local hiring competition lead to economically meaningful increases in startup activity, supporting a causal interpretation of the baseline relationship between labor market competition and entrepreneurship.

4.3.2 Stacked Difference-in-differences with Firm Relocations

To further strengthen identification and address potential concerns about treatment timing heterogeneity and residual imbalance, we implement a stacked difference-in-differences design combined with simple matching and entropy balancing.

We construct treatment cohorts by pairing each treated city with multiple control cities using one-to-many matching with replacement. Matching is restricted to cities located in the same state and calendar year to ensure comparability in institutional and macroeconomic conditions. For each treated city, we define an event window of $[-3, +3]$ years around the relocation event and stack these cohorts to form the estimation sample. To ensure meaningful within-city comparisons, we require treated cities to have at least one pre-event year and one post-event year of available data within the event window. In this stacked framework, the control group consists exclusively of cities that never experience a relocation during the sample period.

To further improve comparability between treated and control cities, we implement entropy balancing using pre-event covariates measured in the year prior to relocation. Table 6 reports covariate balance before and after entropy weighting. All summary statistics are computed using observations from this pre-event year. The column "N" reports the total number of stacked city–year observations in the estimation sample (174,910), while "# Cohorts" reports the number of distinct treated cohorts (157). Panel A shows differences across treated and control cities prior to

weighting, while Panel B demonstrates that entropy balancing effectively eliminates these differences, with standardized differences close to zero across all covariates[19].

[Insert Table 6 Here]

We estimate the following stacked difference-in-differences specification:

$$E[StartUps_{ict}] = \exp\left(\alpha + \beta Relocation_{ct} + \gamma X_{ct} + \delta_{FE} + \varepsilon_{ict}\right) \qquad (5)$$

where the dependent variable is the city-level count of start-ups, and the fixed effects vary across specifications to flexibly absorb cohort-specific and time-specific heterogeneity. In particular, we include combinations of city fixed effects, cohort fixed effects, event-year fixed effects, cohort-by-event-year fixed effects, and cohort-by-city fixed effects, as indicated in Table 7. These increasingly granular fixed effects ensure that identification arises from within-cohort variation around the relocation event, net of cohort-specific trends and persistent city characteristics. All regressions are estimated using PPML, and standard errors are clustered at the county level.

[Insert Table 7 Here]

Table 7 reports the results. Across specifications, the coefficient on *Relocation* remains positive and statistically significant. In column (4), which includes cohort-by-city and cohort-by-event-year fixed effects, the estimated coefficient is 0.373. In a PPML framework, this implies an increase of approximately 45 percent in startup formation following relocation ($\exp(0.373) - 1 = 0.45$). Given the sample mean of 0.695 startups per city-year, this corresponds to roughly 0.31 additional startups per city-year ($0.45 \times 0.695 \approx 0.31$). These magnitudes are economically meaningful and consistent with the baseline staggered DID results.

[Insert Figure 2 Here]

We further examine dynamic patterns using an event-study specification within the stacked framework. Figure 2 reports the corresponding estimates. Consistent with the baseline event-study results, pre-treatment coefficients are statistically indistinguishable from zero, while post-treatment coefficients are positive and persistent. This pattern provides additional support for the

[19] A multivariate joint test of equality in covariate means based on Hotelling's T^2 statistic fails to reject the null hypothesis of equal means between treated and control groups after entropy weighting, confirming the absence of statistically significant differences in observable characteristics.

parallel trends assumption and reinforces the interpretation that increases in local labor market competition induced by relocation events stimulate startup formation.

4.4 Innovation-Based Entrepreneurial Entry

As a final validation test, we examine whether the relationship between local labor market competition and entrepreneurial activity extends to innovation-based entry. Specifically, we redefine the dependent variable as *Innovative Entrants*, measured as the city-level count of first-time patent-filing firms based on data from the United States Patent and Trademark Office (USPTO), restricted to firms with five or fewer total patent applications.

Table 8 reports PPML estimates using the same specification as in Equation (2) and alternative fixed-effect structures. Across all specifications, the coefficient on *LCOMP* remains positive and statistically significant. In column (4), which includes city and state-by-year fixed effects, the estimated coefficient is 1.729 and significant at the 1% level. To assess economic magnitude, a one standard deviation increase in LCOMP (0.166) is associated with an approximate 33.2 percent increase in innovative entry ($\exp(1.729 \times 0.166) - 1 = 0.332$).

[Insert Table 8 Here]

These results indicate that the positive relationship between labor market competition and entrepreneurship extends beyond general startup formation and is also reflected in innovation-oriented entry.

5. Cross-sectional Tests

We next investigate cross-sectional variation in the relationship between local labor market competition and entrepreneurial activity to shed light on the underlying mechanisms. In particular, we focus on three channels, knowledge access and team formation, labor mobility, and financing frictions, by testing whether the effect of *LCOMP* is amplified in environments where these frictions are plausibly weaker or where the relevant inputs are more abundant. These tests correspond to Hypotheses 2 and 3, which predict that the positive effect of labor market competition on startup formation should be stronger in regions with greater innovative capacity, higher labor mobility, and more favorable financing conditions.

5.1 Knowledge Access and Team Formation (Incumbent Knowledge / Spinouts)

The first mechanism examines whether labor market competition expands access to incumbent knowledge and facilitates team formation. A central friction in entrepreneurial entry is that commercially relevant knowledge, particularly tacit know-how, is embedded within incumbent firms and cannot be easily transferred through formal markets. Much of this knowledge resides with employees and is tied to specific projects, routines, and organizational relationships.

Recent evidence shows that innovation within established firms generates substantial entrepreneurial spillovers. Knowledge created inside incumbents frequently seeds new venture formation, either through employee spinouts or through the redeployment of project-based expertise (Babina, 2020; Babina and Howell, 2024). These effects are particularly pronounced in knowledge-dense environments, where local stocks of technological expertise amplify entrepreneurial spawning (Moretti 2019).

Labor market competition can influence how effectively such knowledge is redeployed. When outside options are limited, employees with valuable tacit knowledge may remain locked within incumbent firms, even when entrepreneurial opportunities exist. Stronger labor market competition increases outside options, improves bargaining positions, and lowers the effective cost of leaving incumbents. As a result, employees may be more willing and able to recombine project-based expertise and form new ventures with complementary coworkers.

If this mechanism is operative, the effect of *LCOMP* on startup formation should be stronger in locations with a larger stock of incumbent knowledge. In knowledge-rich environments, labor market competition can unlock and redeploy tacit expertise that would otherwise remain embedded within established firms.

[Insert Table 9 Here]

Columns (1) and (2) of Table 9 provide evidence consistent with this mechanism. In column (1), which uses Inventor Share as a proxy for local knowledge stock, the interaction term for the highest tercile is 0.997, indicating that the effect of *LCOMP* is substantially stronger in knowledge-rich counties. Interpreting this economically, a one standard deviation increase in *LCOMP* (0.160) generates a 17.3 percentage point larger increase in startup formation in high-inventor counties relative to low-inventor counties ($\exp(0.997 \times 0.160) - 1 = 0.173$).

Similarly, in column (2), where patent intensity is used as the knowledge proxy, the interaction term for the highest tercile is 0.731. This implies that the response of startup formation to a one standard deviation increase in *LCOMP* is 12.4 percentage points larger in high-patenting counties relative to low-patenting counties ($\exp(0.731 \times 0.160) - 1 = 0.124$).

Overall, the results are consistent with Hypothesis 2 and indicate that local labor market competition is especially strongly associated with startup entry in regions where incumbent knowledge and inventive capacity are greater, suggesting that knowledge diffusion and team formation are important channels.

5.2 Labor Mobility

The second mechanism examines whether labor mobility amplifies the effect of local labor market competition on startup formation. Even when workers possess valuable ideas and skills, entrepreneurial entry may be constrained by mobility frictions. These frictions can arise from limited outside options, implicit noncompete pressures, switching costs, or information barriers that restrict worker reallocation across firms. Consistent with this view, restrictions such as enforceable noncompete agreements have been shown to reduce spinout formation and new firm creation (Franco and Mitchell, 2008; Samila and Sorenson 2011; Starr et al. 2018; Sevilir and Tian 2020; Jeffers 2024). Moreover, limiting employee mobility weakens workers' outside options and can dampen incentives to innovate and pursue entrepreneurial opportunities, particularly in human-capital-intensive firms (Fulghieri and Sevilir 2011). In such environments, increases in labor market competition may have limited effects if workers are unable or unwilling to move across employers.

By contrast, in regions with higher baseline job-to-job mobility, workers are already more likely to transition across firms. Elevated mobility facilitates the diffusion and recombination of ideas within high-technology clusters (Fallick, Fleischman, and Rebitzer 2006). In these settings, an increase in labor market competition may more effectively translate into knowledge diffusion, team recombination, and spinout formation. Greater competition strengthens outside options, improves bargaining power, and increases the feasibility of forming new ventures with complementary coworkers. If this mechanism is operative, the responsiveness of startup formation to *LCOMP* should be stronger in counties characterized by higher labor mobility.

Column (3) of Table 9 evaluates this prediction using Job-to-Job (J2J) labor mobility, defined as separations from one firm to another with continuous employment, scaled by population and averaged over a four-year rolling window. The interaction term for the highest tercile of J2J mobility is 0.704 and statistically significant, indicating that the effect of *LCOMP* increases monotonically with local labor mobility. Economically, this implies that a one standard deviation increase in *LCOMP* (0.160) generates a 12.0 percentage point larger increase in startup formation in high-mobility counties relative to low-mobility counties ($\exp(0.704 \times 0.160) - 1 = 0.120$). This magnitude suggests that labor market competition is substantially more effective in stimulating entrepreneurial activity where worker reallocation is already more fluid, consistent with Hypothesis 2, which predicts stronger effects in regions with higher labor mobility.

5.3 Financing Frictions

The third mechanism examines whether the effect of local labor market competition depends on local financing conditions. Even if labor market competition facilitates idea discovery and team formation, entrepreneurial entry may remain constrained by limited access to external finance. New firms rely heavily on external debt financing at inception (Robb and Robinson 2014), and variation in local credit supply affects small business lending availability (Craig and Hardee 2007). Access to entrepreneurial finance has real effects on firm survival, growth, and innovation outcomes (Kerr, Lerner, and Schoar 2014). More broadly, credit supply shocks influence labor reallocation and firm dynamics (Bai, Carvalho, and Phillips 2018), and financial disruptions can alter whether innovative activity is organized within incumbent firms or through new ventures (Babina, Bernstein, and Mezzanotti 2023). If financing constraints limit the ability of potential entrepreneurs to exploit opportunities created by labor market competition, the effect of *LCOMP* on startup formation should be stronger in regions with more favorable financing conditions, in line with Hypothesis 3.

Beyond formal credit supply, entrepreneurial entry is also shaped by household balance sheets. Housing wealth serves as collateral for business borrowing, relaxing pledgeability constraints and enabling individuals to finance startup activity. Increases in home equity have been shown to raise the probability of transition into entrepreneurship and to increase borrowing for business investment (Corradin and Popov 2015). Using U.S. Census microdata, Pekkala, Kerr, and

Nanda (2022) further document that local house price growth is strongly associated with increased startup entry, consistent with a collateral-based financing channel.

If labor market competition primarily operates by improving knowledge recombination and worker matching, its effect on startup formation should depend on the availability of external capital and collateralizable wealth. When financing constraints are binding, increases in idea generation may not translate into realized entry. Conversely, in counties with greater credit supply or stronger housing collateral, the same increase in labor market competition should generate a larger response in startup formation.

To examine financing channel, we interact *LCOMP* with two proxies for local financing conditions. Column (4) uses *Small Business Lending*, measured as the total dollar value of small business loans originated in a county, scaled by the number of small business establishments and averaged over a four-year rolling window. Column (5) uses *Housing Collateral*, measured as the change in the House Price Index (HPI), averaged over four years, capturing variation in household collateral values. The interaction terms indicate that the responsiveness of startup formation to *LCOMP* increases with stronger financing conditions. In column (4), the interaction coefficient for the highest lending tercile is 0.610 and statistically significant. Economically, this implies that a one standard deviation increase in *LCOMP* (0.160) generates a 10.3 percentage point larger increase in startup formation in high-lending counties relative to low-lending counties ($\exp(0.610 \times 0.160) - 1 = 0.103$). Similarly, in column (5), the interaction term for the highest housing collateral tercile is 0.804 and statistically significant. This implies that a one standard deviation increase in *LCOMP* generates a 13.8 percentage larger increase in startup formation in counties experiencing stronger housing collateral conditions ($\exp(0.804 \times 0.160) - 1 = 0.138$).

These results suggest that labor market competition stimulates entrepreneurial activity more strongly where access to finance and collateral constraints are less restrictive. Together with the evidence on knowledge stock and labor mobility, the findings indicate that *LCOMP* operates through multiple complementary channels: knowledge diffusion, worker reallocation, and the easing of financial constraints.

6. Conclusion

This paper studies how local labor market competition affects entrepreneurial entry. We argue that the structure of local hiring markets influences the ability of workers to leave incumbent firms, recombine knowledge, and assemble founding teams. Using a measure of labor market competition constructed from occupation level job posting data, we document a strong positive relationship between local labor market competition and startup formation across U.S. cities.

To address endogeneity concerns, we exploit large firm relocation events that change the competitive landscape of local labor markets. Difference in differences analyses show that relocation induced increases in labor market competition lead to higher startup formation. Additional tests suggest that this effect is stronger in regions with greater incumbent knowledge stocks, higher labor mobility, and more favorable financing conditions. These patterns are consistent with a mechanism in which competitive labor markets facilitate the reallocation of human capital and the commercialization of ideas.

Overall, the results highlight labor market competition as an important determinant of entrepreneurial dynamism. While prior research on labor market concentration focuses primarily on wages and employment outcomes, our findings suggest that labor market structure also shapes the creation of new firms. By influencing worker mobility and the recombination of knowledge, competitive labor markets can play an important role in sustaining entrepreneurial activity and economic dynamism. An important direction for future research is to better understand how labor market competition interacts with other institutional and financial frictions that shape entrepreneurship, including worker mobility restrictions, access to entrepreneurial finance, and the broader regional innovation environment.

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Appendix A. Variable Definitions

Dependent Variables	
Start-ups	Defined as the city-level raw count of start-ups based on Pitchbook dataset
Small Business Establishments	Defined as the city-level stock of private-sector establishments with 5–100 employees, constructed using County Business Patterns (CBP) data. The measure excludes nonprofit organizations and public-sector industries (including public administration and related government entities).
Innovative Entrants	Defined as the city-level raw count of first-time patent-filing companies. This measure is based on data from the United States Patent and Trademark Office (USPTO) and includes companies with five or fewer patent applications
Local Labor Market Competition Measures	
LCOMP	A local labor market competition index defined as $1 - HHI$, where *HHI* is the Herfindahl–Hirschman Index of employer concentration. Local labor markets are defined at the commuting zone (CZ) × occupation (6-digit SOC) level. For each commuting zone cz, occupation o, and year t, *HHI* is computed as the sum of squared shares of job postings across firms hiring for that occupation in that CZ. Occupation-level HHIs are aggregated to the CZ–year level using occupation posting shares as weights. The resulting CZ-level measure is mapped to counties using the standard CZ–county crosswalk.
Relocation	Constructed as the interaction between a *Treated* indicator and a *Post* indicator. *Treated* equals one for a city if a relocating firm that moves in year t has a hiring overlap of at least 20% with incumbent firms based on hiring data from the two years prior to the relocation (i.e., years $t-2$ and $t-1$). *Post* equals 1 for all years $\geq t$ for treated cities. The variable therefore equals 1 only for treated cities in years following the relocation event. In the Stacked DID framework, the control group consists of cities located in counties with no relocations at all
County Characteristics	
Total Pop.	Defined as the total population of the county
Δ Population	Defined as the percentage change in the population of the county
White %	Defined as the percentage of the county population that identifies as White
Bachelor %	Defined as the percentage of the county population holding at least a bachelor's degree
Unemployment %	Defined as the county-level unemployment rate
Republican %	Defined as the share of Republican votes within the county
Median Income	Defined as the logged measure of median household income in the county
Inventor Share	Defined as the share of inventors located in a given county relative to the total number of inventors nationwide in that year, averaged over a four-year rolling window (*t* to *t−3*)
Number of Patent	Defined as the log of the total number of patent applications filed in a given county, summed over a four-year rolling window (*t* to *t−3*)

J2J Labor Mobility	Defined as job-to-job transitions (separations from one firm to another with continuous employment) within a county, scaled by county population and averaged over a four-year rolling window (*t* to *t−3*). Data are obtained from the U.S. Census Bureau's Longitudinal Employer–Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) program
Small Business Loans	Defined as the total dollar value of small business loans originated in a county, scaled by the number of small business establishments and averaged over a four-year rolling window (*t* to *t−3*). Loan data are obtained from the Federal Reserve's Small Business Lending Data portal
Housing Collateral	Defined as the change in the Federal Housing Finance Agency (FHFA) House Price Index (HPI) at the county level, averaged over a four-year rolling window (*t* to *t−3*). HPI data are obtained from the FHFA

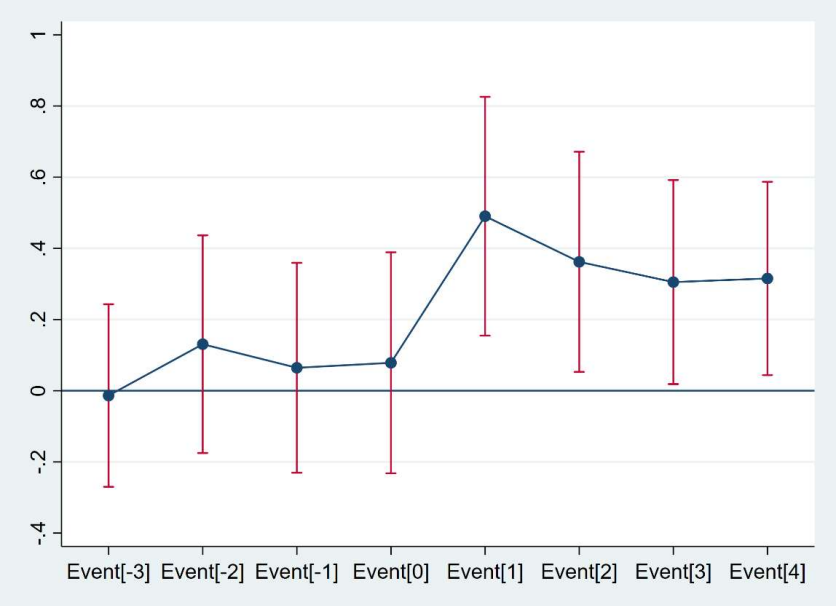


Figure 1. Dynamic Effects of Firm Relocations: Staggered DID Estimates

This figure reports estimates from the event-study specification examining pre- and post-relocation dynamics in startup formation. The base category is *Event [-4]*, representing four or more years before the event. Each point on the plot corresponds to a separate event-time indicator, with *Event [4]* indicating four or more years after the event. The specification includes the fixed effects and control variables from column 4 of Table 5. The dependent variable is the raw count of start-ups at the city level, and standard errors are clustered at the county level.

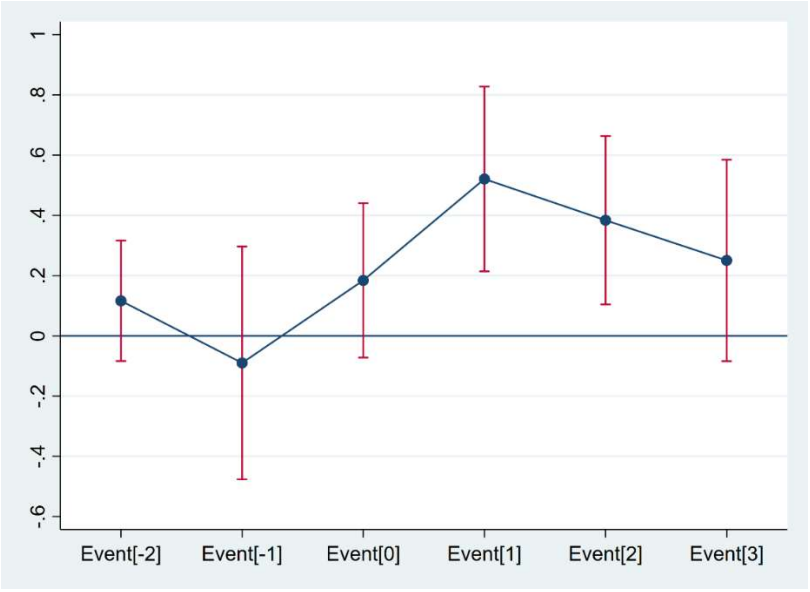


Figure 2. Dynamic Effects of Firm Relocations: Entropy-Balanced Stacked DID Estimates

This figure reports PPML estimates based on the specification in column (4) of Table 7. The plotted coefficients correspond to event-time indicators defined relative to the relocation year. The omitted base category is *Event [−3]*, which represents three years prior to the event. *Event [−2]* and *Event [−1]* denote two and one year before relocation, respectively; *Event [0]* denotes the relocation year; and *Event [1]*, *Event [2]*, and *Event [3]* denote one, two, and three years after relocation. The dependent variable is the city-level raw count of start-ups. Standard errors are clustered at the county level.

Table 1. Summary Statistics

This table reports summary statistics for the main variables used in the empirical analysis.

	N	Mean	Std. Dev.	1st	p10	p25	Median	p75	p90	99th
Start-ups	87,919	.695	2.782	0	0	0	0	0	1	14
Innovative Entrants	165,799	.418	1.201	0	0	0	0	0	1	6
Small Business Establishments	538,286	35.139	116.277	0	0	0	1	11	75	842
LCOMP	76,324	.632	0.160	.206	.397	.53	.659	.758	.821	.88
Total Pop.	87,919	12.361	1.533	8.839	10.289	11.238	12.457	13.513	14.15	16.1
Δ Population	87,919	.006	0.010	-.017	-.005	-.001	.004	.011	.019	.04
White %	87,919	.707	0.199	.148	.409	.584	.754	.866	.931	.966
Bachelor %	87,919	.269	0.125	.002	.124	.186	.269	.346	.436	.568
Unemployment %	87,919	.06	0.025	.023	.032	.04	.054	.075	.096	.135
Republican %	87,919	.488	0.148	.174	.287	.388	.477	.592	.692	.816
Median Income	87,919	10.999	0.287	10.391	10.639	10.792	10.971	11.2	11.4	11.682

Table 2. Baseline Results

This table reports PPML estimates based on Equation (2). The dependent variable is the city-level count of start-ups from the PitchBook dataset. Because labor hiring flows are observed at the county level, our measure of local labor market competition (LCOMP) is constructed at the county level and assigned to cities within the same county. Variable definitions are provided in the Variable Definition Table in the Appendix. Column (1) includes year and county fixed effects. Column (2) includes year and city fixed effects. Column (3) includes county fixed effects and state-by-year fixed effects, with year fixed effects subsumed. Column (4) includes city fixed effects and state-by-year fixed effects, with year fixed effects subsumed. Standard errors are clustered at the county level.

	(1)	(2)	(3)	(4)
VARIABLES	Start-ups			
LCOMP	**4.212*** **	**3.632*** **	**4.290*** **	**4.124*** **
	(8.55)	**(8.78)**	**(8.56)**	**(9.34)**
Total Pop.	-0.084	-0.002	0.501	0.042
	(-0.23)	(-0.01)	(1.12)	(0.11)
Δ Population	-0.488	-1.007	0.689	0.305
	(-0.35)	(-0.73)	(0.50)	(0.24)
White %	-0.225	0.254	2.203**	2.404**
	(-0.20)	(0.24)	(2.02)	(2.31)
Bachelor %	-0.022	-0.104	-0.419*	-0.487**
	(-0.10)	(-0.54)	(-1.73)	(-2.56)
Unemployment %	1.083	0.799	0.533	0.931
	(0.97)	(0.99)	(0.33)	(0.83)
Republican %	0.598*	0.442*	0.607	0.467
	(1.95)	(1.65)	(1.49)	(1.41)
Median Income	-0.097	-0.223	-0.266	-0.400**
	(-0.40)	(-0.99)	(-1.17)	(-2.01)
Observations	73,764	68,411	73,724	68,372
Year FE	YES	YES	Subsumed	Subsumed
County FE	YES	Subsumed	YES	Subsumed
City FE	NO	YES	NO	YES
State - Year FE	NO	NO	YES	YES
Pseudo R2	0.346	0.668	0.351	0.672

Table 3. LCOMP and Small Business Establishments: High-Tech vs. Non-High-Tech Sectors

This table reports PPML estimates in which the dependent variable is the stock of small private-sector establishments, and the main independent variable is LCOMP. Small business establishments are defined as establishments with 5–100 employees. In columns (2)–(4), we additionally include the interaction between LCOMP and a high-tech indicator. Using 6-digit NAICS-level County Business Patterns (CBP) data, we aggregate the data to the city × year × sector level and group all industries into two categories: high-tech and non-high-tech. The final sample therefore consists of city × year × high-tech indicator observations. The high-tech classification follows the literature (Goldschlag and Miranda, 2020; Decker and Haltiwanger, 2024) and includes eleven 4-digit NAICS industries. All specifications include city fixed effects and state-by-year fixed effects, with additional sector-by-year and city-by-sector fixed effects as indicated. Standard errors are clustered at the county level. Variable definitions for all control variables are provided in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Small Business Establishments			
LCOMP	0.407***	0.278**	0.277**	0.415***
	(3.67)	(2.51)	(2.47)	(3.60)
LCOMP × high-tech		4.555***	5.566***	1.085**
		(13.36)	(12.74)	(1.98)
High-tech	-3.090***	-6.149***		
	(-52.10)	(-30.66)		
Observations	531,650	531,650	531,650	388,918
County Controls	YES	YES	YES	YES
Year FE	Subsumed	Subsumed	Subsumed	Subsumed
County FE	Subsumed	Subsumed	Subsumed	Subsumed
City FE	YES	YES	YES	YES
State - Year FE	YES	YES	YES	YES
Sector - Year FE	NO	NO	YES	YES
City - Sector FE	NO	NO	NO	YES
Pseudo R2	0.928	0.932	0.933	0.938

Table 4. Staggered DID Estimates: Large Firms' Relocations

This table reports estimates from the difference-in-differences specification in Equation (3). A city is classified as *treated* if it receives a relocating firm whose hiring overlap with the occupational distribution of job postings in the destination commuting zone during the two years prior to relocation is at least 20%. The control group consists of cities located in counties that never experience a relocation meeting this 20% hiring-overlap threshold. The dependent variable is the count of new start-ups. The indicator variable *Relocation* equals one for treated cities in years following the relocation and zero otherwise. Column (1) includes year and county fixed effects. Column (2) includes year and city fixed effects (with county fixed effects subsumed). Column (3) includes county fixed effects and state-by-year fixed effects (with year fixed effects subsumed). Column (4) includes city fixed effects and state-by-year fixed effects. Standard errors are clustered at the county level. Variable definitions for all variables and controls are provided in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Start-ups			
Relocation	**0.654*** **	**0.431*** **	**0.490*** **	**0.261*** **
	(4.12)	**(2.68)**	**(6.73)**	**(3.95)**
Total Pop.	0.468	0.487	0.512	0.416
	(1.09)	(1.17)	(1.37)	(1.17)
Δ Population	0.951	0.629	0.761	0.266
	(0.54)	(0.37)	(0.52)	(0.19)
White %	0.332	0.489	1.781	1.868*
	(0.25)	(0.38)	(1.62)	(1.73)
Bachelor %	-0.091	-0.259	-0.415**	-0.531***
	(-0.45)	(-1.33)	(-1.99)	(-2.81)
Unemployment %	1.126	0.740	0.120	-0.184
	(1.01)	(0.74)	(0.11)	(-0.17)
Republican %	0.568*	0.491	0.256	0.207
	(1.65)	(1.49)	(0.74)	(0.63)
Median Income	-0.422*	-0.411*	-0.367*	-0.316
	(-1.79)	(-1.78)	(-1.76)	(-1.57)
Observations	87,167	84,556	87,130	84,519
Year FE	YES	YES	Subsumed	Subsumed
County FE	YES	Subsumed	YES	Subsumed
City FE	NO	YES	NO	YES
State - Year FE	NO	NO	YES	YES
Pseudo R2	0.353	0.672	0.359	0.677

Table 5. Dynamic Effects of Firm Relocations: Staggered DID Estimates

This table reports PPML estimates from the staggered difference-in-differences specification of the dynamic effects of relocation events on startup formation. The reported coefficients correspond to $Event[m] \times Treated$, where event time is defined relative to the relocation year. The omitted category is *Event [−4]*, which captures four or more years prior to relocation. *Event [−3], Event [−2]*, and *Event [−1]* indicate three, two, and one year before relocation, respectively; *Event [0]* denotes the relocation year; and *Event [1]* through *Event [4]* indicate one to four or more years after relocation. The dependent variable is the city-level count of start-ups. Column (1) includes year and county fixed effects. Column (2) includes year and city fixed effects, with county fixed effects subsumed. Column (3) includes county fixed effects and state-by-year fixed effects, with year fixed effects subsumed. Column (4) includes city fixed effects and state-by-year fixed effects, with both year and county fixed effects subsumed. Standard errors are clustered at the county level. Variable definitions for all variables and controls are provided in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Start-ups			
Event [-3] * Treated	-0.292	-0.070	-0.280	-0.014
	(-1.38)	(-0.55)	(-1.31)	(-0.10)
Event [-2] * Treated	0.006	0.077	0.063	0.131
	(0.04)	(0.63)	(0.32)	(0.84)
Event [-1] * Treated	0.186	0.147	0.097	0.064
	(0.88)	(0.79)	(0.59)	(0.43)
Event [0] * Treated	0.114	0.100	0.112	0.078
	(0.68)	(0.59)	(0.93)	(0.50)
Event [1] * Treated	0.795***	0.596***	0.731***	0.490***
	(4.02)	(2.70)	(4.60)	(2.87)
Event [2] * Treated	0.816***	0.513**	0.660***	0.362**
	(3.45)	(2.39)	(3.89)	(2.29)
Event [3] * Treated	0.749***	0.474**	0.537***	0.305**
	(2.71)	(2.27)	(3.17)	(2.09)
Event [4] * Treated	0.751***	0.562**	0.483***	0.315**
	(2.89)	(2.31)	(3.70)	(2.28)
Observations	87,167	84,556	87,130	84,519
County Controls	YES	YES	YES	YES
Year FE	YES	YES	Subsumed	Subsumed
County FE	YES	Subsumed	YES	Subsumed
City FE	NO	YES	NO	YES
State - Year FE	NO	NO	YES	YES
Pseudo R2	0.354	0.673	0.359	0.678

Table 6. Covariate Balance in the Stacked DID Matched Sample

This table reports covariate balance in the stacked difference-in-differences design. Entropy balancing is implemented using covariates measured in the year prior to the relocation event ($t = -1$). All summary statistics in Panels A and B are computed using observations from this pre-event year. The column "N" reports the total number of stacked city–year observations in the estimation sample. "# Cohorts" reports the number of distinct treated cohorts. Panel A presents covariate balance before entropy weighting, and Panel B presents balance after entropy weighting. Variable definitions for all covariates are provided in the Appendix.

Panel A. Pre-Entropy Balancing

		Control			Treatment		
Variable	N	Mean	Std. Dev.	# Cohorts	Mean	Std. Dev.	Std. Diff.
Total Pop.	174,910	13.1023	1.5736	157	14.7529	0.7598	2.1725***
Δ Population	174,910	0.0096	0.0108	157	0.0067	0.0097	-0.3001***
White %	174,910	0.6108	0.2054	157	0.5221	0.1193	-0.7437***
Bachelor %	174,910	0.2651	0.0928	157	0.3023	0.0647	0.5756***
Unemployment %	174,910	0.0582	0.0232	157	0.0534	0.0139	-0.3397***
Republican	174,910	0.4972	0.1202	157	0.3854	0.1091	-1.0249***
Median Income	174,910	10.9576	0.2311	157	10.9400	0.1577	-0.1118***

Panel B. Post-Entropy Balancing

		Control			Treatment		
Variable	N	Mean	Std. Dev.	# Cohorts	Mean	Std. Dev.	Std. Diff.
Total Pop.	174,910	14.7503	0.7656	157	14.7529	0.7598	0.0033
Δ Population	174,910	0.0067	0.0097	157	0.0067	0.0097	-0.0006
White %	174,910	0.5222	0.1192	157	0.5221	0.1193	-0.0009
Bachelor %	174,910	0.3023	0.0647	157	0.3023	0.0647	0.0002
Unemployment %	174,910	0.0534	0.0140	157	0.0534	0.0139	-0.0005
Republican	174,910	0.3855	0.1091	157	0.3854	0.1091	-0.0003
Median Income	174,910	10.9399	0.1579	157	10.9400	0.1577	0.0005

Table 7. Entropy-Balanced Stacked DID Estimates: Firm Relocations

This table reports estimates from the stacked difference-in-differences specification in Equation (5). One-to-many matching with replacement is implemented at the city–county level. Each cohort consists of one treated city and its matched control cities within a $[-3, +3]$ event window around the relocation year. Matching is restricted to cities located in the same state and calendar year, and entropy balancing is applied using pre-event covariates to improve comparability between treated and control units. The control group consists of cities that never experience a relocation during the sample period. The dependent variable is the city-level raw count of start-ups. The variable *Relocation* is defined as the interaction of *Treated* and *Post* indicators. Column (1) includes city, cohort, and event-year fixed effects. Column (2) includes cohort-by-city and event-year fixed effects, with city and cohort fixed effects subsumed. Column (3) includes city fixed effects and cohort-by-event-year fixed effects, with cohort and event-year fixed effects subsumed. Column (4) includes cohort-by-city and cohort-by-event-year fixed effects, with city, cohort, and event-year fixed effects subsumed. Standard errors are clustered at the county level. Variable definitions for all variables and controls are provided in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Start-ups			
Relocation	**0.261*** **	**0.266*** **	**0.365*** **	**0.373*** **
	(2.81)	**(2.86)**	**(7.30)**	**(7.65)**
Total Pop.	0.026	0.023	0.116	0.109
	(0.24)	(0.21)	(1.64)	(1.55)
Δ Population	4.798	4.775	13.149**	13.785**
	(0.96)	(0.96)	(1.99)	(1.98)
White %	-2.691	-2.454	-5.951	-5.605
	(-0.54)	(-0.48)	(-0.80)	(-0.75)
Bachelor %	-1.156**	-1.124**	-11.248**	-10.909**
	(-2.42)	(-2.34)	(-2.22)	(-2.20)
Unemployment %	-5.791***	-5.687***	-10.493	-10.991
	(-3.15)	(-3.04)	(-1.15)	(-1.19)
Republican %	0.740	0.799	-1.625	-1.761
	(0.53)	(0.58)	(-0.69)	(-0.73)
Median Income	-2.913***	-2.845***	-0.024	0.323
	(-3.91)	(-3.69)	(-0.02)	(0.27)
Observations	116,234	103,816	116,156	103,792
City FE	YES	Subsumed	YES	Subsumed
Cohort FE	YES	Subsumed	Subsumed	Subsumed
Event Year FE	YES	YES	Subsumed	Subsumed
Cohort - Event Year FE	NO	NO	YES	YES
Cohort - City FE	NO	YES	NO	YES
Pseudo R2	0.754	0.749	0.783	0.779

Table 8. LCOMP and Innovation-Based Entrepreneurial Entry

This table reports PPML estimates based on Equation (2). The dependent variable is the city-level raw count of innovative entrants, defined as first-time patent-filing companies using data from the United States Patent and Trademark Office (USPTO) and restricted to firms with five or fewer total patent applications. The variable of interest is LCOMP, which measures local labor market competition. Column (1) includes year and county fixed effects. Column (2) includes year and city fixed effects. Column (3) includes county fixed effects and state-by-year fixed effects. Column (4) includes city fixed effects and state-by-year fixed effects. Standard errors are clustered at the county level. Variable definitions for all variables and controls are provided in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Innovative Entrants			
LCOMP	**1.892*** **	**1.748*** **	**1.906*** **	**1.729*** **
	(7.21)	**(7.62)**	**(7.17)**	**(7.08)**
Total Pop.	1.218***	1.118***	0.888***	0.662***
	(6.10)	(6.81)	(3.31)	(3.06)
Δ Population	-2.445**	-1.022	-1.828	-0.490
	(-2.07)	(-1.20)	(-1.51)	(-0.54)
White %	0.624	0.833	0.322	0.611
	(0.87)	(1.39)	(0.44)	(1.04)
Bachelor %	-0.411	-0.374	0.204	0.277
	(-0.76)	(-0.84)	(0.40)	(0.62)
Unemployment %	-0.088	0.175	-0.125	-0.018
	(-0.10)	(0.33)	(-0.11)	(-0.02)
Republican %	0.211	0.113	0.369	0.130
	(0.95)	(0.78)	(1.40)	(0.63)
Median Income	-0.141	-0.098	-0.285*	-0.265**
	(-0.95)	(-0.83)	(-1.91)	(-2.24)
Observations	141,074	120,402	141,064	120,392
Year FE	YES	YES	Subsumed	Subsumed
County FE	YES	Subsumed	YES	Subsumed
City FE	NO	YES	NO	YES
State - Year FE	NO	NO	YES	YES
Pseudo R2	0.203	0.453	0.206	0.455

Table 9. Mechanism Tests Using Split-Sample Analysis

Columns (1)–(5) examine alternative mechanisms using FIPS-level measures constructed over a four-year rolling window (t to t−3). All regressions are estimated using PPML, and the dependent variable is the number of start-ups. Column (1) uses Inventor Share, defined as the share of inventors in a given FIPS-year relative to the total number of inventors nationwide in that year, averaged over the four-year period. Column (2) employs the log of total number of patent applications filed in a FIPS, summed over the same window. Column (3) measures Job-to-Job (J2J) labor mobility, defined as separations from one firm to another with continuous employment, scaled by population and averaged over four years. Column (4) captures small business lending activity, measured as the total dollar value of small business loans originated in a county, scaled by the number of small business establishments and averaged over the same period. Column (5) examines housing collateral shocks, measured as the change in the House Price Index (HPI), averaged over four years. For each mechanism, we construct state-level terciles (Medium and High) and interact these indicators with LCOMP; the omitted category corresponds to the lowest tercile. All specifications include city fixed effects and state-by-year fixed effects, with standard errors clustered at the county level.

	(1) Inventor Share	(2) # Patents	(3) J2J Labor Mobility	(4) Small Business Loans	(5) Housing Collateral
VARIABLES			Start Ups		
LCOMP	3.396***	3.596***	3.132***	3.480***	3.502***
	(6.62)	(7.13)	(5.90)	(7.27)	(7.39)
LCOMP X Medium	0.883***	0.464*	0.636**	0.417***	0.488***
	(2.78)	(1.69)	(2.56)	(2.63)	(3.03)
LCOMP X High	0.997***	0.731**	0.704**	0.610***	0.804***
	(2.91)	(2.32)	(2.09)	(2.88)	(4.39)
Medium	-0.613***	-0.253	-0.419**	-0.300***	-0.360***
	(-2.92)	(-1.57)	(-2.38)	(-2.68)	(-3.24)
High	-0.764***	-0.395*	-0.442*	-0.483***	-0.662***
	(-3.10)	(-1.93)	(-1.69)	(-3.11)	(-4.85)
Observations	68,372	68,372	54,685	62,657	68,005
Year FE	Subsumed	Subsumed	Subsumed	Subsumed	Subsumed
County FE	Subsumed	Subsumed	Subsumed	Subsumed	Subsumed
City FE	YES	YES	YES	YES	YES
State - Year FE	YES	YES	YES	YES	YES
Pseudo R2	0.672	0.672	0.678	0.670	0.672