The Local Origins of Business Formation*

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Abstract

What locations generate more business ideas, and where are ideas more likely to turn into businesses? Using comprehensive administrative data on business applications, we analyze the spatial disparity in the creation of business ideas and the formation of new employer startups from these ideas. Startups per capita exhibit enormous variation across granular units of geography. We decompose this variation into variation in ideas per capita and in their rate of transition to startups, and find that both components matter. Observable local demographic, household economic, and incumbent firm characteristics account for a significant fraction of the variation in startups per capita, and more so for the variation in ideas per capita than in transition rate. Income, education, age, and foreign-born share are generally strong positive correlates of both idea generation and transition. Overall, the relationship of local conditions with ideas differs from that with transition rate in magnitude, and sometimes, in sign: certain conditions (notably, the African-American share of the population) are positively associated with ideas, but negatively with transition rates. We also find a close correspondence between the actual rank of locations in terms of startups per capita and the predicted rank based only on observable local conditions—a result useful for characterizing locations with especially high and low startup activity.

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1 Introduction

Business startups contribute disproportionately to job creation, innovation, and productivity.[1] They also offer distinct economic opportunities for entrepreneurs. Yet, the nascent stages of entrepreneurship are not well understood. Characterizing environments conducive to early-stage business activity and entry is critical for assessing the spatial inequality in entrepreneurship across the United States, as the extent of this inequality has implications for economic vitality of locations and policies promoting entrepreneurship.[2] Moreover, to the extent local conditions that influence business entry evolve over time, changes in business dynamism may also be rooted, at least locally, in the evolution of these conditions.

A major impediment to progress in research on the early stages of entrepreneurship and entry has been the absence of systematic data on potential entrants, some of whom ultimately start new employer businesses. Without measures of the volume and types of potential entrants, it is impossible to assess precisely the underlying likelihood of success or entry rate of would-be entrepreneurs. As a result, we know little about what locations yield more potential entrants, and where potential entrants are more likely to start employer businesses. With only data on startups, we cannot ascertain whether spatial variation in startup rates is driven by a lack of business ideas, the difficulty of turning ideas into actual businesses, or both. Information on the pool of potential entrants and the nature of their selection into employer startups is needed.

To provide new insights on nascent entrepreneurship, we use unique and comprehensive micro data from the U.S. Census Bureau that contain information on the universe of applications for new businesses in the U.S. and their transition to employer startups over the period 2011-2016. We conduct an in depth analysis of spatial variation in startup activity and nascent entrepreneurial activity. We decompose the startup rate in a location into two components of nascent entrepreneurship—entrepreneurial idea generation and the transition rate of ideas to employer businesses. We show that both components help explain observed spatial variation in startup activity across the United States, and document that observable local demographic, household economic, and incumbent firm characteristics help account for a significant fraction of the spatial variation in startups, business ideas, and transition rates. We also show that observable local conditions are especially useful for ranking locations with both high and low startup activity.

To motivate our decomposition of startup activity and guide our empirical analysis, we

[1]See e.g., Haltiwanger, Jarmin and Miranda (2013), Kerr, Nanda and Rhodes-Kropf (2014), and Decker, Haltiwanger, Jarmin and Miranda (2014)

[2]Glaeser, Rosenthal and Strange (2010a) provides a review of the literature on the spatial dispersion of entrepreneurship and start-up activity.

introduce a simple model with a two-stage entry process where entrepreneurs first consider whether to make a business application based on the quality of their ideas and then decide whether to start an employer business after observing a signal of the value of the potential business. The model highlights the distinct roles of entrepreneurial idea generation and selection that underlie startup activity. We exploit a simple identity that employer startups per capita in a location can be expressed as the product of applications per capita and the transition rate of those applications to startups. Our model highlights that there may be distinct variation in these two components across locations, and guides us to explore how local conditions on a variety of dimensions either work in the same or opposite directions.

We conduct our empirical analysis using the micro data behind the Census Bureau's Business Formation Statistics (BFS) program. BFS integrates administrative data on the universe of applications for Employer Identification Numbers (EINs) from the IRS with the universe of employer businesses in the Longitudinal Business Database (LBD).[3] We measure startup activity in a location as the count of business applications filed in that location that transition into employer businesses within eight quarters of the application date. We proxy the intensity of idea generation in a location by the count of business applications filed there.[4] We calculate the transition rate as the fraction of business applications that turn into employer businesses within eight quarters of the application date. Because our focus is on employer startups, the analysis takes advantage of additional information on the EIN application to identify cases with a more clear intent to become new employer businesses. Specifically, we consider a subset of applications that indicate plans to pay wages as the primary group of applications at risk of transitioning to employer businesses (WBA).[5]

It is useful to understand the nature of variation in the BFS integrated with the LBD, and how we exploit and interpret that variation in our empirical analysis. The location information is at a very detailed level so we can easily identify the tract and county of the application. This location information primarily reflects the residential location of the nascent entrepreneur. Interestingly, we find that when a successful transition occurs, the business and application locations are often close to one another. About 90% of applications at the county level that successfully transit to new employer businesses operate in the same

[3]For details on the development of the BFS see Bayard, Dinlersoz, Dunne, Haltiwanger, Miranda and Stevens (2018).

[4]Business applications in our data reflect applications for new EINs. All new employer businesses must have an EIN. An application for a new EIN reflecting nascent entrepreneurship activity is consistent with the evidence from the Panel Study of Entrepreneurship Dynamics (PSED—see Reynolds, Carter, Gartner and Greene (2004)).

[5]For robustness, we also consider the entire set of applications (BA) even if the applicant did not indicate planned wages—there is a non-trivial fraction of transitions from applicants that do not explicitly signal an intent to pay wages. The analysis of BA is relegated to the appendix.

county. The analogous statistic is nearly 80% at the tract level. Given this, we interpret our spatial variation of applications as primarily reflecting the location of the nascent entrepreneur, and that most successful transitions operate locally relative to the location of the nascent entrepreneur. We also note that while we have considerable information on the application in terms of location, detailed industry and reason for the application, we do not have person-level characteristics of the nascent entrepreneur. Instead, as will become clear, we use granular spatial information to characterize the local population where the nascent entrepreneur is located.

A striking feature of the data is that both variation in applications and transition rates contribute substantially to variation in startups at both the county and tract level. Using publicly available data, Figure 1 shows that startup intensity varies considerably across counties, with counties in the top quintile having more than twice the rate of those in the bottom quintile. Figure 2 shows that when we decompose startups per capita into applications per capita and transition rates, the dispersion in each component is also high.[6] Counties with high applications per capita have more than five times or more the application rate as low counties, while high transition counties have more than five times the transition rate as low counties.[7] Yet, counties with high startups per capita are not uniformly characterized by both high applications per capita and transition rates.

Turning to our micro data we confirm that spatial variation in startup activity at the county and tract levels is explained by both spatial variation in idea generation and transition rates. Using a variance decomposition of WBA startups per capita, we find that at both the county and tract levels, around two-thirds of the spatial variation in startups per capita is accounted for by variation in applications per capita, nearly one-third by transition rates, and only a small fraction by the covariance between the two. It is worth highlighting the similarity in the county and tract variance decomposition results, despite that fact that the variation in startups per capita and its components is substantially higher at the tract level than the county level—e.g., the coefficient of variation in startups per capita is ten times larger at the tract level than county level.

These findings help motivate our analysis quantifying the contribution of observable local conditions to the spatial variation in entrepreneurial activity that we have documented.

[6] We use publicly available data for these illustrative maps since disclosure restrictions prevent us from releasing sub-state data. In our analysis of micro data, we exploit county and tract level variation but do not report results for individual counties or tracts.

[7] The BDS provides annual employer business startups rather than the targeted 8 quarters ahead startups from the BFS. To overcome this limitation we use applications from 2011-16 from the BFS and employer startups from 2013-18 from the BDS. The use of BA rather than WBA also implies some caution in interpretation. We depict these spatial patterns with public domain data to illustrate the patterns on county based maps. Disclosure restrictions prohibit our release of county-level tabulations from our micro data.

For this purpose, we exploit granular level data at the neighborhood (tract) level, since this provides characteristics of the local population where the nascent entrepreneur is located. Our model highlights that spatial variation in applications (creation of ideas) and transition rates to new employer startups reflects a wide range of factors. Such factors include: characteristics of the nascent entrepreneurs, characteristics of neighbors relevant for peer or agglomeration effects, market opportunities, opportunity costs, local business conditions, and the local regulatory environment. We think a number of these factors reflect conditions beyond the own tract of the nascent entrepreneur. In our baseline specification, we include county by year fixed effects. We interpret the contribution of these as capturing market opportunity, labor market, regulatory, and business conditions that vary at the county level and beyond. These county by year effects are important, but account for only about 20% of the variation in applications per capita across tracts, 11% of the variation in transition rates across tracts, and 11% of the variation in startups per capita. Importantly, most variation appears to be between tracts withn counties. We exploit variation in local tract characteristics within counties to explain some of the remaining variation.

Our empirical approach is to initially exploit variation at the own tract level within counties—i.e., the location of the the nascent entrepreneur. However, the between tract variation within counties may also reflect conditions in nearby neighborhoods. We therefore also consider specifications with both own tract and adjacent tract local conditions. In an alternative specification, instead of controlling for county by year effects we control for commuting zone by year effects but in turn include observable county local conditions.[8]

In our baseline tract level analysis, we find that observable local conditions account for a larger fraction of spatial variation in startups per capita and applications per capita than transition rates— but even for transition rates, we find a number of systematic relationships. Some covariates work in the same direction for applications per capita and transition rates, and hence, startups per capita. This holds, for example, for the fraction of the local population that has a bachelor's degree (Bachelors+ share). Even controlling for many other local conditions, a higher share of the local population that has a bachelor's degree is associated with higher applications per capita and higher transition rates. However, for some covariates these factors work in opposite directions. The most dramatic and interesting result along these lines reflects the variation accounted for by the local population that is African American (African American share). Startups per capita are negatively related to

[8]The current draft does not include results from the alternative specification in process where we control for commuting zone by year effects and include observable county covariates. An earlier draft of this paper estimated specifications with the unit of observation being the county by year. In these specifications, we controlled for commuting zone by year effects and included county-level covariates. Results were broadly similar.

the African American share—even after controlling for many other factors. This pattern reflects offsetting effects of a positive relationship between applications per capita and the African American share and a negative relationship for transition rates. We find that these patterns are largely robust to extending the analysis to the inclusion of covariates in neighboring (adjacent) tracts. We find some interesting contribution for the latter but most of the between tract, within county variation is accounted for by own tract covariates.

The micro data also enables us to examine whether there are distinct patterns in the contribution of local conditions across applications for new businesses in different industries. We have two motivations for doing so. First, we know the objectives of entrepreneurs vary across industries, and are often also reflected in dramatic differences in the post entry outcomes of startups across industries. On the one hand, growth oriented entrepreneurship is much more prevalent in the innovative intensive industries (see, e.g., Decker, Haltiwanger, Jarmin and Miranda (2016)). On the other hand, Hurst and Pugsley (2011, 2017) emphasize that non-pecuniary benefits, such as being one's own boss, incentivize entrepreneurship in small business intensive sectors. Second, the target market varies considerably across industries. For instance, while some industries, such as restaurants, have a very local non-tradable focus (e.g., Mian and Sufi (2007)), others, such as the non-store retailers or high-tech, target a broader market. We take a number of steps towards exploring how the contribution of different local conditions changes across industries. We do so by conducting a sub-sample analysis of applications, transition rates and startups in different industry groups. Specifically, we consider a subsample of innovative intensive sectors (identified by the STEM intensity of workers in the industry), a subsample of non-store retailers, a subsample of small business intensive industries, and a subsample of locally focused industries (i.e., grocery stores and restaurants).[9]

We also use our estimates to conduct a ranking analysis exploring the question of how well observable factors account for the ranking of local areas (counties and tracts) in terms of startups per capita. We find that locations in the top deciles of startups per capita have especially high idea generation (i.e., application intensity), while those in the bottom deciles have especially low transition rates of applications. We find that even though observable local conditions typically account for less than half of the between tract variation, they predict a ranking that closely corresponds to the actual ranking. We also find that spatial variation in startup activity and the covariates underlying this variation are positively related to the social/economic mobility indices of Chetty, Hendren, Kline and Saez (2014). This positive relationship holds especially for transition rates—locations with low social/economic mobility

[9]The current draft only has the results for the high-tech industries. The analysis of the other sub-samples is in process.

are also locations with low transitions of business applications to new employer businesses.

Our analysis of the contribution of observable covariates does not identify causal mechanisms. However, our finding that some local conditions systematically contribute to the spatial variation in applications and transition rates offers insights into the type of variation that could be used to identify causal mechanisms. For example, some barrier is likely at work adversely impacting the transition rates for applications in high African American tracts, even though such locations have high applications per capita. We leave identifying such barriers and the underlying causal mechanisms for future research.

The paper proceeds as follows. Section 2 provides a review of the literature. Section 3 presents a model to motivate the empirical approach. Section 4 provides a description of the data. The decomposition of the variance in startups per capita into its components is presented in section 5. The relationship between these components and local conditions is presented in section 6. Section 7 concludes.

2 Review of literature

The insights from the theoretical literature on firm entry, selection, and growth helps guide our choice the local conditions we consider in our empirical analysis. In the canonical models of Lucas (1978) and Hopenhayn (1992), entrants pay a sunk cost of entry, learn their productivity draw, and then face a profit function with curvature and a fixed cost of operation. Firms with high productivity draws become large, those with low draws stay small, and those with sufficiently low draws exit because of their inability to cover fixed costs. Over time, the literature has introduced additional features and frictions that generate interesting entry and post-entry dynamics. Among them include passive and dynamic learning (Jovanovic, 1982; Ericson and Pakes, 1995), financial frictions (Evans and Jovanovic, 1989; Cagetti and De Nardi, 2006), human capital (Polkovnichenko, 2003; Poschke, 2013), investment risk (Vereshchagina and Hopenhayn, 2009; Bianchi and Bobba, 2013; Choi, 2017), non-pecuniary benefits (Hurst and Pugsley, 2011, 2017), as well as other factors (Hombert, Schoar, Sraer and Thesmar, 2020; Vardishvili, 2023). Additionally, models of entry with imperfect competition (Nocke, 2006; Asplund and Nocke, 2006) allow for local competition and market size to effect entry and selection.

While the theortical literature (at least implictly) assumes that idea creation and business enry occur at the same time, the empirical literature has more explicitly studied the nascent *phases* of entrepreneurship. We contribute to three stands of this literature. The first strand studies survey data. The Panel Study of Entrepreneurship Dynamics (PSED) is one such effort (Reynolds et al., 2004; Reynolds, 2017).[10] A more recent effort is by Bennett and Chatterji (2023) and Bennett and Robinson (2023), who conduct an internet-based and voluntary survey about nascent entrepreneurship.[11] Bennett and Robinson (2023) find from a sample of about 50 thousand respondents that about 30 percent have considered opening a business. Both Reynolds et al. (2004) and Bennett and Robinson (2023) find that nascent entrepreneurs spend tme and resources in the "conceptual" and "gestational" period prior to the actual commencement of business operations. Importantly, both surveys find that most nascent entrepreneurs identified application for EIN as a critical activity, and that most nascent entrepreneurs never transition to employer businesses.

While the BFS does not contain the rich individual data available in a survey, our comprehensive administrative data enables a focus on spatial variation in startup activity, idea creation, and transition rates. Specifically, our analysis has three key advantages to the survey data. First, it tracks the universe of applications for new EINs. Second, it contains detailed application information, including industry, location, legal form, and motivation for the application. Importantly, these application characteristics also provide useful proxies for the quality and viability of the underlying business idea. Third, by linking the BFS to the universe of employer businesses (LBD), we accurately track the incidence and timing of the transition of ideas to startups.

A second strand of the empirical literature use the state business registries to study the quantity and quality of entrepreneurship (Andrews, Fazio, Liu, Guzman and Stern, 2018; Guzman and Stern, 2020). Guzman and Stern (2020) use high impact outcomes (IPO or a high-profile merger) originating from state business registrations in 32 states between 1988 and 2014 to assess the quality of entrepreneurship, and model these outcomes as a function of a set of registration characteristics. Using data from 8 states and leveraging the surge in business applications during the Covid pandemic, Fazio, Guzman, Liu and Stern (2021) examine the relationship between the growth rate of state business registrations and local conditions across Zipcode Tabulation Areas (ZCTAs).

Our relative contribution to this strand of the empirical literature is two-fold. First, we focus on the universe of employer startups in the US, and decompose it into business ideas (applications) and transition rates. Second, this decomposition allows us to assess the contribution of local conditions on startups into the contribution of local conditions on idea creation and transition rates. We are sympathetic to the interest in high-impact outcomes

[10]The PSED identified about 5,000 nascent entrepreneurs, defined as individuals who have taken steps within the last 12 months toward creating a venture but have not yet paid employees for more than 3 months. PSED Wave I identified 4,000 and Wave II identified 1,500 individuals that satisfied this criteria.

[11]It is worth noting that the survey is re-weighted to be nationally representative in terms of key demographic characteristics.

for new businesses. Yet, even for such cases a first critical step is transitioning to an employer business. Moreover, startups are an important source of job creation and economic mobility (i.e, hiring) for local areas.[12]

Finally, our research also contributes to the literature on spatial aspects of entrepreneurship. Glaeser et al. (2010a) provide an overview of the how entrepreneurship has been examined in the urban economics literature. One main line of the literature assesses the impact of entrepreneurship on urban success. A second avenue pursues examinations of the relationship between local characteristics and entrepreneurial activity, attempting to shed light on what factors explain differences in the local supply of entrepreneurs. Research in this line include work by Doms, Lewis and Robb (2010) that examine human capital and entrepreneurial activity and Kerr and Kerr (2020) that looks at the role of immigrants and entrepreneurship in the United States. Rosenthal and Strange (2003) focus on the industrial organization of the local environment and its impact on firm births.

This paper adds to this third empirical literature by examining the association between local characteristics and entrepreneurial activity, distinguishing between the business idea generating process and the transitioning of ideas to employer businesses.

3 A model of business ideas and startups

The model highlights pre-entry heterogeneity among potential entrants in the quality of latent business ideas, and explores how the decision to pursue an idea and the idea's transition to an actual startup are related to local conditions potential entrepreneurs face. Startup formation involves two distinct decisions. The first decision is whether to pursue an idea and explore its feasibility further. Additional information about the viability of an idea is revealed in the gestational state during which the potential entrant pursues the idea and takes steps to potentially implement it. Based on the information revealed, the second decision is whether to start an employer business. The model's analysis indicates that local conditions can play distinct roles in an entrepreneur's decision to pursue an idea versus the ultimate decision to start a business.

Consider an economy where economic activity takes place in a large number of locations denoted by the set, $\mathcal{L}$. In each location $l \in \mathcal{L}$ there is a continuum of N_l individuals, each of whom has an idea, $\iota \in [0, \infty)$, for an employer business.[13] Higher values of ι indicate better

[12] We note that the LBD and associated integrated data (e.g., COMPUSTAT) does permit examining the role of local conditions for high-impact businesses – in fact, for a large number of business outcomes, such as startup size, growth rate, or failure rate. We leave that for future work.

[13] We assume that all ideas come from the local population and are aimed for potential businesses in the same location. While business ideas can be aimed at locations other than the entrepreneurs' own locations,

(or higher quality) ideas in terms of expected return to an employer business, in a sense made more precise below. The distribution of ideas is given by the c.d.f. F_l (with density f_l).

An idea owner has to make an initial investment, $I_l > 0$, to pursue the idea. This investment pertains to various tasks of planning for the potential employer business, including major tasks, such as estimating demand and costs, seeking and securing financing, understanding relevant regulations, socializing the idea and obtaining advice, searching for potential employees and suppliers, as well as more mundane, but necessary tasks, such as applying for an EIN, and obtaining necessary permits and licenses. Many of these tasks involve frictions, such as financial or labor-market related, and can take time and resources to accomplish. Some ideas may thus take longer to transition to an employer business, or not transition at all, due to various local frictions involved.

Over the course of the investment, the idea owner sojourns in a state during which he observes a random signal, $V \in \mathbb{R}$, of the net value of an employer business. V can be thought of as an estimate of the idea owner's net payoff from the business—a scalar index of payoff-relevant factors for his business in location l, such as demand, entry costs (including any startup funding), various fixed and variable costs, the degree of competition, and his own productivity or ability.[14]

The value of V depends on the quality of the idea, summarized by the conditional distribution $G_l(V|\iota)$. A better idea (higher ι) may correspond to a higher V in a first order stochastic dominance sense. Each idea owner can choose to not pursue the idea and obtain a return of $R_l > 0$ (e.g. income from salary work or a nonemployer business). Importantly, R_l can reflect various labor market frictions. It can also reflect the disutility from being an employee rather than one's own boss (e.g., Hurst and Pugsley (2011). For simplicity, we assume R_l and I_l do not depend on ι, though such dependence is plausible—for instance, individuals with a higher ι may earn higher wages. Higher investment can also improve the idea quality or change G_l, in the spirit of Ericson and Pakes (1995). While these considerations can be incorporated, we proceed with a simpler setup to illustrate our key points.

Each idea owner is "small" with respect to the local economy, and takes as given the local environment $\mathcal{E}_l = \{N_l, F_l(\cdot), G_l(\cdot|\cdot), R_l, I_l\}$. We do not study the determination of $\mathcal{E}_l$.

empirically we find that the addresses of planned businesses substantially overlap with the addresses of businesses that actually form.

[14] The index V can thus include an initial signal of unknown cost or productivity parameter as in Jovanovic (1982) and the idea owner may continue to learn about that parameter after the business starts. Alternatively, V can depend on a known distribution of productivity as in Hopenhayn (1992), but one that depends on ι—reflecting pre-entry heterogeneity among potential entrants, in contrast to the identical potential entrants in Hopenhayn (1992). Chen, Croson, Elfenbeinand and Posen (2018) also explore learning dynamics in the pre-entry nascent entrepreneurship phase. A distinguishing feature of our model is that we specify that there are explicit costs associated with this pre-entry learning process. We think this is important in accounting for the spatial variation we observe in both idea creation and transitions.

In the background there is a set of spatial equilibrium conditions that ensure businesses and individuals optimize and have no incentive to move across locations, free entry holds in each location, and all markets clear. These equilibrium conditions pin down $\mathcal{E}_l$ for all $l \in \mathcal{L}$. Our focus is on the determination of what ideas are pursued and which ones turn into employer businesses in each location in a spatial equilibrium that generates $\mathcal{E}_l$.[15]

After observing V, an idea owner decides whether to start an employer business. The expected return from pursuing an idea is

$$\mathcal{V}_l(\iota) = E[\max\{V, R_l\}|\iota] = (1 - p_l(\iota))R_l + p_l(\iota)E[V|V \geq R_l; \iota] \tag{1}$$

where $p_l(\iota)$ is the probability that the pursued idea transitions to an employer business

$$p_l(\iota) = P(V \geq R_l|\iota) = 1 - G_l(R_l|\iota). \tag{2}$$

An idea owner will pursue the idea (e.g., make an EIN application, among other steps) if $\mathcal{V}_l(\iota) \geq R_l + I_l$. Assume now that $\mathcal{V}_l(\iota)$ is increasing in ι—better ideas lead to higher expected potential return.[16] As long as $R_l + I_l < \mathcal{V}_l(\iota)$ for some ι, there exists a threshold (marginal idea) $\iota_l^* \in [0, \infty)$, such that all ideas in $[\iota_l^*, \infty]$ are pursued. The marginal idea satisfies

$$\mathcal{V}_l(\iota_l^*) = R_l + I_l, \tag{3}$$

and the mass of pursued ideas (business applications) per capita is

$$A_l = \frac{N_l \int_{\iota_l^*}^{\infty} f_l(\iota) d\iota}{N_l} = \int_{\iota_l^*}^{\infty} f_l(\iota) d\iota = 1 - F_l(\iota_l^*), \tag{4}$$

If $R_l + I_l > \mathcal{V}_l(\iota)$ for all ι, no idea is pursued ($A_l = 0$).

Startups per capita originating from applications is then

$$S_l = \frac{N_l \int_{i_l^*}^{\infty} p_l(\iota) f_l(\iota) d\iota}{N_l} = \int_{i_l^*}^{\infty} p_l(\iota) f_l(\iota) d\iota. \tag{5}$$

There are no startups ($S_l = 0$) if no idea is pursued ($A_l = 0$).

[15] In particular, we do not explicitly study the selection of individuals into a location, which determines the distribution of ideas, F_l. For instance, entrepreneurs may sort into locations based on their ideas and ability as in Nocke (2006). This sorting, however, may not be perfect since amenities and mobility frictions also factor in the determination of F_l.

[16] This is the case, for instance, if higher ι implies higher V in a first order stochastic sense, i.e. $G_l(\cdot|\iota)$ is decreasing in ι.

When $A_l > 0$, the (average) transition rate for applications is

$$T_l = \frac{S_l}{A_l} = \int_{\iota_l^*}^{\infty} p_l(\iota) f_l^*(\iota) d\iota = E[p_l(\iota) | \iota \geq \iota_l^*], \tag{6}$$

where $f_l^*(\iota) = \frac{f_l(\iota)}{1-F_l(\iota_l^*)} = \frac{f_l(\iota)}{A_l}$ is the density of ideas conditional on application. Note that T_l is undefined when $A_l = 0$. By construction, the following holds

$$S_l = \begin{cases} A_l T_l & \text{if } A_l > 0, \\ 0 & \text{if } A_l = 0. \end{cases} \tag{7}$$

Expressions (1)-(7) hold in any spatial equilibrium. Now, we make explicit the fact that in equilibrium, each element of the local environment $\mathcal{E}_l$ will in general be a function of C, the collection of all relevant local characteristics or conditions, C_l, and conditions C_k in other locations $k \in \mathcal{L}$, $k \neq l$. These conditions can pertain to demographics, demand and costs, agglomeration, amenities, industrial composition, labor markets, laws and regulations, etc.[17] The individual elements of $\mathcal{E}_l$ need not depend on all elements of C. For instance, the distribution of ideas, F_l, may only depend on certain demographic characteristics of the population (e.g., age and education) in location l, but the initial investment, I_l, may, in addition, depend on financial frictions. The key variables of interest, A_l, T_l, and S_l, are then functions of the entire set of characteristics, C, because they depend on $\mathcal{E}_l$ by the definitions (3)–(6).[18]

Now consider the change in A_l, S_l, and T_l as a local characteristic or condition $c_l \in C_l$ changes from one location to another. Assume that A_l, T_l, and S_l are differentiable functions. Then, for values of c_l for which $A_l > 0$, we have

$$\frac{dA_l}{dc_l} = -f_l(\iota_l^*) \frac{d\iota_l^*}{dc_l} - \int_0^{\iota_l^*} \frac{df_l(\iota)}{dc_l} d\iota, \tag{8}$$

$$\frac{dS_l}{dc_l} = -p_l(\iota_l^*) f_l(\iota_l^*) \frac{d\iota_l^*}{dc_l} + \int_{\iota_l^*}^{\infty} \left[\frac{dp_l(\iota)}{dc_l} f_l(\iota) + p_l(\iota) \frac{df_l(\iota)}{dc_l} \right] d\iota, \tag{9}$$

$$\frac{dT_l}{dc_l} = -p_l(\iota_l^*) f_l^*(\iota_l^*) \frac{d\iota_l^*}{dc_l} + \int_{\iota_l^*}^{\infty} \left[\frac{dp_l(\iota)}{dc_l} f_l^*(\iota) + p_l(\iota) \frac{df_l^*(\iota)}{dc_l} \right] d\iota. \tag{10}$$

[17] Some of these conditions can be determined in spatial equilibrium (e.g., wages and rents), and some others (e.g., natural amenities) can be exogenous.

[18] A_l is a function of F_l and ι_l^*, which depends, through (3), on I_l, R_l, and G_l – which itself may be a function of local population (local market size), N_l, that can matter for expected post-entry profit (see, e.g., Nocke (2006) and Asplund and Nocke (2006)). Similarly, S_l is a function of F_l, $p_l(\iota)$, and ι_l^*, which depend on I_l, R_l, and G_l. Finally, T_l is a function of S_l and A_l, and hence, a function of all conditions that the latter two depend on.

Note that, for values of c_l for which $A_l = 0$, $\frac{dT_l}{dc_l}$ is undefined.[19]

Based on (8), A_l changes as c_l changes because not only the marginal idea ι_l^* changes, but also the distribution of ideas shifts. Similarly, (9) and (10) indicate that S_l and T_l change because the marginal idea, the distribution of ideas, and their transition rates all change. Observe that the sign of $\frac{dA_l}{dc_l}$ is in general unrestricted, and depends on the signs of $\frac{d\iota_l^*}{dc_l}$, and $\frac{df_l(\iota)}{dc_l}$.[20] Similarly, $\frac{dT_l}{dc_l}$ can be positive or negative, and its sign can differ from that of $\frac{dA_l}{dc_l}$. Note that by (6)

$$\frac{dT_l}{dc_l} = \frac{1}{A_l}\left(\frac{dS_l}{dc_l} - T_l\frac{dA_l}{dc_l}\right).$$

Thus, $\frac{dT_l}{dc_l}$ is negatively related to $\frac{dA_l}{dc_l}$, holding S_l constant. But $\frac{dS_l}{dc_l}$ can be positive or negative, and hence, the sign of $\frac{dT_l}{dc_l}$ is not the same as the sign of $\frac{dA_l}{dc_l}$ in general. From (8) and (9), the signs and magnitudes of $\frac{dA_l}{dc_l}$ and $\frac{dS_l}{dc_l}$ depend on how the idea distribution and the marginal idea change as c_l changes. However, the sign and magnitude of $\frac{dS_l}{dc_l}$ depends, in addition, on how the transition probabilities, $p_l(\iota)$, change. Depending on the nature of this change, the sign of $\frac{dT_l}{dc_l}$ can be the same as, or different from, the sign of $\frac{dA_l}{dc_l}$.

As an example, consider how A_l and T_l may vary as a local characteristic, such as the average level of educational attainment, changes. Suppose that a higher education is associated with higher idea quality: the idea distribution F_l associated with a higher education level dominates, in a first-order stochastic sense, the distribution associated with a lower education level. All else equal, (4) then implies A_l is higher. Furthermore, (5) implies that S_l also higher, as long as $p_l(\iota)$ is an increasing function – i.e. better ideas transition with higher likelihood. However, a higher education level may also "shift" the transition probabilities up, resulting in a higher $p_l(\iota)$, for every ι – for instance, higher level of education may result in a stochastically higher signal, V, equivalent to a lower value of $G_l(R_l|\iota)$ in (2). Then, (5) implies a higher S_l, but there would be no similar effect on A_l. However, the marginal idea, ι_l^*, also changes, since it is a function of G_l. Competition may become more intense when the quality of the ideas are higher, leading to a stochastically lower G_l. Depending on the signs and magnitudes of these various effects, $\frac{dA_l}{dc_l}$ and $\frac{dT_l}{dc_l}$ may have different signs and magnitudes.

This model is best suited for providing guidance regarding the creation of ideas for

[19]The system of partial derivatives (8, 9, 10) should be interpreted as comparative statics with respect to a local characteristic c_l in a cross section of locations in spatial equilibrium. That is, given an equilibrium, we are interested in the change in the key variables attributable to a change in c_l from one location to another.

[20]Using (3), $\frac{d\iota_l^*}{dc_l} = \left[\frac{dI_l}{dc_l} + \left.\frac{dp_l}{dc_l}\right|_{\iota=\iota_l^*}(R_l - E_l) + p_l(\iota_l^*)\left(\frac{dR_l}{dc_l} - \frac{dE_l}{dc_l}\right)\right]\left(\frac{d\mathcal{V}_l}{d\iota_l}\right)^{-1}$, which depends on the rates of change in I_l, R_l, and G_l – the latter through the changes in p_l and $E_l = E[V|V \geq R_l; \iota_l^*]$. While $\frac{d\mathcal{V}_l}{d\iota} > 0$ by assumption, and $R_l < E_l$ by the definition of E_l, the rest of the terms cannot be signed without further restrictions. Similarly, $\frac{df_l(\iota)}{dc_l}$ can be positive or negative.

potential employer businesses and in turn the factors that influence the transition of such ideas to actual startups. In our empirical analysis, we have applications that have indicated an intent to pay wages at some point, and we observe transitions of such applications into actual startups. This aspect of our empirical work more tightly connects to this model.

4 Data

4.1 Business applications

We use the administrative micro data underlying the Business Formation Statistics (BFS). The BFS provides high-frequency statistics on entrepreneurial activity based on applications for employer identification numbers (EINs).[21] The Census Bureau receives applications for all new EINs on a weekly basis from the IRS. From the universe of EIN filings, the BFS program constructs a subset of EINs that restrict applications to those are associated primarily with new business formation, as opposed to applications associated with other reasons, such as applications for trusts, estates, and other financial filings.[22] The restrictions are based on information on the EIN application including reason for applying and type of entity.[23] The details of the micro data are provided in Bayard et al. (2018).

Importantly for our analysis, all employer businesses in the United States are required to have an EIN to file payroll taxes. All new businesses (employer or nonemployer) also file for an EIN if forming a partnership or a corporation. There are some potential business formations that we are not tracking in applications and startups. Specifically, sole proprietor nonemployers do not need to have an EIN, though some choose to obtain one. As discussed in Davis, Haltiwanger, Krizan, Jarmin, Miranda, Nucci and Sandusky (2009), nonemployers with an EIN (including sole proprietors) are about three times as large in terms of revenue than those without an EIN. Many small (in terms of revenue) nonemployer sole proprietors also have other activity (e.g., their main activity as a wage and salary worker). While there are many sole proprietor nonemployers without EINs, they account for a small fraction of aggregate economic activity. Thus, the application micro data we rely on offers nearly full coverage of all economically significant business initiations.

The application form includes the name and address of the applicant and business, application week, business start date, reason for application (hiring, banking, etc.), type of

[21] For more information on the publicly available data, visit the BFS website.

[22] In our analysis of the micro data, we also exclude applications for purchasing or a change of ownership type for existing businesses—to avoid using applications from potentially existing employer businesses.

[23] See Bayard et al. (2018) for the specific set of filters applied to the application data to exclude applications with no business intent based on the application characteristics.

business entity, previous application for an EIN, principal industry, and planned date of initial wage payments—these are potential proxies for the underlying idea quality (ι). We are especially interested in employer startups. This focus motivates our analysis of applications that indicate a planned date for initial wage payments. Following the naming conventions of the public domain BFS, we refer to all business applications as BA and applications with planned wages as WBA.[24]

A business application includes a mailing address and potentially a business address. In most cases it is the mailing address (and even in cases where the business address is given it is often the same as the mailing address). Given the nascent stage at the time of the application, the location information thus primarily reflects the place of residence. The application addresses are geocoded to the Census county, tract and block-levels.[25]

For the set of business applications that transition, we can evaluate the relationship between the location of the application and the business location of the startup. Specifically, for the set of business applications that transition, in Table 1 we compare the address of the location in the application and the address for the startup in the administrative data (LBD). At the county level, over 90 percent of BA and WBA transition in the same county as in the application. This statistic is nearly 80 percent at the tract level. In other words, the application address and the actual address of the business, if it forms, largely coincide at the county and tract levels. For the tract level variation there is a larger fraction of applications where business location differs from application location. Since we find that most of between tract variation is within counties, our analysis using neighboring tract characteristics helps capture the impact of nearby local conditions.

4.2 Business formations

BFS complements the confidential micro data underlying the EIN applications with the Longitudinal Business Database (LBD). The LBD is the longitudinal version of the Census Bureau's Business Register and contains firm and establishment-level information on age, location, industry, number of employees, quarterly payroll, and EIN for the near-universe of employer businesses in the United States. Using the EIN, business applications are matched to the LBD to identify the incidence and timing of transitions to new employer businesses, or startups. In tracking startups, we use the LBD's identification of new firms that do not reflect changes in ownership or M&A activity (that is we focus on transitions to firms with

[24]We use data on business applications for business purposes (BA). Business applications with planned wages (WBA) are a subset of BA that indicate a date for (planned) first wage payments.

[25]Over 99 percent of applications are geocoded to the state and county level, while over 85 percent are coded to the tract and block levels, see Bayard et al. (2018).

firm age equal to zero). Importantly, we are able to separately identify transitions that stem from BA and WBA.

The startups we focus on are those that occur within 8 quarters of the application date for the cohort of applications in a year. These startups (in per capita terms) are our empirical counterpart for S in the model. We construct the empirical analog of the transition rate, T, in the model as the ratio of the transitions within 8 quarters to applications, both for BA and WBA. Overall, the micro data that we exploit track millions of applications and startups. On an annual basis, we track more than 2.5 million applications and more than 300 thousand actual employer startups that are linked to these applications over the subsequent eight quarters.

Figure 3 provides the motivation for our focus on applications that occur within 8 quarters. Only one-fourth (BA) to one-third (WBA) of applications that transition within 16 quarters, transition in the same quarter as when the application is received. By eight quarters, after which transition rates flatten out, 90 (BA) to 95 (WBA) percent of transitions have occurred.

5 Variation in startups, ideas, and transition rates

5.1 County and Tract Statistics

Summary statistics for BA and WBA startups, applications, and transition rates at the county and tract level are presented in Table 2 and Table 3. Focusing on the BA statistics first, startup per capita (defined as per 1,000 prime age adults) averaged 1.34 and 1.58, at the county and tract levels, respectively. This reflects applications per capita of 10.48 and 13.24 with transition rates of 0.123 and 0.12, for the county and tract data. The average applications per capita for WBA is 2.15 and 2.28 for counties and tracts with mean transition rates of 0.41 and 0.37. This results in startups from WBA averaging 0.88 and 0.94, respectively.

The statistics highlight the fact that while WBA accounts for a relatively small proportion of overall (BA) applications (roughly 15 to 20 percent) they account for (60 to 65 percent) of employer-business startup activity, reflecting relatively high transition rates. While the means of startups, applications and transition rates are quite similar across counties and tracts, the variation across tracts is much larger. The coefficient of variation is roughly eight times larger for tracts compared to counties for startups and applications and twice as large in the case of the transition rate variable.

5.2 Variance decomposition

For the set of locations where $A_l > 0$, Equation (7) in Section 3 implies:

$$\log S_l = \log A_l + \log T_l, \tag{11}$$

The variation in S_l can then be decomposed into into the variation in A_l, the variation in T_l, and their covariance:[26]

$$Var(\log S_l) = Var(\log A_l) + Var(\log T_l) + 2Cov(\log A_l, \log T_l). \tag{12}$$

Note that the covariance term can, a priori, be positive or negative, depending on how A_l and T_l change across locations. The analysis of the rates of change for A_l and T_l in Equations (8) and (10) indicates that A_l and T_l do not have to move in the same direction as local conditions change from one location to another.

This identity holds for all cases with nonzero BA and WBA. Our variance decomposition is conditional on county-year cells where there are positive applications—not much of a restriction at the county level. Our tract-level analysis, where zeros are more prevalent, aggregates application and startup activity over time from 2011 to 2016 and then constructs the S, A, and T. This results in significantly fewer zero observations, but omits time variation. In the next section, we incorporate cases with zeroes in our analysis of local conditions.

It is apparent in Table 4 that variation in both ideas (applications) and transition rates are important in accounting for the spatial variation in WBA startups per capita. Focusing on the variance decomposition of WBA startups, we find that about 68 percent of the spatial variation across counties in startups per capita is accounted for by variation in applications per capita, 38 percent by transition rates and about -5 percent due to the covariance. At the tract level, we find much greater variation in startups per capita and its components (e.g., the coefficient of variation in startups per capita is ten times larger at the tract level than county level). Even with the greater variation at the tract level, we find similar fractions of the variation in startups per capita due to applications vs. transition rates. About 66 percent of between tract variation in startups per capita is accounted for by applications per capita, 33 percent by transition rates and 2 percent due to the covariance. It is worth noting that population weighting increases the relative importance of ideas in counties, as seen in the second row of Table 4. Weighted results also generally increase the negative covariance between applications per capita and transition rates in the county analysis.

[26]With a slight abuse of notation, we use the model variables to also refer to their observed counterparts, which are treated as random variables.

6 The role of local conditions

6.1 Empirical approach

Next, we examine the relationship between the three key variables: WBA startups per capita (S_l), WBA per cpaita (A_l), and WBA transition rates (T_l), and local conditions (C_l) in a regression framework using panel data at the tract level, spanning 2011-2016:

$$\widetilde{S}_{lzt} = \beta^{S'} C_{lt-k} + f_{zt} + \epsilon^{S}_{lzt}, \tag{13}$$

$$\widetilde{A}_{lzt} = \beta^{A'} C_{lt-k} + f_{zt} + \epsilon^{A}_{lzt}, \tag{14}$$

$$T_{lzt} = \beta^{T'} C_{lt-k} + f_{zt} + \epsilon^{T}_{ltz}, \tag{15}$$

where in our baseline analysis, C_{lt-k} is a vector of lagged tract characteristics measured in year $t-k$, which hedges against the potential simultaneity of these characteristics; f_{zt} is county-year fixed effects; and ϵ^{i}_{lzt} $(i = S, A, T)$ is an error term.

Regarding our outcome variables: while the identity $S = AT$ suggests a log-linear specification (11), it only holds when $A > 0$. At the tract level, some location-year observations with no business applications or startups, and the log transformation would not allow us to incorporate these cases in estimation. Instead, the dependent variables $\widetilde{S}$ and $\widetilde{A}$ in (13) and (14) are the Davis, Haltiwanger and Schuh (1996) (DHS) transformations of the variables S and A that represent them in terms of deviations from their grand mean, respectively ($\widetilde{Y} = 2\frac{(Y-\bar{Y})}{(Y+\bar{Y})}$, where $\bar{Y}$ is the grand mean of $Y = S, A$).[27] We leave the transition rate, $T = S/A$, untransformed in (15) because, by definition, $T \in [0,1]$. Note that because T is defined only for $A > 0$, the regression (15) is conditional on $A_{lzt} > 0$.

The choice of local conditions (C_l) is influenced by factors discussed in the existing literature. The tract characteristics are based on measures of local conditions from the American Community Survey (ACS), the Bureau of Economic Analyais (BEA) and the LBD. Table 5 describes all of the local condition variables used for analysis. We separate local conditions, C_l, into four groups:

- **Demographic conditions:** age, education, race, ethnicity, and foreign born.[28]

[27] This type of transformation was recommended by Tornqvist, Vartia and Vartia (1985) and also implemented by Davis et al. (1996) for employment growth rates at the establishment-level. We note that this transformation is scale-free avoiding the pitfalls for transformations such as the inverse hyperbolic sine described in Chen and Roth (2023). This transformation is a second order approximation of the log difference between Y and the grand mean of Y. As we show in the appendix, the implied elasticities of Y with respect to covariates X are easily derived – indeed if X is a log based measure then the elasticity is the estimated coefficient.

[28] See, for example, Doms et al. (2010), Fairlie and Miranda (2016), Azoulay, Jones, Kim and Miranda

- **Household economic conditions:** income per capita, employment-to-population ratio, and owner occupied housing share.[29]

- **Incumbent firm characteristics:** Percent employment in young firms, percent of employment in large firms, and average firm size.[30]

- **Commercial share:** ratio of employment to the employment plus population.

Conditions constructed from the ACS are measured over five year intervals. The other conditions are measured at an annual frequency. All local conditions are measured with a lag, k, with respect to the outcomes. For the ACS based variables, we use $k = 5$. For all other conditions, we use the average across the lags $k = 1, .., 5$.

Controlling for detailed county by year fixed effects (f_{zt}) implies we are controlling for any broader area conditions that influence startup activity. We think this controls for most of the variation in market opportunities, financing, labor markets, and business and regulatory conditions that operate at broader levels, but don't operate at the very local level. As such, we think that the contribution of local demographic factors should primarily reflect the contribution of nascent entrepreneur and peer effects. However, we recognize that very local market conditions likely matters more for some entrepreneurs – particularly those with very local customer bases (e.g., restaurants and grocery stores but also local service providers). It may also be that agglomeration effects operate very locally. It is for this reason that in our baseline analysis, we also include measures of tract business activity. In subsequent analysis, we also control for adjacent tract business activity, and explore industry sub-samples where very local variation is likely to be more important.

Before turning to our baseline results, it is worth emphasizing that the estimates of these specifications cannot be interpreted as identifying causal mechanisms. The problem is not reverse causality, especially given our use of lagged local conditions and county-year fixed effects. A host of factors may underlie why a tract after controlling for county has idiosyncratic variation in idea creation, transition rates and its local conditions. Our objective is a first step: to quantify the extent to which the observable local covariates account for variation in startups per capita, applications per capita, and transition rates.

(2020), Azoulay, Jones, Kim and Miranda (2022), Kerr and Kerr (2017), Bennett and Robinson (2023).

[29]See, for example, Evans and Jovanovic (1989), Hurst and Lusardi (2004), Adelino, Schoar and Severino (2015).

[30]See, for example, Nocke (2006), Michelacci and Silva (2007), Glaeser, Kerr and Ponzetto (2009), Glaeser, Kerr and Ponzetto (2010b), Glaeser et al. (2010a).

6.2 Baseline results

Table 7 reports the variation in tract-level startups, applications and transition rates explained by county by year fixed effects. The R^2 is analogous to the share accounted for by the between component in a standard within-between variance decomposition. The core message is that county by year effects account for less than a quarter of the tract by year variation in all three tract-level models.

We interpret these results as implying that spatial variation in startup activity and its components reflect rich between and within variation on several dimensions. The fraction of between tract variation accounted for by county by year effects highlights that market opportunity, labor market, regulatory and business conditions matter. However, most of the between tract variation is within county highlighting that tract specific factors are important.

Turning to the regression results in Table 8 and focusing on the explained variation, local conditions help account for the enormous spatial variation in these outcomes, even after taking into account model fixed effects. They explain 22 and 26 percent of the variation in startups per capita and applications per capita in the tract models, respectively. Local conditions are far less relevant for variation in transition rates, explaining less than five percent of the variation. At the individual entrepreneur level, it is not surprising that it is difficult to account for transition rates since the quality of the idea likely dominates but there is systematic variation in transition rates that vary across geographies that at first glance local conditions do not provide much guidance.

Turning to specific local conditions, we start with an examination of demographic characteristics, which reflect the characteristics of potential entrerneurs and their ppers. First, education contributes to variation in startups per capita through both applications per capita and transition rates: tracts with a higher share of the population with a bachelors degree are associated with higher startups per capita, applications per capita, and transition rates, while tracts with a higher share of population with some college education are associated with lower startups per capita, applications per capita, and transition rates. Second, median age is only significantly (and positively) associated with applications per capita. Third, the patterns for race and ethnic groups are mixed. The Asian population share is not significantly correlated with any of the outcomes of interest, while Hispanic population share is only (significantly) negatively associated with startups per capita. Strikingly, a tract with a higher African American share of the population has higher applications per capita but lower startups per capita, underlying the pattern are lower transition rates.[31] In contrast, a tract

[31] Bennett and Robinson (2023) find related evidence that blacks are more likely than whites to consider starting a business but less likely to transition to starting a business. A distinguishing feature of our focus and evidence is that such variation is important in accounting for local spatial variation in employer startup

with a higher foreign born share of the population has higher applications per capita and higher startups per capita, despite having lower transition rates. In interpreting all results, it is instructive to recall that these effects hold after controlling for a wide variety of local household economic conditions and incumbent firms characteristics.

Turning to local household economic conditions, which in part reflect financial resources and opportunity costs of potential entrepreneurs and their peers, we see that per capita income is positively associated with startups per capita and applications per capita, but not strongly related to transition rates. Meanwhile, there is a negative relationship between the employment-to-population ratio for all three of dependent variables. This negative relationship may reflect that employment opportunities are more robust for workers that reside in higher employment-to-population ratio tracts, so that there is less incentive to pursue self or entrepreneurial employment, holding other factors constant.

We next turn to incumbent firm characteristics, which are informative about the existing (very local) business environment that nascent entrepreneurs face. Young firm employment share is positively related to startup activity and application activity, whereas large firm employment share and average firm size are negatively related to startups, applications and transition rates. In short, locations with larger and more mature firms are less conducive to application or idea generations, transition rates, and subsequently startup activity. Finally, the commercial share variable is positively related to all three measures of startup activity. The finding that the incumbent firm characteristics matter even in the presence of county by year effects is prima facie evidence that the between tract, within county variation does at least in part reflect business conditions in the very local area.

To show the quantitative implications of the estimates, we compute the implied percentage change in a dependent variable of interest corresponding to a one standard deviation change in the covariate relative to the mean (in percent). This requires converting the estimates to elasticities as described in Appendix A. Given that the covariates differ significantly in their variation across locations, we quantify their economic significance by taking into account this variation and multiplying each elasticity with the coefficient of variation of the corresponding covariate. This quantification exercise is summarized in Table 9.

Our quantification exercise reveals that per capita income, bachelors+ degree share, and foreign born share are the variables associated with the highest positive percentage change for startups per capita. The highest negative percentage change in startups is associated with average firm size and African American population share. We observe that per capita income and foreign born share are more strongly (positively) associated with applications per capita than transition rates, while bachelors+ degree share is more strongly (positively)

activity.

associated with transition rates. Meanwhile average firm size has astrong negative association with applications per capita, while African American population share has a strong negative association with transition rates. This highlights the fact that the lower startup rates in neighborhoods with higher African American share are driven by low transition rates. While the commercial share magnitudes are the largest in Table 9, our view is that this variable acts as an important control for spatial distribution of commercial activity versus residential activity across tracts within a county but in and of itself is not the focus of our analysis.

We also evaluate how important each group of covariates is in explaining the variation in the outcomes of interest. In order to do so, we use the variance decomposition methodology in Hottman, Redding and Weinstein (2016) and Eslava, Haltiwanger and Urdaneta (2024). This decomposition methodology assigns to each covariate the combination of the direct variance contribution along with half of the covariance with each of the other covariates.[32] By construction this method yields a decomposition where all terms (including the residual) sum to one.[33] Table 10 provides the decomposition for the baseline model. Demographics and household economic conditions contribute similarly to explaining variation in startups per capita, while household economic conditions (primarily income per capita) are relatively more important for applications per capita. Somewhat surprisingly the incumbent firm characteristics contribute negatively to the explained variation in startups per capita and application rates. This can happen through the contribution of covariances.[34] In the transition rate, the demographic group provides the largest contribution to the admittedly-small, explained within variation, with the African American share variable accounting for over 50 percent of the demographic variable group explained variation.

6.3 Controlling for neighboring tract characteristics

Own tract characteristics and county-year fixed effects together may not adequately reflect the consumer, product, and labor market conditions nascent entrepreneurs face, as the former controls only for very local characteristics and the latter for much broader area char-

[32]The contribution of a covariate is given by the product of the estimated coefficient, its covariance with the dependent variable and the ratio of its standard deviation to that of the dependent variable.

[33]Moreover, the residual contribution matches the regression results in Table 8 by construction. We note that we use variance decomposition methodology for the observable local conditions. The reported contribution of common market conditions in Table 10 and subsequent decomposition tables is the contribution of county by year in the tract level results.

[34]The covariance contribution is allocated evenly across variables in the covariance. The covariance contribution is the product of the estimated regression coefficients and the covariance of the covariates. When the sign of estimated regression coefficients are opposite signs with a positive covariance between the covariates, the covariance contribution can be negative. For the overall contribution of a covariate to be negative, it must that the direct contribution of the covariate (the regression estimate squared times the variance) is small relative to a negative covariance contribution.

acteristics. We therefore also estimate a set of models for the tract-level data that include neighboring-tract characteristics as additional control variables. We use the same set of variables that are included in the base model, only now these variables are measured using the respective means across adjacent tracts.

Table 11 reports the regression results, Table 12 the magnitudes, and Table 13 the regression decomposition. Strikingly, the results for the own tract effects are very similar to those reported above. The only substantive difference is found in the applications model where the bachelors or higher degree variable is no longer statistically significant. In addition, the inclusion of neighbor controls adds only modestly to the explained variation for the three models. However, there are some neighboring tract covariates that have a notable influence. A higher African American share in a neighboring tract contributes positively to higher applications per capita and negatively to transition rates. However, the impact of the latter is smaller than for the own tract resulting in essentially no relationship between the neighboring tract African American share and startups per capita. The neighboring tract young firm share contributes positively to higher applications per capita, higher transition rates and higher startups per capita with effects about the same as the own tract effects. Meanwhile, the neighboring tract average firm size contributes negatively to all three outcomes of interest, with the magnitude of these effects being much smaller than the own tract effects.

We interpret these findings as providing support for the view that there is an important component of spatial variation in startups, applications, and transition rates that is truly tract-specific. However, neighboring tract effects are also present, oftentimes reinforcing the own-tract effects. Taken together our baseline and adjacent tract analyses suggest that spatial variation in nascent entrepreneurs is in fact very local.

6.4 High technology startup activity

Up to this point, we have not exploited any industry-level variation of startup or application activity across tracts. In this section, we examine, as an important example of industry-level analysis, how local conditions influence startups in innovation-intensive industries—what we denote as high-tech startups. The motivation for this analysis is that we expect to find two key differences relative to our baseline analysis. First, we anticipate that high-tech nascent entrepreneurs are somewhat different than the overall pool of entrepreneurs, which would be reflected in differences in the demographic covariates. Second, we anticipate that high-tech entrepreneurs target a broader market, which would be reflected in a weakening in the contribution of very local business conditions to explaining variation in our outcomes of interest.

In this analysis, we take advantage of the fact that each application is assigned to a specific industry and this allows us to identify applications associated with high tech industries. Using the linked LBD-BFS application data from the 14 four-digit NAICS industries identified in Hecker (2005) as high technology industries based on the STEM intensity of workers in the industry. Note that these are the industries that Decker et al. (2014) find have especially right skewed post-entry growth distributions. They are also the industries that have disproportionately contributed to innovation and productivity growth in the last few decades. We construct startups per capita, application per capita, and transition rates utilizing the same approach as above, focusing on the subset of high technology WBA. It should be noted that in the high tech sample there are many tract-years without high tech applications and this substantially reduces the number of observations in our startup and transition rate models.

First, consistent with our hypothesis that high-tech entrepreneurs are different, we find in Table 14, is that parameter estimates on the bachelors or higher share have increased in size, especially in the applications models. Utilizing the regression magnitude approach described above, a one standard deviation increase in bachelors or higher share relative to its mean would be associated with a 6.68 percent increase in high tech startups and a 17.01 percent increase in applications per capita.[35]

There are other additional findings to note as well. Some college share is negatively associated with high tech startup activity, which is driven by fewer applications per capita. In addition, we find that Asian share is positively associated with startups, applications, and transition rates. This contrasts to the overall WBA results where there was little correlation between Asian share and startups, applications or transition rates. We find a generally weaker relationship between foreign born share and high technology activity compared to our earlier, more general analysis where we observed a positive correlation between foreign born share and startups and applications. We also find a somewhat weaker relationship between applications per capita and African American share for the high-tech startups compared to all WBA startups.

We report the results from the regression decomposition analysis for the high tech analysis in Table 15. Demographic effects contribute substantially more to applications and

[35]The small increase in the calculated magnitude for high technology startups associated with bachelors degree or higher share compared to the corresponding WBA results is puzzling given the increase in the calculated magnitudes for high technology applications in the tract analysis. We are exploring the source of this result but note that the samples are quite different as the number of tracts with zero applications rises sharply in the high tech sample and these observations are omitted from the startup model but not the application model.

startups for high tech startups relative to the overall results, reflecting the larger impact of the Bachelors+ share. However, both incumbent firm characterstics and commercial share contribute substantially less to high tech startups. These results suggest that high-tech startups are less sensitive to local business activity than overall startups, which is consistent with the target market for high-tech ventures being less local.

Overall, the qualitative patterns we detect for high tech startups and their components are broadly similar to the baseline WBA results. These patterns suggest that our findings have similar qualitative implications over a wide range of entrepreneurial activity—from those entrepreneurs that have objectives of being a potentially high growth startup in an innovative intensive industry to those that reflect distinct objectives like being one's own boss. That being said, while qualitatively similar, the quantitative patterns differ in notable ways—with the two most striking results being the much larger role of the Bachelors+ share for high tech startups and the lower contributions of local incumbent firm characteristics and commercial share.[36]

6.4.1 Small Business Intensive Industries

TBC

6.4.2 Locally Oriented Industries

TBC

6.5 Accounting for application characteristics in transition

A finding of our analysis so far is that there is substantial spatial variation in transition rates across tracts but accounting for observable local conditions still leaves substantial variation unexplained. To dig deeper, we also conduct an application-level analysis of transitions. We observe a set of characteristics, x, of a business application, which provide information on the type of business applied for, and may also be informative about the quality of the underlying idea, ι.

Using these characteristics, we examine the relationship between the probability of transition $p_l(\iota)$ in (2) and local characteristics C_l in a linear probability (LPM) framework

$$p_{ilzt} = \gamma' x_{ilzt} + \beta^{p'} C_{lt-k} + f_{zt} + \epsilon^p_{ilzt}, \tag{16}$$

[36]These inferences are tentative given that other industry subsample analysis is in process.

where $p_{ilzt} \in \{0, 1\}$ is an indicator of whether application i transitions.[37]

The estimates of β^p are informative about the relationship between the transition rate of an idea and local characteristics, conditional on application characteristics (proxies for the quality of the idea). Because locations differ in the distribution of ideas F_l, it is important to control for the composition of applications in assessing the relationship between transition rate and local characteristics. The LPM in (16) does so by directly incorporating the individual application characteristics. We also compare the estimate of β^p with that of β^T based on (15) to see whether controlling for application characteristics alters the general nature of the relationship between transition rate and local characteristics.

Our WBA sample includes over 2.3 million individual applications and the BA sample includes over 13.8 million individual applications, providing us with a large set of observations to carry out this analysis. We include the BA sample here in this individual level analysis because we can control for application type directly in the statistical analysis (i.e., we control for the type of application in the analysis, including whether an application is part of WBA—the focus of our analysis earlier).

The control variables include the local condition variables used in the tract-level regressions, as well as a set of variables that control for application characteristics. These characteristics include controls for detailed industry of the application (4-digit NAICS), reason for applying (planned wages, obtaining a business bank account) , type of entity applying (e.g, incorporation), LLC status, inclusion of a trade name, business start date, and quarter of application.[38] The models include county-year fixed effects, and standard errors are clustered at the county level.

The results are presented in Table 16, where only the coefficients of the local condition variables are presented. The coefficients on the application characteristics are omitted as they involve a large number of estimates which are not our main focus. Overall, the results are consistent with the tract-level regression coefficients reported in Table 8, even after controlling for detailed application characteristics. Local demographic and household economic variables such as African American share, some college share and foreign born share are associated with a lower probability of an application transitioning to employer status, while the share of the population with at least a bachelors degree and owner-occupied share are associated with a higher likelihood of transitioning. With regards to incumbent firm results,

[37] As in (15), the regression above is conditional on $A_l > 0$.

[38] See Bayard et al. (2018) for a detailed discussion of estimating transition probabilities based on application characteristics. Our analysis here follows closely that approach with two caveats. The model estimated here includes detailed tract-level characteristics but excludes the detailed interactions among variables. Importantly, our model is estimated pooled across states, whereas in Bayard et al. (2018) the models are estimated individually at the state level with a rich set of industry-application characteristic interactions.

locations with higher share of employment in young firms have higher transition rates while those with higher share of employment in big or large average size have lower transition rates. The commercial share variable is positively associated with transition rates. In short, the relationships between local conditions and transition rates observed above are robust when application characteristics are controlled for to account for application heterogeneity across tracts.

The R^2 values in Table 16, especially for WBA, are low in absolute terms and relative to our tract-level results. This is not surprising since idiosyncratic variation in the quality of ideas emphasized in the model in section 3 likely dominates the overall variation.[39] This finding highlights the importance of the nascent entrepreneurship phase (including the creation and the pursuit of an idea) for understanding variation in startups per capita. Note also that the higher R^2 for BA is expected given that a control variable in the linear probability model for BA is an indicator of whether the application is a WBA application (i.e. has planned wage payments). The latter is highly predictive of an application transitioning to an employer business.[40]

6.6 Average duration analysis

The final analysis examines the average length of time it takes an application that transitions within the 8 quarters. The theory section highlighted the fact that the length of time an application takes to become an employer business can also depend on local characteristics, in part due to a variety of local frictions. For each application that transitions, we calculate the length of time in the number of quarters it takes to transition and then take the average value across all applications that transition in a location-year cell. We then regress this measure against our local control variables.

We report the results of this exercise in Table 17. We find that there are slower transitions for higher Bachelors+ share and African American share for both WBA and BA. These patterns suggest to us that variation in duration reflects complex factors. On the one hand, a slower transition may reflect greater frictions for making a transition, and the African American share results are potentially consistent with this interpretation. On the other hand, a slower transition may reflect variation in the type of startups being contemplated. It may be, for example, that a business application with a high growth potential takes longer to startup—potentially consistent with the Bachelors+ result.

[39] Among such factors that some of existing literature has thought about include "home bias" (Dahl and Klepper, 2015) and outside options (Manso, 2016; Choi, 2017; Dillon and Stanton, 2017; Gottlieb, Townsend and Xu, 2022).

[40] See also Bayard et al. (2018) for a similar finding.

6.7 Local conditions and ranking of locations

In this section, we conduct a ranking analysis exploring how well observable factors account for the ranking of local areas in terms of startups per capita. We conduct this analysis using tract level data, focusing on WBA and associated transitions.[41] If the ranking of the locations in startup activity based on the covariates alone captures well the actual ranking, the observable conditions we consider can be used to characterize locations with high versus low startup activity.

To start, we rank all tracts in terms of their startup rates per capita, applications per capita, and transition rate. We then classify each tract into the deciles of the startup rates per capita distribution. In turn, we compute the average mean rank of applications per capita and transition rates in each of the deciles of the startup rate per capita distribution.

The left panel of Figure 4 shows the results for this exercise. By construction, the mean of the average rank of startups per capita rises monotonically (and linearly) by startup per capita decile. Both applications per capita and transition rates rankings increase with the startup deciles but with distinct nonlinear patterns. In particular, the top decile tracts are especially characterized as having high rankings of high applications per capita, rather than transition rates. *Superstar* startup areas can thus be characterized as those with high idea creation. In contrast, the bottom decile tracts are especially characterized as having low rankings of transition rates, rather than low rankings of applications per capita.[42]

We next evaluate how well our models account for these ranking patterns. The right panel of Figure 4 provide the results. Here we compute the mean predicted rank of applications per capita and transition rates for each decile from only the county-year fixed effects versus from only the observable covariates. Strikingly, the observable covariates yield a predicted ranking pattern that corresponds reasonably closely to the actual ranking pattern. Thus, even though the observable covariates account for less than half of the observed overall spatial variation, they provide substantial guidance with respect to the ranking of counties and tracts in terms of startups per capita.

The observables also capture more of the nonlinearities at the top and bottom deciles discussed above. That is, the observables account for the steeper slope of applications per capita at the top deciles and the steeper slope of transition rates at the bottom deciles. For neighborhoods that have especially poor transition rates and associated startup activity, observable factors are highly informative.

Finally, we explore how entrepreneurial activity varies by a measure of social/economic

[41] An earlier draft of this paper conducted this analysis at the county level with broadly similar results.

[42] These inferences are based on the observation that the ranking by applications per capita has a steeper slope at high deciles while the ranking by transition rates has a steeper slope at low deciles.

mobility at the tract level. Utilizing information constructed by the Equality of Opportunity project, we replace the rank of startups (the X-axis) with the rank of a variable that measures social/economic mobility – specifically, "the mean household income rank for children whose parents are at the 25th percentile of the national income distribution, where incomes for children were measured as mean earnings in 2014-2015 when they were between 31-37."[43] The layout of Figure 5 mimics that of Figure 4. The left panel shows that the rank of transition rate rises along with social/economic mobility, though in a nonlinear fashion on the lower end, whereas the rank of applications is U-shaped. The right panel shows the relationship between social/economic mobility rank and the predicted ranks based on the regression components. The regression component that corresponds most closely to the social/economic mobility ranking is that based on the predicted transition rate using observable covariates. These findings are consistent with our interpretation that an important component of spatial variation in transition rates reflects frictions that vary across locations that are in turn related to observable factors such as demographics.

This exercise shows that using a relatively parsimonious set of observable characteristics, we can infer the relative position of counties and tracts in their performance with respect to startups per capita. This result is useful in the sense that it identifies some key observable local conditions that can be used to gauge the startup formation potential of locations without having to know detailed information on the volume of applications or their characteristics, or a large set of local characteristics that are hard to come by or measure. For example, policymakers and local planners can make use of this finding to assess local conditions correlated with startup activity. Designing policies to potentially improve these conditions is also important, to the extent some conditions we consider (such as household economic conditions and incumbent firm characteristics) can be influenced by local policies. However, for such purposes identifying causal mechanisms that generate the observed relationships is crucial – a key task for future work. In fact, some of the conditions we observe may not themselves be causal drivers of entrepreneurship, but they may be the symptoms or results of local policies or other, unobserved factors.

7 Conclusion

Startups offer important economic opportunities for entrepreneurs and the workers they hire. Relatively little is known about the nascent phase of startups both at the aggregate and the micro level. In this paper, we have focused on the spatial variation in the nascent phase of entrepreneurship using novel data that permits us to decompose startups per capita at the

[43] Source: Codebook for Table 1: opportunityinsights.org/data/.

local level into idea creation (applications per capita) and transitions of business ideas to employer startups.

We find enormous variation in startups per capita at the granular levels of geography. Much of this variation is *within* in the sense that most of the tract-level variation is not accounted for by county by year effects. Variation in both applications per capita and transition rates contribute substantially to this spatial variation, with applications per capita accounting for about two-third and transition rates accounting for one-third of the observed variation in startups per capita.

Local environment, captured by demographic and household economic conditions and incumbent firm characteristics, accounts for a substantial fraction of the within variation at tract level—even after accounting for county by year effects. In general, per capita income, African American population share, and foreign born share are important local factors that have a strong positive association with business applications, while college educated share, owner-occupied housing share, and per capita income have a strong positive association with transition rates. Interestingly, specific conditions have distinct relationships with idea creation and transition rates. For example, we find that local areas with a higher share of African Americans have a lower startup rate per capita, but this reflects an offsetting positive relationship with applications per capita and a negative relationship with transition rates. These patterns for own tract effects are robust to including neighboring tract characteristics. The latter help account for some of the spatial variation, but the own tract characteristics dominate.

Local observable conditions account for less than half of the observed spatial variation in startups per capita, applications per capita, and especially, transition rates. Nevertheless, we find that the predicted ranking of startups per capita based only on local observable conditions is closely related to the actual ranking. Policymakers and analysts exploring the sources of variation in entrepreneurship can thus use variation in these local observable conditions as a useful indicator to assess the startup potential of an area.

Appropriate caution is needed for the interpretation of our analysis of observable factors in that we are quantifying the contribution of observable covariates without causal inference. Our findings highlight that exploring such causal factors should be a high priority for future research. With variation in startup rates per capita that vary by as much as a factor of five across local areas and accompanying variation in idea creation and transition rates, there is enormous disparity in entrepreneurship and its key determinants across local areas (including and especially across neighborhoods in the same county). Understanding the determinants of this variation should be a high priority. Entrepreneurship has important aggregate implications, but it is also a pathway and opportunity for economic mobility both for the entrepreneurs and the workers hired by such firms. In this respect, our finding of enormous spatial variation in entrepreneurship patterns including idea creation and transition rates is related to the findings of Chetty et al. (2014) who emphasized enormous spatial variation in distinct measures of social/economic mobility. Indeed, we show there is a close correspondence between the spatial variation in transition rates and the spatial variation in these social/economic mobility measures.

We regard this analysis as a first step in exploring nascent entrepreneurship with a number of areas open for future research. The relationship between applications, startups, and post-entry dynamics (e.g., high growth outcomes) is a natural area of interest. Another is to explore the transitions to nonemployer businesses. Yet another area of research is the potentially changing relationships of startups, applications, and transition rates in the pandemic at the local level. The surge in overall applications as well as those that are likely employers has received considerable attention (see, Dinlersoz, Dunne, Haltiwanger and Penciakova (2021), Haltiwanger (2022), and Decker and Haltiwanger (2023)). The evidence is just emerging that this surge in applications has yielded a surge in employer startups but there has not been the type of analysis at the local level during the pandemic of the type in the current paper. Part of this analysis will have to await the development of the underlying micro data on transitions of applications for the post-2020 period.

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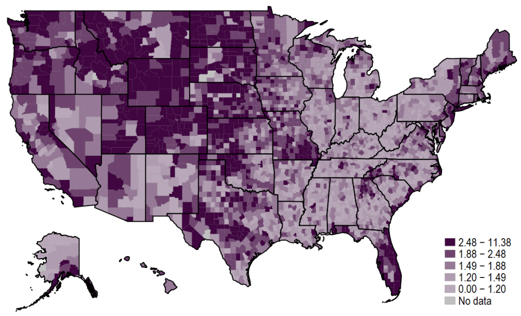
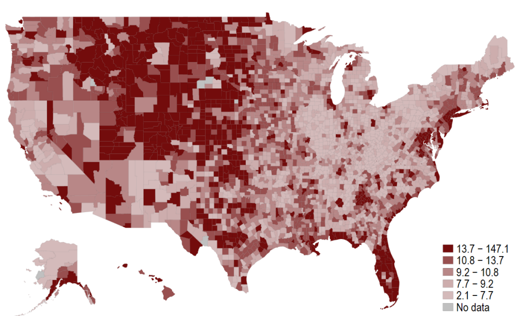
Figures

Figure 1: Startups per capita, by county

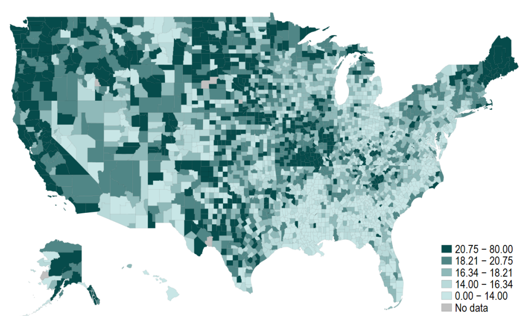


Notes: Depicts average BDS startups per 1,000 prime-age (20-64 years old) people (startups per capita) at the county level between 2012 and 2018. BDS startups are defined as age 0 firms. Note that to account for the time it takes applications to transition into employer businesses (around 8 quarters), we interpret startups between 2012 and 2018 as arising from applications filed between 2011 and 2016.

Figure 2: Decomposing startups per capita, by county



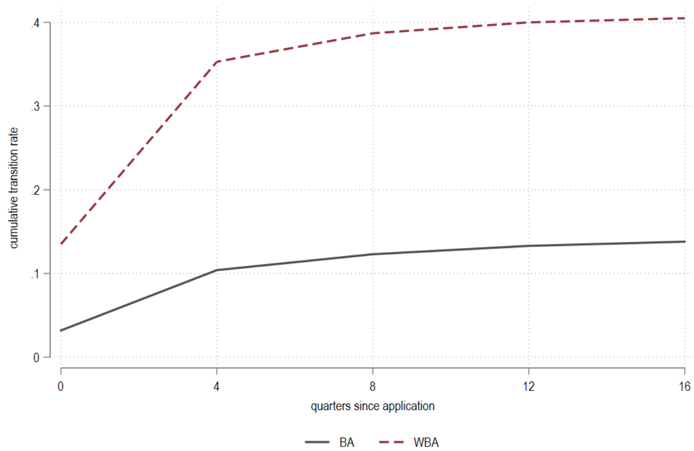
(a) Applications per capita



(b) Transition rate

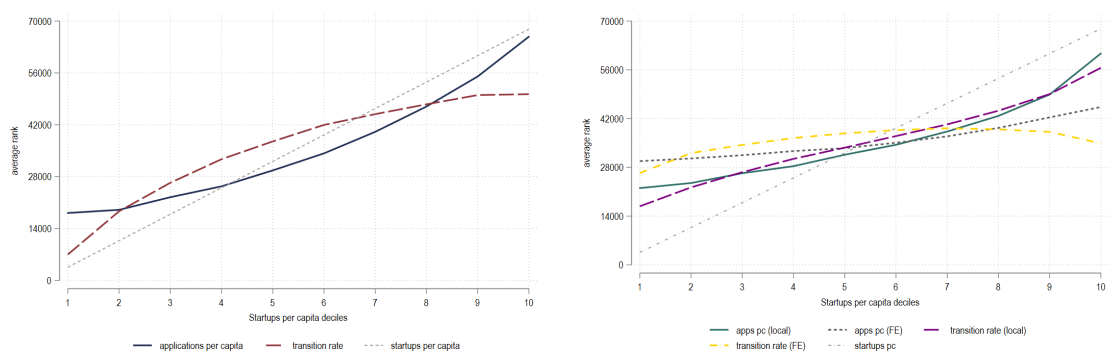
Notes: Depicts average BA per 1,000 people (applications per capita) in the left figure and transition rate (applications divided by BDS startups) in the right figure at the county level between 2010 and 2016. BDS startups are defined as age 0 firms. Note that to account for the time it takes applications to transition into employer businesses (around 8 quarters), we interpret startups between 2012 and 2018 as arising from applications filed between 2011 and 2016.

Figure 3: Cumulative transition rates for BA and WBA, time Since application



Notes: Depicts the cumulative transition rate of BA and WBA between 0 and 16 quarters after application. Due to disclosure considerations, the cumulative transition rates are calculated only for quarters 0, 4, 8 and 16. Transitions (startups) are defined as applications that transition to an employer business within eight quarters after application.

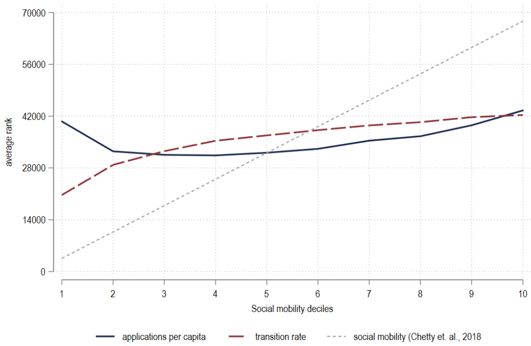
Figure 4: Tract-level Rank Analysis



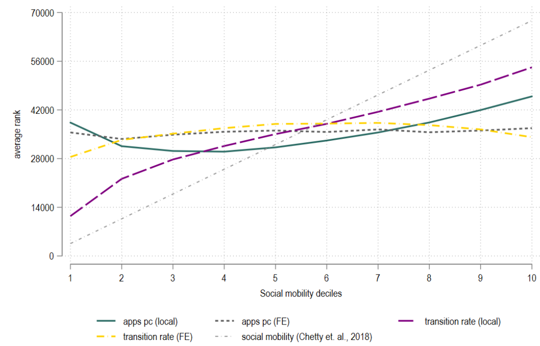
(a) Apps pc and transition rates (b) Estimated local conditions and FEs

Notes: The rank analysis focuses on WBA and associated transitions. "pc" refers to per capita (per 1000 prime-age (20-64 years old) people). In both figures, the x-axis is the deciles of startups pc (averaged at the tract-level over 2011-2016). Figure (a) depicts the average rank, by decile, of applications pc (solid blue), transition rate (dashed red), and startups pc (dotted grey). Figure (b) depicts the average rank based on predicted applications pc from local conditions (solid green), county fixed effects (tight dash grey), transition rate local conditions (long dashed purple), transition rate county conditions (long dash-dot yellow), and raw startups pc (short dash-dot grey).

Figure 5: Tract-level Social Mobility Rank Analysis



(a) Apps pc and transition rates



(b) Estimated local conditions and FEs

Notes: The rank analysis focuses on WBA and associated transitions. "pc" refers to per capita (per 1000 prime-age (20-64 years old) people). In both figures, the x-axis is the deciles of social mobility (Chetty et. al., 2018). Figure (a) depicts the average rank, by decile, of applications pc (solid blue), transition rate (dashed red), and startups pc (dotted grey). Figure (b) depicts the average rank based on predicted applications pc from local conditions (solid green), county fixed effects (tight dash grey), transition rate local conditions (long dashed purple), transition rate county conditions (long dash-dot yellow), and raw startups pc (short dash-dot grey).

Tables

Table 1: Percent of WBA and BA that transition in the same location as application

	(1) WBA	(2) BA
County	91.2	90.3
Tract	79.4	77.7

Notes: Reports the percent of WBA and BA between 2011 and 2016 that transition in the same county or tract as the one in which the application was filed. Transitions (or startups) are defined as applications that transition to an employer business within eight quarters since application.

Table 2: All startups, applications, and transition rates: summary statistics

	County			Tract		
	(1)	(2)	(3)	(4)	(5)	(6)
	Startups pc	Applications pc	Transition rate	Startups pc	Applications pc	Transition rate
Mean	1.337	10.480	0.128	1.582	13.240	0.117
SD	0.894	6.109	0.053	9.296	56.870	0.091
CV	0.669	0.583	0.414	5.876	4.295	0.779

Notes: Reports the mean, standard deviation (SD), and coefficient of variation (CV) of BA startups per 1,000 prime-age (20-64 years old) people (startups pc), BA per 1,000 prime-age people (applications pc), and BA transition rate (startups divided by applications) between 2011 and 2016, separately for county- and tract-level data.

Table 3: Wage startups, applications, and transition rates: Summary Statistics

	County			Tract		
	(1)	(2)	(3)	(4)	(5)	(6)
	Startups pc	Applications pc	Transition rate	Startups pc	Applications pc	Transition rate
Mean	0.877	2.149	0.407	0.940	2.284	0.373
SD	0.628	1.273	0.150	5.207	10.990	0.289
CV	0.716	0.592	0.369	5.540	4.812	0.775

Notes: Reports the mean, standard deviation (SD), and coefficient of variation (CV) of WBA startups per 1,000 prime-age (20-64 years old) people (startups pc), WBA per 1,000 prime-age people (applications pc), and WBA transition rate (startups divided by applications) between 2011 and 2016, separately for county- and tract-level data.

Table 4: Variance decomposition for wage startups per capita

	County			Tract		
	(1)	(2)	(3)	(4)	(5)	(6)
	Applications pc	Transition rate	2 $\times$ covariance	Applications pc	Transition rate	2 $\times$ covariance
Unweighted	0.676	0.376	-0.052	0.659	0.325	0.016
Weighted	0.919	0.369	-0.288	0.645	0.321	0.034

Notes: Reports the variance decomposition of log(WBA startups pc) into log(WBA pc) and log(WBA transition rate) for the period 2011-2016. The first three columns reports the county-level results, and the last three columns report the tract-level results. county and tract population is used for weighting, as appropriate. Startups are defined as applications that transition to an employer business within eight quarters after application. "pc" refers to per capita (per 1000 prime-age people).

Table 5: Description of Local Condition Variables

Variable	**Definition**	**Source**
log(median age)	log of median age	ACS
BA or higher share	share of pop. with BA or higher degree	ACS
some college share	share of pop. with some college	ACS
African American share	African American pop. share	ACS
Asian share	Asian pop.share	ACS
Hispanic share	Hispanic pop. share	ACS
foreign born share	foreign both pop. share	ACS
log(per capita income)	log of per capita income	ACS
emp-pop ratio	employment to pop. ratio	ACS
owner-occupied share	share of owner-occupied housing units	ACS
share of emp in young firms	share of emp. in firms aged 1-5	LBD
share of emp in large firms	share of emp. in firms with 500+ emp	LBD
DHS(average emp)	DHS of the average emp. of firms	LBD
Industry emp. shares	3-digit NAICS employment shares	LBD
commercial share	emp. share = emp./ (pop. + emp.)	ACS & LBD

Notes: "DHS" refers to the transformation based on Davis et al. (1996), where the deviation is taken from the grand mean.

Table 6: Regression Variable Summary Statistics: Baseline

	(1) Mean	(2) SD	(3) CV
DHS(WBA startups pc)	-0.520	0.977	-1.879
DHS(WBA pc)	-0.371	0.782	-2.109
WBA transition rate	0.373	0.289	0.775
log(median age)	3.629	0.200	0.055
bachelors or higher share	0.278	0.184	0.665
some college share	0.287	0.079	0.277
African American share	0.137	0.223	1.628
Asian share	0.045	0.087	1.929
Hispanic share	0.153	0.211	1.376
foreign born share	0.123	0.137	1.114
log(per capita income)	10.140	0.455	0.045
emp-pop ratio	0.582	0.106	0.182
owner-occupied share	0.646	0.227	0.352
share of emp in young firms	0.175	0.124	0.705
share of emp in large firms	0.063	0.160	2.545
DHS(avg firm emp)	-0.287	0.664	-2.309
commercial share	0.179	0.170	0.946

Notes: "pc" refers to per capita (per 1000 prime-age (20-64 years old) people). Reports the mean, standard deviation (SD), and coefficient of variation (CV) of variables used as dependent and control variables in county and tract level regressions. The years covered are 2011-2016. Startups are defined as applications that transition to an employer business within eight quarters after application. "DHS" refers to the transformation based on Davis et al. (1996).

Table 7: Contribution of location fixed effects: WBA

	(1)
DHS(WBA startups pc)	0.111
DHS(WBA pc)	0.208
WBA transition rate	0.108

Notes: Reports the share of variance in DHS(WBA startups pc), DHS(WBA pc), and WBA transition rates accounted for by county by year FE for data at the tract-year levels in 2011-2016. “pc” refers to per capita (per 1000 prime-age people).

Table 8: WBA Baseline Regression Results

	(1) DHS(startups pc)	(2) DHS(applications pc)	(3) Transition rate
log(median age)	0.0349	0.0897***	0.00803
	(0.0317)	(0.0294)	(0.00662)
bachelors or higher share	0.341***	0.0994***	0.0875***
	(0.0426)	(0.0374)	(0.0107)
some college share	–0.241***	–0.202***	–0.0417***
	(0.0577)	(0.0539)	(0.0126)
African American share	–0.286***	0.543***	–0.203***
	(0.0404)	(0.0443)	(0.00692)
Asian share	0.0585	0.106	0.00785
	(0.12)	(0.0969)	(0.0231)
Hispanic share	–0.164**	–0.064	–0.0198
	(0.0762)	(0.101)	(0.0144)
foreign born share	0.332***	0.380***	–0.0273**
	(0.117)	(0.134)	(0.0123)
log(per capita income)	0.297***	0.336***	0.00487
	(0.0178)	(0.0154)	(0.00462)
emp-pop ratio	–0.310***	–0.159***	–0.0235***
	(0.0435)	(0.0467)	(0.00848)
owner-occupied share	–0.00261	–0.0327	0.0307***
	(0.028)	(0.036)	(0.00403)
share of emp in young firms	0.231***	0.198***	0.00576
	(0.0276)	(0.0203)	(0.00664)
share of emp in large firms	–0.530***	–0.550***	–0.0243***
	(0.024)	(0.0176)	(0.00491)
DHS(avg firm emp)	–0.188***	–0.151***	–0.0114***
	(0.00588)	(0.00572)	(0.00143)
commercial share	2.666***	2.429***	0.152***
	(0.0295)	(0.0273)	(0.00606)
Ind emp. shares	yes	yes	yes
Observations	398,000	430,000	398,000
Fixed effects	fips x yr	fips x yr	fips x yr
SE clustering	fips	fips	fips
R-squared	0.305	0.416	0.1443
Within R-squared	0.2186	0.2623	0.04071

Notes: Regressions use tract-level data and include county × year FE. The observation counts have been rounded for disclosure reasons. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. Standard errors are clustered at the county level.

Table 9: WBA Regression Magnitudes

	(1) DHS(startups pc)	(2) DHS(applications pc)	(3) Transition rate
median age	0.684	1.758	0.421
bachelors or higher share	6.304	1.835	4.336
some college share	-1.917	-1.607	-0.889
African American share	-6.382	12.112	-12.145
Asian share	0.502	0.926	0.174
Hispanic share	-3.454	-1.349	-1.115
foreign born share	4.545	5.202	-1.003
per capita income	15.385	17.405	0.679
emp-pop ratio	-3.283	-1.684	-0.668
owner-occupied share	-0.060	-0.743	1.873
share of emp in young firms	2.848	2.439	0.190
share of emp in large firms	-8.500	-8.831	-1.043
avg firm emp	-27.580	-22.152	-4.489
commercial share	45.143	41.132	6.896

Notes: Reports the estimated % change in the LHS variable induced by the percent change in the RHS variable equivalent to a one standard deviation multiple of the mean. The LHS variable of the regression is listed in the columns, and each RHS variable is listed in the rows. "DHS" refers to the transformation based on Davis et al. (1996). "pc" refers to per capita (per 1000 prime-age (20-64 years old) people).

Table 10: WBA Regression Decomposition

	(1) DHS(startups pc)	(2) DHS(applications pc)	(3) Transition rate
Groups			
Demographic	0.029	0.009	0.029
HH economic conditions	0.029	0.039	0.002
Incumbent firm characteristics	-0.011	-0.020	0.002
Commercial share	0.171	0.235	0.007
Categories			
Local conditions	0.219	0.262	0.041
Common market conditions	0.086	0.154	0.104
Residual	0.695	0.584	0.856

Notes: Reports the contribution of groups of control variables (below *Groups* heading) to total R^2 of regressions where the dependent variables are DHS(WBA startups pc), DHS(WBA pc) and WBA transition rate for county- and tract-level analysis. Note that all control variables are included, along with location $\times$ fixed effects. "DHS" refers to the transformation based on Davis et al. (1996). Startups are defined as applications that transition to an employer business within eight quarters after application. The fifth row is the sum of the contribution of all individual variables (or the sum of the contribution of all grouped variables), and corresponds to the within R^2; the sixth row is the contribution of location $\times$ year FE; and the last row is the remaining variation that is unexplained by either local conditions or common market conditions.

Table 11: WBA Neighboring Tract Regression Results

	DHS(startups pc)		DHS(applications pc)		Transition rate	
	(1)	(2)	(3)	(4)	(5)	(6)
	Own	Neighboring	Own	Neighboring	Own	Neighboring
log(median age)	0.0211	0.0333	0.0678***	0.0211	0.00446	0.0394***
	(0.025)	(0.0524)	(0.0231)	(0.0489)	(0.00545)	(0.011)
bachelors or higher share	0.319***	–0.175**	0.0285	–0.0483	0.0963***	–0.00693
	(0.0344)	(0.0719)	(0.0298)	(0.0629)	(0.00957)	(0.0186)
some college share	–0.210***	–0.112	–0.214***	0.126	–0.0312***	–0.0779***
	(0.0405)	(0.0982)	(0.0371)	(0.1)	(0.0112)	(0.0221)
African American share	–0.265***	0.0344	0.346***	0.321***	–0.156***	–0.0582***
	(0.0304)	(0.0462)	(0.0242)	(0.061)	(0.00679)	(0.00843)
Asian share	0.0393	0.117	0.127**	0.0545	–0.0176	0.0495
	(0.0603)	(0.16)	(0.0538)	(0.161)	(0.0155)	(0.0385)
Hispanic share	–0.0660*	–0.0617	0.0365	–0.0664	–0.00874	–0.0107
	(0.0401)	(0.0794)	(0.0405)	(0.101)	(0.0093)	(0.0191)
foreign born share	0.204***	0.215	0.198***	0.32	–0.00241	–0.0663***
	(0.0582)	(0.163)	(0.0506)	(0.215)	(0.0118)	(0.0239)
commercial share	2.642***	0.00197	2.400***	0.0476	0.155***	–0.0161
	(0.0305)	(0.0393)	(0.0269)	(0.0417)	(0.00583)	(0.01)
log(per capita income)	0.249***	0.201***	0.303***	0.184***	0.00507	–0.0137*
	(0.0152)	(0.0312)	(0.0124)	(0.0291)	(0.00408)	(0.00728)
owner-occupied share	0.0139	–0.0993**	0.0133	–0.203***	0.0220***	0.0151**
	(0.0183)	(0.0494)	(0.0188)	(0.0577)	(0.00429)	(0.00675)
emp-pop ratio	–0.281***	–0.193**	–0.123***	–0.300***	–0.0359***	0.0714***
	(0.0348)	(0.0865)	(0.0355)	(0.0925)	(0.0081)	(0.016)
share of emp in young firms	0.204***	0.417***	0.175***	0.408***	0.00512	0.0158
	(0.0242)	(0.0551)	(0.0184)	(0.0496)	(0.00623)	(0.0141)
share of emp in large firms	–0.530***	0.0325	–0.545***	–0.0525	–0.0248***	0.0229**
	(0.0237)	(0.0456)	(0.0172)	(0.0401)	(0.0048)	(0.0114)
DHS(avg firm emp)	–0.175***	–0.0589***	–0.142***	–0.0472***	–0.00984***	–0.00641***
	(0.00558)	(0.00833)	(0.00521)	(0.00837)	(0.0014)	(0.00203)
Observations	398000		430000		398000	
Ind emp. shares	NAICS3		NAICS3		NAICS3	
Fixed effects	fips x yr		fips x yr		fips x yr	
SE clustering	fips		fips		fips	
R-squared	0.308		0.4209		0.1457	
Within R-squared	0.222		0.2685		0.04223	

Notes: Regressions use tract-level data and include county × year FE. We run one regression each for DHS(startups pc), DHS(applications per capita), and Transition Rate. For each outcome variable, we report results across two columns: DHS(startups pc) (col. 1-2), DHS(applications pc) (col. 3-4), and Transition rate (col. 5-6), where the first column in the set reports the coefficients for own tract characteristics and the second column reports the coefficients for neighboring tract characteristics. The observation counts have been rounded for disclosure reasons. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. Standard errors are clustered at the county level.

Table 12: WBA Neighboring Tract Regression Magnitudes

	DHS(startups pc)		DHS(applications pc)		Transition rate	
	(1)	(2)	(3)	(4)	(5)	(6)
	Own	Neighboring	Own	Neighboring	Own	Neighboring
median age	0.414	0.473	1.329	0.300	0.235	1.500
bachelors or higher share	5.899	-2.742	0.525	-0.754	4.775	-0.293
some college share	-1.670	-0.690	-1.701	0.778	-0.665	-1.288
African American share	-5.910	0.680	7.717	6.323	-9.328	-3.068
Asian share	0.347	0.895	1.099	0.422	-0.405	1.013
Hispanic share	-1.390	-1.175	0.771	-1.263	-0.495	-0.543
foreign born share	2.796	2.670	2.718	3.974	-0.089	-2.211
per capita income	12.898	8.462	15.695	7.746	0.705	-1.545
emp-pop ratio	-2.976	-1.558	-1.303	-2.423	-1.019	1.546
owner-occupied share	0.317	-1.714	0.303	-3.509	1.341	0.700
share of emp in young firms	2.517	2.897	2.157	2.836	0.169	0.295
share of emp in large firms	-8.500	0.249	-8.729	-0.415	-1.069	0.487
avg firm emp	-25.673	-4.647	-20.831	-3.724	-3.873	-1.357
commercial share	44.736	0.024	40.640	0.528	7.038	-0.480

Notes: Reports the estimated % change in the LHS variable induced by the percent change in the RHS variable equivalent to a one standard deviation multiple of the mean. The LHS variable of the regression is listed in the columns, and each RHS variable is listed in the rows. We run one regression each for DHS(startups pc), DHS(applications per capita), and Transition Rate. For each outcome variable, we report results across two columns: DHS(startups pc) (col. 1-2), DHS(applications pc) (col. 3-4), and Transition rate (col. 5-6), where the first column in the set reports the magnitudes associated with own tract characteristics and the second column reports the magnitudes associated with neighboring tract characteristics. "DHS" refers to the transformation based on Davis et al. (1996). "pc" refers to per capita (per 1000 prime-age (20-64 years old) people).

Table 13: WBA Neighboring Tract Regression Decomposition

	(1) DHS(startups pc)	(2) DHS(applications pc)	(3) Transition rate
Groups			
Own demographic	0.025	0.003	0.024
Own HH economic conditions	0.025	0.034	0.001
Own incumbent firm characteristics	-0.010	-0.019	0.002
Own commercial share	0.170	0.232	0.007
Categories			
Own local conditions	0.209	0.251	0.035
Neighboring tract conditions	0.013	0.018	0.007
Common market conditions	0.086	0.152	0.104
Residual	0.692	0.579	0.854

Notes: Reports the contribution of groups of control variables (below *Groups* heading) to total R^2 of regressions where the dependent variables are DHS(high-tech WBA startups pc), DHS(high-tech WBA pc) and high-tech WBA transition rate for tract-level analysis. Note that all control variables are included, along with location $\times$ fixed effects. "DHS" refers to the transformation based on Davis et al. (1996). Startups are defined as applications that transition to an employer business within eight quarters after application. The fifth row is the sum of the contribution of all individual variables (or the sum of the contribution of all grouped variables), and corresponds to the within R^2; the sixth row is the joint contribution of all neighboring tract variables; the seventh row is the contribution of location $\times$ year FE; and the last row is the remaining variation that is unexplained by either local conditions (own and neighboring tract) or common market conditions.

Table 14: High-tech WBA Regression Results

	(1) DHS(startups pc)	(2) DHS(applications pc)	(3) Transition rate
log(median age)	0.0721	–0.361***	0.016
	(0.0629)	(0.0286)	(0.0194)
bachelors or higher share	0.362***	0.922***	0.0958***
	(0.098)	(0.0504)	(0.0312)
some college share	–0.281**	–0.216***	0.0213
	(0.136)	(0.0764)	(0.0437)
African American share	–0.303***	0.0795***	–0.175***
	(0.0622)	(0.0257)	(0.0205)
Asian share	0.429***	0.607***	0.0710**
	(0.147)	(0.212)	(0.0336)
Hispanic share	–0.175*	–0.288***	–0.0441
	(0.0977)	(0.0676)	(0.0295)
foreign born share	–0.114	0.432***	–0.0858**
	(0.105)	(0.1)	(0.0336)
log(per capita income)	0.0596*	0.302***	–0.00885
	(0.0348)	(0.0228)	(0.0108)
emp-pop ratio	–0.0842	–0.0683	0.0595**
	(0.0888)	(0.0475)	(0.0273)
owner-occupied share	–0.00149	–0.0168	–0.00292
	(0.0478)	(0.0351)	(0.0156)
share of emp in young firms	0.109	0.199***	0.00684
	(0.0683)	(0.0202)	(0.0234)
share of emp in large firms	–0.124**	–0.190***	0.00393
	(0.0516)	(0.0241)	(0.0169)
DHS(avg firm emp)	–0.147***	–0.0330***	–0.0119**
	(0.0158)	(0.00659)	(0.00502)
commercial share	1.110***	1.107***	0.0456***
	(0.0719)	(0.0501)	(0.0173)
Ind emp. shares	yes	yes	yes
Observations	64,000	430,000	64,000
Fixed effects	fips x yr	fips x yr	fips x yr
SE clustering	fips	fips	fips
R-squared	0.1365	0.1922	0.09759
Within R-squared	0.04724	0.08963	0.01104

Notes: Regressions use tract-level data and include county × year FE. The observation counts have been rounded for disclosure reasons. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. Standard errors are clustered at the county level.

Table 15: High-Tech WBA Regression Decomposition

	(1) DHS(startups pc)	(2) DHS(applications pc)	(3) Transition rate
Groups			
Demographic	0.014	0.035	0.008
HH economic conditions	0.002	0.021	-0.000
Incumbent firm characteristics	0.004	0.008	0.003
Commercial share	0.027	0.026	0.001
Categories			
Local conditions	0.047	0.090	0.011
Common market conditions	0.089	0.103	0.087
Residual	0.864	0.808	0.902

Notes: Reports the contribution of groups of control variables (below *Groups* heading) to total R^2 of regressions where the dependent variables are DHS(high-tech WBA startups pc), DHS(high-tech WBA pc) and high-tech WBA transition rate for tract-level analysis. Note that all control variables are included, along with location $\times$ fixed effects. "DHS" refers to the transformation based on Davis et al. (1996). Startups are defined as applications that transition to an employer business within eight quarters after application. The fifth row is the sum of the contribution of all individual variables (or the sum of the contribution of all grouped variables), and corresponds to the within R^2; the sixth row is the contribution of location $\times$ year FE; and the last row is the remaining variation that is unexplained by either local conditions or common market conditions.

Table 16: Tract-Level Linear Probability Model (LPM) Estimates

	(1) WBA transition	(2) BA transition
log(median age)	0.003	–0.004
	(0.00722)	(0.00343)
bachelors or higher share	0.0644***	0.0210***
	(0.0097)	(0.00429)
some college share	–0.0332***	–0.0155***
	(0.0124)	(0.00433)
African American share	–0.159***	–0.0491***
	(0.00698)	(0.00226)
Asian share	0.012	0.0263***
	(0.0193)	(0.00985)
Hispanic share	–0.022	–0.011
	(0.0156)	(0.00652)
foreign born share	–0.0334**	–0.0188***
	(0.0142)	(0.00685)
log(per capita income)	0.004	0.002
	(0.00376)	(0.00189)
emp-pop ratio	–0.0121*	–0.002
	(0.00664)	(0.00287)
owner-occupied share	0.0236***	0.00800***
	(0.00359)	(0.00149)
share of emp in young firms	0.0145***	0.0102***
	(0.00538)	(0.00187)
share of emp in large firms	–0.0100**	–0.00667***
	(0.00394)	(0.00169)
DHS(avg firm emp)	–0.00811***	–0.00396***
	(0.00108)	(0.000335)
commercial share	0.0794***	0.0347***
	(0.00384)	(0.00204)
Ind emp. shares	yes	yes
Observations	2,355,000	13,840,000
R-squared	0.113	0.2
Within R-squared	0.0098	0.0777

Notes: Regressions include county × year FE. The observation counts have been rounded for disclosure reasons. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. Standard errors are clustered at the county level.

Table 17: Average Transition Duration Analysis

	(1) WBA	(2) BA
log(median age)	–0.0556**	–0.0376
	(0.0246)	(0.0236)
bachelors or higher share	0.342***	0.388***
	(0.0442)	(0.0414)
some college share	0.219***	0.269***
	(0.0517)	(0.0465)
African American share	0.230***	0.139***
	(0.0313)	(0.0303)
Asian share	0.146**	–0.0543
	(0.0672)	(0.0631)
Hispanic share	–0.0709	–0.0873
	(0.0686)	(0.0559)
foreign born share	0.225***	0.264***
	(0.0808)	(0.0686)
log(per capita income)	0.0373*	0.0238
	(0.0192)	(0.0201)
emp-pop ratio	0.0763*	0.187***
	(0.0399)	(0.0378)
owner-occupied share	–0.0565***	–0.0464**
	(0.0199)	(0.0194)
share of emp in young firms	0.0971***	0.0273
	(0.0294)	(0.0266)
share of emp in large firms	0.0112	0.0383*
	(0.0232)	(0.0218)
DHS(avg firm emp)	0.0109	0.0128*
	(0.00706)	(0.00662)
commercial share	–0.146***	–0.329***
	(0.0246)	(0.0273)
Observations	309,000	361,000
Ind emp. shares	yes	yes
Fixed effects	fips x yr	fips x yr
SE clustering	fips	fips
R-squared	0.078	0.08729
Within R-squared	0.003109	0.004556

Notes: Regressions use tract-level data and include county × year FE. The observation counts have been rounded for disclosure reasons. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. Standard errors are clustered at the county level.

Appendices

A Estimated elasticities and magnitudes

A.1 Elasticities

Consider the relationships (13), (14), and (15). The transformation of startups per capita is

$$\widetilde{S}_{lzt} = 2\left(\frac{S_{lzt} - \overline{S}}{S_{lzt} + \overline{S}}\right), \tag{17}$$

where $\overline{S}$ is the grand average over locations l and time t

$$\overline{S} = \frac{1}{N}\sum_{t}\sum_{l\in z} S_{lzt}. \tag{18}$$

We can write the analogous transformation, $\widetilde{A}_{lzt}$, for applications per capita, A_{lzt}. The transition rate, T_{lzt}, is untransformed.

To get the point elasticity of the original variable S_{lzt} with respect to any covariate c_{lt-k} expressed in levels, we proceed by differentiating (17). Note that $\overline{S}$ in (18) is a function of S_{lzt}, which depends on c_{lt-k}. However, the linear model (13) assumes that $S_{kz\tau}$ does not depend on c_{lt-k} for $k \neq l$ and $\tau \neq t$. Thus,

$$\frac{\partial \overline{S}}{\partial c_{lt-k}} = \frac{1}{N}\frac{\partial S_{lzt}}{\partial c_{lt-k}}.$$

Differentiation of (17) yields

$$\begin{aligned}
\frac{\partial}{\partial c_{lt-k}} 2\left(\frac{S_{lzt} - \overline{S}}{S_{lzt} + \overline{S}}\right) &= 2\frac{\frac{\partial S_{lzt}}{\partial c_{lt-k}}\left[(1-\frac{1}{N})(S_{lzt}+\overline{S}) - (1+\frac{1}{N})(S_{lzt}-\overline{S})\right]}{\left(S_{lzt}+\overline{S}\right)^2} \\
&= -\frac{4}{N}\frac{\left(S_{lzt} - N\overline{S}\right)}{\left(S_{lzt}+\overline{S}\right)^2}\frac{\partial S_{lzt}}{\partial c_{lt-k}} \\
&= \beta_c^S.
\end{aligned}$$

The elasticity of the original variable is then

$$\begin{aligned}
\epsilon_c^S(S_{lzt}, c_{lt-k}) &= \frac{\partial S_{lzt}}{\partial c_{lt-k}}\frac{c_{lt-k}}{S_{lzt}} \\
&= \frac{\left(S_{lzt}+\overline{S}\right)^2}{-\frac{4}{N}\left(S_{lzt} - N\overline{S}\right)}\beta_c^S \frac{c_{lt-k}}{S_{lzt}}.
\end{aligned}$$

For N large (which is the case in our application because (l,t) pairs constitute a large sample), we can write

$$-\frac{4}{N}\left(S_{lzt}-N\overline{S}\right)\simeq 4\overline{S},$$

and hence we can approximate $\epsilon_c^S(S_{lzt},c_{lt-k})$ using

$$\epsilon_c^S(S_{lzt},c_{lt-k})\simeq\frac{1}{4}\beta_c^S\frac{\left(S_{lzt}+\overline{S}\right)^2}{\overline{S}}\frac{c_{lt-k}}{S_{lzt}}.$$

Similarly, for applications per capita

$$\epsilon_c^A(A_{lzt},c_{lt-k})\simeq\frac{1}{4}\beta_c^A\frac{\left(A_{lzt}+\overline{A}\right)^2}{\overline{A}}\frac{c_{lt-k}}{A_{lzt}}.$$

The elasticity of the (untransformed) transition rate is

$$\epsilon_c^T(T_{lzt},c_{lt-k})=\beta_c^T\frac{c_{lt-k}}{T_{lzt}}.$$

Using the point elasticities above, the elasticites at the means $(\overline{S},\overline{c})$, $(\overline{A},\overline{c})$, $(\overline{T},\overline{c})$ are given by

$$\begin{aligned}
\epsilon_c^S(\overline{S},\overline{c}) &\simeq \frac{1}{4}\beta_c^S\frac{\left(\overline{S}+\overline{S}\right)^2}{\overline{S}}\frac{\overline{c}}{\overline{\overline{S}}}=\frac{1}{4}\beta_c^S\frac{4\overline{S}^2}{\overline{S}}\frac{\overline{c}}{\overline{\overline{S}}}=\beta_c^S\overline{c},\\
\overline{\epsilon}_c^A(\overline{A},\overline{c}) &\simeq \beta_c^A\overline{c},\\
\overline{\epsilon}_c^T(\overline{T},\overline{c}) &= \beta_c^T\frac{\overline{c}}{\overline{\overline{T}}}.
\end{aligned}$$

In our analysis, some covariates are expressed in logs or are transformed using (17). For these, we derive the elasticities with respect to the original (untransformed) covariate. For a covariate in logs, we have

$$\begin{aligned}
\epsilon_c^S(\overline{S},\overline{c}) &\simeq \frac{1}{4}\beta_c^S\frac{4\overline{S}^2}{\overline{S}}\frac{1}{\overline{\overline{S}}}=\beta_c^S,\\
\overline{\epsilon}_c^A(\overline{A},\overline{c}) &\simeq \beta_c^A,\\
\overline{\epsilon}_c^T(\overline{T},\overline{c}) &= \beta_c^T\frac{1}{\overline{\overline{T}}}.
\end{aligned}$$

For a covariate transformed using (17), we have

$$\frac{\partial}{\partial c_{lt-k}}2\left(\frac{S_{lzt}-\overline{S}}{S_{lzt}+\overline{S}}\right)=\frac{\partial}{\partial c_{lt-k}}\beta_c^S 2\left(\frac{c_{lt-k}-\overline{c}}{c_{lt-k}+\overline{c}}\right),$$

which implies

$$\frac{\left(S_{lzt}-N\overline{S}\right)}{\left(S_{lzt}+\overline{S}\right)^2}\frac{\partial S_{lzt}}{\partial c_{lt-k}}\frac{c_{lt-k}}{S_{lzt}}=\beta_c^S\frac{(c_{lt-k}-N\overline{c})}{(c_{lt-k}+\overline{c})^2}\frac{c_{lt-k}}{S_{lzt}},$$

and

$$\begin{aligned}\epsilon_c^S(S_{lzt}, c_{lt-k}) &= \beta_c^S \frac{\left(S_{lzt}+\overline{S}\right)^2}{\left(S_{lzt}-N\overline{S}\right)} \frac{\left(c_{lt-k}-N\overline{c}\right)}{\left(c_{lt-k}+\overline{c}\right)^2} \frac{c_{lt-k}}{S_{lzt}}, \\ &\simeq \beta_c^S \frac{\left(S_{lzt}+\overline{S}\right)^2}{\overline{S}} \frac{\overline{c}}{\left(c_{lt-k}+\overline{c}\right)^2} \frac{c_{lt-k}}{S_{lzt}}.\end{aligned}$$

Therefore,

$$\epsilon_c^S(\overline{S}, \overline{c}) \simeq \beta_c^S \frac{\left(\overline{S}+\overline{S}\right)^2}{\overline{S}} \frac{\overline{c}}{\left(\overline{c}+\overline{c}\right)^2} \frac{\overline{c}}{\overline{\overline{S}}} = \beta_c^S,$$

and similarly

$$\epsilon_c^A(\overline{A}, \overline{c}) \simeq \beta_c^A.$$

Finally,

$$\begin{aligned}\epsilon_c^T(T_{lzt}, c_{lt-k}) &= \frac{\partial T_{lzt}}{\partial c_{lt-k}} \frac{c_{lt-k}}{T_{lzt}} = \frac{\partial}{\partial c_{lt-k}} \left\{ \beta_c^T 2 \left(\frac{c_{lt-k}-\overline{c}}{c_{lt-k}+\overline{c}} \right) \right\} \frac{c_{lt-k}}{T_{lzt}} \\ &= -\beta_c^T \frac{4}{N} \frac{(c-N\overline{c})}{(c+\overline{c})^2} \frac{c_{lt-k}}{T_{lzt}},\end{aligned}$$

which implies

$$\epsilon_c^T(\overline{T}, \overline{c}) \simeq \beta_c^T \frac{4\overline{c}}{\left(\overline{c}+\overline{c}\right)^2} \frac{\overline{c}}{\overline{\overline{T}}} = \beta_c^T \frac{1}{\overline{\overline{T}}}.$$

The above elasticities can be estimated by replacing the unknown parameters (β's) with their estimates, yielding $\widehat{\epsilon}_c^Y(\overline{Y}, \overline{c})$ for $Y = S$, A, T.

A.2 Quantification of the magnitudes

Note that for any covariate c the estimated percent change in $Y = S$, A, T induced by the percent change in c equivalent to one standard deviation multiple of the mean is given by

$$\widehat{\Delta} Y_l = \widehat{\epsilon}_c^Y(\overline{Y}, \overline{c})(100 \times s_c/m_c) = \widehat{\epsilon}_c^Y(\overline{Y}, \overline{c})(100 \times CV_c),$$

where s_c, m_c, and $CV_c = s_c/m_c$ denote the sample standard deviation, mean, and the coefficient of variation for the untransformed covariate c, respectively.