Entrepreneurial Migration*

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Abstract

We track the movement of high-potential startups using cross-state business registrations and estimate the utility of cities to moving startups using a revealed preference approach. 6.6% of these startups move across state borders during their first five years. Startup hubs like Silicon Valley and Boston tend to *lose* startups to other cities. Our findings show that startups prefer traditional hubs when they move soon after being founded, but later prefer cities with lower taxes. This pattern is not due to vertical sorting or industrial specialization.

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1 Introduction

Most high-growth startups are born in a small set of cities (Guzman and Stern, 2020). These "startup hubs" often have resources that are difficult for other cities to replicate, such as major technical universities, keystone firms that spin out founders, or a venture finance ecosystem. That said, in addition to *birthing* startups, cities can also *attract* young, fast-growing firms to move from their initial location. While most startups remain near where they were born (Dahl and Sorenson, 2012; Michelacci and Silva, 2007; Guzman, 2023), some prominent firms, including Microsoft, Facebook, and Slack, moved when they were young. This raises several questions: how common is entrepreneurial migration? What cities do startups prefer when they move? And what leads startups to choose one city over another?

Policymakers in practice, and canonical models of spatial economics in theory, offer wildly different explanations for firm mobility. Consider the following three cases, each of which is not simply a vignette, but also a datapoint in our empirical analysis:

> Tableau Software, a visualization and data analytics company, was founded in 2003 by a group of Stanford researchers. The next year, they moved their company headquarters from Silicon Valley to Seattle, where the company would grow before being acquired for $15.7 billion by Salesforce. The founders argued it was simply a lifestyle decision. Both wanted to live in Seattle even though "[i]t's clearly no Silicon Valley in terms of sheer volume of technology companies."[1]
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> Stason Animal Health was founded in 2011 in the suburbs of Portland, Oregon, as a venture-backed company focused on pharmaceuticals for pets. In 2013, they moved their headquarters to Kansas City, Kansas, attracted by the booming ecosystem for their industry in the 'KC Animal Health Corridor'. "The culture of Kansas City and concentration of animal health companies here made the selection quite easy. There is no place like the KC Animal Health Corridor for a company looking to serve the animal health industry," remarked the CEO Diana Wood.[2]
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> Vbrick Systems launched a video platform in 2015 following a pivot from a focus on video encoders, which are a hardware product. The new CEO following this business model switch moved the company's headquarters to Herndon, Virginia from Wallingford, Connecticut "to get access to technical talent in the D.C. area."

[1] https://xconomy.com/seattle/2008/09/08/tableau-raises-10m-in-second-venture-round-wants-to-be-the-adobe-of-data/

[2] https://www.kansascity.com/news/local/article326075.html

> The firm quickly raised $20 million to expand sales and marketing of the new product.[3]

These examples illustrate a variety of reasons for startup mobility, including founder preferences (Tableau), Marshallian agglomeration effects (Stason), and labor availability (Vbrick). They touch on aspects of both firm productivity and founder utility, the potential substitutability of these two dimensions, and their diverging consequences for startup performance. For example, founders prioritizing amenities may move to sunny locations with lower-quality labor, while founders seeking strong ecosystems may move to cities which are colder or rainier as long as the talent pool is sufficiently deep.

Part of the reason that entrepreneurial migration is so poorly understood is that it is very challenging to track the migration of high-growth startups. They are often too small or young to appear in censuses or other standardized datasets. Even when they can be identified, it is challenging to separate growth-oriented young firms from laundromats and pizza parlors.[4] We use a technique developed in Guzman and Stern (2015) and Guzman (2023) to cull high-quality startups using the information in their initial state-level business registration. We then take advantage of the uniqueness of names in the Delaware business registry to trace cross-state moves. This method lets us track changes in the headquarters location of startups with high growth potential at birth ("startups"). Our data includes the universe of Delaware-registered startups born between 1988 and 2014 in 36 jurisdictions (35 states plus the District of Columbia, hereafter referred to as "states") representing roughly 82% of the U.S. population.

We begin in Section 2 by documenting three stylized facts. First, entrepreneurial migration is common; indeed, these firms move across state lines about as often as working-age adults. Second, the rich do not get richer: more startups move *out* of major hubs like Boston, San Francisco, and Silicon Valley than move *to* these hubs. Third, very new startups and

[3]https://technical.ly/dc/2018/06/20/vbrick-20-million/

[4]The vast majority of new firms do not intend to grow. Separating migration of potentially high growth firms from, for example, an LLC holding an individual's investments is particularly important in our setting. See Schoar (2010) and Hurst and Pugsley (2011) for more on this point.

slightly more advanced ones do not value cities equally when they move. While very young startups move to traditional hubs, startups between their third and fifth years after firm formation are much more likely to move to low-tax jurisdictions. This final pattern is seen most strongly in the highest-quality startups as measured by growth intention at birth.

In section 3, we formally model the underlying average utility of a city for entrepreneurs directly from revealed preference. Our model of firm location choice modifies a technique employed by Sorkin (2018) in the context of worker revealed preference over companies. The bilateral patterns of movements across cities identifies the average utility to cities of moving firms relative to that which justifies the pattern of startup births, and further can identify the relative utility of startups who move soon after being founded from those who move later. In particular, even when most city pairs have zero moves between them, and even when some bilateral pairs are missing in the data, we can nonetheless use the information in the *network* of moves to recover the average utility of each city. Further, these utilities are recovered analytically and nonparametrically via an application of the Perron-Frobenius Theorem. The estimated rank of city utilities for migrating entrepreneurs does not therefore require any prespecification by the analyst of explanatory covariates. Roughly, the model will suggest that one city is "better" for entrepreneurs than another if it attracts firms from other good cities, and loses few firms. Further, the model suggests both that the highest-quality firms of any vintage are more likely to move and that the probability a startup moves falls in the age of the firm.

In section 4, we describe the dataset we draw on in more detail. We track 27 years of headquarter locations of over 400,000 startups with high ex-ante growth potential. Unlike many other studies of young firms, we do not restrict to VC-funded firms, to firms in industries well-covered by censuses such as manufacturing, or to definitions of young firms where many have limited at-birth likelihood of ever growing (Shane, 2009). As our dataset does not depend on future sales or other aspects of performance correlated with location, we can track moves without concerns about post-birth selection.

Section 5 contains our primary empirical results. The recovered vector of utilities shows a striking pattern: as was suggested by our second stylized fact, the utility to movers looks quite unlike the relative ranking of cities by high-quality startup *births*. The highest ranking large cities for movers are Dallas, Phoenix, Austin, and Charlotte. University towns, poorly educated small cities, and startup hubs like Boston and the Bay Area all have lower than average utility for these firms. The pattern of city moves is also not consistent with a model where firms predominantly move for idiosyncratic reasons with all cities possessing identical common utility: there are in fact cities that are disproportionately attractive or unattractive for migrating entrepreneurs.[5]

To explain this pattern, note that startups are unusual in that they face a fundamental tension between the preferences of the founders, and the profitability of the firm. One might therefore imagine that startups, when choosing where to locate, hold an intermediate position between individual workers selecting a new city and established firms selecting a new plant location. The individual worker selects a location on the basis of wages as well as non-pecuniary benefits of a city like nice weather or its "Bohemian" nature. Established firms select plant location based on the local labor pool, tax advantages, and other formal incentives. Of course, the majority of firms do not move at all from where they begin operations, due to switching costs.

In line with this tension, we establish the following empirical regularities. When young firms move, they go to startup hubs, meaning cities with an existing agglomeration of startups. This pattern is particularly strong for the highest-quality young firms. As the firms age, their relocation decisions tilt toward cities that are more business-friendly. That is, for the highest-quality startups, we observe patterns consistent with a *"nursery cities"* model à la Duranton and Puga (2001), where diversity of ideas is useful for young firms, but Mar-

[5]As the theoretical section clarifies, we use "idiosyncratic" to mean factors determining migration which depend on preferences of individual firms rather than a common component of utility shared by all firms. This common component may, and does, contain factors beyond pure profit potential. Other authors studying location choice, such as Dahl and Sorenson (2009), define idiosyncratic as all non-pecuniary motives, including things like a preference for sunny weather which may be widely shared by founders.

shallian agglomeration is useful once those firms have figured out a product and business model. Lower-quality startups weigh amenities differently, and on the margin are more likely to move to cities that provide high utility for the founder via factors like weather or overall amenities as in Albouy (2016).

This paper builds on the literature in both urban economics and entrepreneurship. First, it provides important empirical evidence on migration and the value of locations for migrant startups. Though there is a large literature on the birth and evolution of entrepreneurial clusters (Saxenian, 1994; Michelacci and Silva, 2007; Delgado et al., 2010; Kerr and Robert-Nicoud, 2020; Chatterji et al., 2014; Glaeser and Kerr, 2009), the vast majority focuses on the differences in local characteristics that lead to different levels of firm formation. Only recently have a small number of papers begun to consider migration (e.g. Dahl and Sorenson, 2012; Guzman, 2023; Conti and Guzman, 2023), but this work has remained purely focused on identifying the impact of moving on individual startup performance. Relative to this prior work, our contributions include the first systematic measurement and benchmarking of startup migration rates in the United States and a new way to use the network of moves to understand the underlying value of all destinations. We report that startup migration is indeed relatively common. Our approach allows us to characterize the value of each city using relatively weak assumptions, and report the most valuable cities throughout the United States.

Second, we also use these results to understand which urban characteristics correlate with startup mover utility. This allows us to shed light on how various theories of agglomeration might explain the migration choices of high growth startups. Because startups are a key driver of regional and national economic growth (Glaeser et al., 2015; Haltiwanger et al., 2013), their desired urban characteristics are critical to understanding urban productivity.

At a policy level, these results emphasize the presence of geographic misallocation of productive activity in the United States (Hsieh and Moretti, 2019) and the important role of migration in mediating it. Destinations with high livability attract entrepreneurial migrants, but are not particularly attractive to the high-growth set of Delaware-registered corporations which includes virtually all venture-backed startups. As well, while local idea diversity, bohemian culture, a highly educated population, and the presence of universities play a central role in producing a large supply of new startups, they are not particularly attractive for migrants. Consistent with evidence on innovator location choices (Moretti and Wilson, 2017; Akcigit et al., 2016), personal tax rates appear particularly important.

To be clear, our results are about what factors are *relatively* important for migrants compared to the factors that cause cities to vary in how many entrepreneurs they create. We are agnostic when it comes to the importance of any of these factors on shifting the nature of human capital in a region, or the choice residents make between paid labor and entrepreneurship. Nonetheless, the primary policy interest in startup migration involves attracting firms to cities which otherwise have trouble generating high-growth entrepreneurship locally, and the primary managerial question involves understanding how startups operate geographically after their founding: in both cases, the relative utility we estimate is the most appropriate theoretical construct.

2 Three Facts about Entrepreneurial Migration

Before deriving a theory of entrepreneurial migration and explaining our data in detail, we begin by documenting three facts on the migration of high-growth startups across the United States. As we will discuss in greater depth in Section 4, "startup" here refers to a firm registered in Delaware at birth as either an LLC or a corporation. Delaware registration at birth is highly indicative of growth intention (see also Andrews et al. (2022) and references therein).

Fact 1. *6.6% of startups move across state-lines to different cities (metropolitan areas) within five years of founding.*

This figure is our baseline estimated migration rate for startups born between 1988 and

2014, after making a few assumptions to account for the fact that we only observe migrations between 36 states. In particular, for each source-destination state pair in our data, we run a regression on the number of movers using 7 controls: the source and destination populations in 2010, the ratio of the two, the source and destination population squared, and the source and destination population growth since 1990.[6] We then use the predicted value of this regression to estimate the number of movers leaving each of the states in our data to destinations we do not observe. Our estimated startup migration rate is slightly lower than the 5-year interstate migration rate for individuals in the US, which was 8.0% in 2005 and has decreased significantly since (Frey, 2017).[7]

Fact 2. *Many important startup hubs lose more startups to migration than they gain.*

Figure 1 shows this graphically, plotting startup births and net startup moves per capita in large CBSAs. In both pictures, high per capita figures are represented by blue and low per capita figures by white. The cities with the most startups per capita are what one would expect: San Jose, San Francisco, Boston, New York City, Austin, Los Angeles, and so on. However, many of these locations lose more startups in their first five years, including San Jose and San Francisco. Yet many sunbelt cities, Charlotte, Seattle and Minneapolis attract many more startups than they lose.

Fact 3. *There is no correlation overall between startup hubs and net startup moves. Instead, very young startups are more likely to move to hubs, and older startups are more likely to move to business-friendly locations.*

Figure 2 plots the net migration ratio — the number of arrivals divided by the number of departures within five years of a company's founding — against the number of startups

[6]In Appendix Table A9, we show that conditional on making a cross-state move, distance between origin and destination city plays only a tiny role in move rates.

[7]While our dataset only includes U.S. firms registered in Delaware at birth, Braun and Weik (2021) examine HQ moves of venture-backed European startups and find that a minimum of 3.5% of all European venture-backed startups since 2000 moved to the US, a median of 3 years after founding, and that these companies are positively selected for quality. Incredibly, every European company in their sample has net outmigration: of the 457 European startups who moved to a new country, including a new country within Europe, 389 moved to the US. Even large countries like France and Italy had zero in-migrating startups, while US states *other than* California, New York and Massachusetts had nearly 100.

founded in each city per capita. There is in general no correlation between the two. However, this null result hides an important lifecycle effect, which we will demonstrate in Section 5: cities with many startups per capita see net inmigration of startups less than two years old, but net outmigration of startups between their third and fifth year after birth. Cities with few startups born there see the opposite pattern.

We will show in the following section that these patterns can be interpreted precisely, under fairly nonrestrictive assumptions, by extracting the average utility of each city for all potential movers *relative* to the spatial distribution of utilities that would justify the initial distribution of startup locations.

3 A Revealed Preference Model of Startup Migration

Rather than fitting a hedonic gravity model to estimate the utility of cities to startups, which would require prespecifying covariates which determine that utility, we construct a rank of cities based purely on revealed preference. In particular, we will assume that the spatial distribution of startups at birth is driven by idiosyncratic firm-level factors plus common city-level fixed effects. We then assume that startups in any given period consider moving when the expected utility of doing so exceeds the cost of investigating where to move. If they pay this cost, they receive another set of utility draws for all cities including their home city, and move to wherever they get the highest draw.

This model induces a network structure, where moves between cities A and B, and B and C, are informative about the relative average utility of A versus C. Assume we only observe data on, for every pair of cities, the number of bilateral moves in each direction. The *full network* of all moves helps back out a revealed preference ranking among *all* cities even though we only observe a small number of possible pairwise comparisons. We will then have a rank-order of utility constructed without any a priori assumptions about what features drive startup choice. This utility ranking can then be brought either to secondstage explanatory regressions, or to direct rank-order comparisons with alternative MSA- or state-level rankings of cities along some other dimension (its bohemian nature, its business climate, its natural amenities, and so on).

There are benefits and costs of a revealed preference rather than a hedonic approach. A hedonic approach to firm migration requires the analyst to prespecify the firm- and city-level variables she expects to matter to the firm's migration choice. It is not at all obvious ex-ante what these should be. On the other hand, incorporating firm-level heterogeneity is straightforward in a hedonic model. Our revealed preference approach gains the ability to rank-order cities in a formally identified way at the cost of ruling out heterogeneous yet correlated preferences across firms over cities. We discuss theoretically in this section, and empirically in Section 5, how this limitation affects the interpretation of our results.

3.1 Model Assumptions

The technique we use here is a modification of one developed in Sorkin (2018) for the purpose of understanding the non-wage component of jobs from different employers, given data on wages and firm-to-firm voluntary transitions. The model requires three assumptions, one about how startups are born, one about how they decide whether to investigate moving, and one about what costly information they receive when they consider moving.

Assumption 1. *Assume there are N potential entrepreneurs in society, and J cities. Each potential entrepreneur i receives a utility draw of $B_j + \mu_{ij}$ from beginning a new startup in each city $j \in J$ and a draw $B_0 + \mu_{0j}$ from a null option of not forming a startup. Let each μ be a draw from a mean-zero i.i.d. extreme value type 1 distribution with scale 1.*

The first assumption says that there is some otherwise unmodeled rationale for the observed pattern of startup births. The literature on firm formation often assumes that differential startup rates across cities depend on factors like the number of existing firms a startup could spin out of, the number of potential founders living in the city, and so on (e.g., Buenstorf and Klepper (2009), Saxenian (1994)). For instance, if higher populations birth more startups, then ceteris paribus B will be higher in cities with more people.

Using standard results from discrete choice theory, the expected number of firms born in city j is

$$N \frac{e^{B_j}}{e^{B_0} + \sum_{k \in J} e^{B_k}}$$

Assumption 2. *In future periods t, startups consider whether to move. By paying a firm- and time-specific cost C_{it} drawn from a distribution F_t, startups will receive another utility draw from each city equal to $V_{jt} + \epsilon_{ijt}$. As before, ϵ are draws from a mean-zero i.i.d. extreme value type 1 distribution with scale 1.*

We will call V_j the "common utility" component of a city's utility to a startup, and ϵ_{ij} the idiosyncratic component. This assumption implies that firms can, in each period, acquire information about the value of moving to a different city at a cost C_{it}, which we interpret as a cost per unit of expected future profitability.[8] Firms consider moving as long as the expected payoff exceeds the cost of this search.

Assumption 3. *Before deciding whether to pay the cost of acquiring information about the value of potential moves, startups hold the prior that the common utility of all cities in the following period is drawn from $V_{jt} = v + \gamma_{jt}$, where γ_{jt} are i.i.d., normally distributed with mean zero and variance σ.*

The final assumption says that firms hold the uninformative prior each period that all cities are ex-ante equally likely to be good for startups of their particular birth-year, and that the common utility of cities will be normally distributed. A higher σ means that firms believe the common utility of cities will be more variable. Note that there is no persistence in beliefs across periods: a very young startup that investigated cities and learned that Louisville was a high-utility city for them at the time would nonetheless have only an uninformative prior

[8] Note that utilities $V_{jt} + \epsilon_{ijt}$ are normalized and not, for example, scaled by revenue or expected future profit.

about whether Louisville or New Orleans would be more promising five years after the firm was founded.

Putting these assumptions together, the model says that potential entrepreneurs are either born or else stay in non-entrepreneurial employment. Each period after birth, these startups can move cities if they like, but they only learn the utility benefits of moving by paying a cost. The firms that pay for this investigation get a new utility draw from all cities, and move to the city with the highest draw (or else stay in their birth city if that is maximal).

The fact that the idiosyncratic component is uncorrelated across cities and time is an important assumption. It rules out that, for instance, cities with similar industrial bases have correlated utility for a given firm beyond that which drives common value for all firms. That is, if firm moves are largely pure industrial sorting, this model is inappropriate. In that case, cities in a given industry give firms correlated utility, and this correlated utility is not common utility because it applies only to firms in that specific industry.[9] However, if the industrial *diversity* of a city, or the level of industrial specialization, or the amenity value of cities is what drives firm moves, and firms merely differ in the importance they place idiosyncratically on those features, the assumption holds. Note also that our model identifies utility solely from revealed preference of movers; in our city-firm matching process, there is no equivalent of wages in the firm-worker matching process of Abowd et al. (1999) and the literature that followed. These models permit heterogeneity in preferences at the level of the mover beyond the fact that origins differ in their propensity to generate moves, but use wages to close the model.

[9]Note that it is possible to perform the algorithm described in this section industry-by-industry to examine the extent of heterogeneity in common utility values. As we do not observe industry, and can only guess it based on firm name with nontrivial error, we do not use this heterogeneity in our primary results, but will discuss robustness to limiting the data to IT and Health industry subsamples in Section 5.

3.2 Deriving Utility from Revealed Preference

We now show how to analytically extract the vector of *relative utilities* $\bar{V}_t = V_t - B$. We call these relative utilities because they are the attractiveness of a city for a startup relative to that which would keep the spatial distribution of startups constant. If $\bar{V}_{jt}$ is positive, startups get higher utility on average in period t from a city than that which would rationalize the at-birth spatial distribution. That is, we are interested in identifying which cities have factors more conducive to attracting movers than to birthing startups, and how that attractiveness varies at different times in the startup lifecycle.

Importantly, we are able to identify $\bar{V}_t$ even if we do not know the size of the potential entrepreneur set N or the average utility of abstaining from entrepreneurship B_0. All that we will require in the data is that for every city pair $\{j, k\}$ and time period t, we observe the total number of bilateral moves between that pair. Further, the model identifies the relative utility of cities even when there are no bilateral moves between some city pairs, as long as the network of moves between all cities is strongly connected. The fundamental idea is that even if we observe no direct moves from Shreveport to Spokane, or vice versa, the former is more attractive if we observe firms from Spokane moving to Biloxi and firms from Biloxi moving to Shreveport. Finally, the model is identified even if we do not observe bilateral moves for some subset of cities, such as within-state moves or moves to or from the 15 missing states in our data.

Let us now derive $\bar{V}_t$, beginning with the decision to consider moving. A firm will pay the cost of moving C_{it} if the expected payoff to moving is sufficiently high. Note that since beliefs about the utility of cities are not persistent across periods, we can analyze this decision myopically. In particular, a firm i will move if

$$\mathbb{E}[\max_j(V_{jt} + \epsilon_{ijt}) - V_{ct} - \epsilon_{ict}] \geq C_{it}$$

where c is the current city the firm is considering leaving. That is, the expected utility of the best draw they receive needs to be at least C_{it} higher than their expected utility from remaining in the current city c.

Using the prior that $V_{jt} = v + \gamma_j$, the firm will consider moving if and only if

$$\mathbb{E}[\max_j(v + \gamma_j + \epsilon_{ijt}) - v - \gamma_c - \epsilon_{ict}] = \mathbb{E}[\max_j(\gamma_j - \gamma_c + \epsilon_{ijt} - \epsilon_{ict})] \geq C_{it}$$

Since the difference of two standard Gumbel distributions is a standard logistic, and the difference of the two mean-zero normal distributions is a mean-zero normal with standard deviation $\sqrt{1+\sigma^2}$, we have that the firm will consider moving if and only if

$$\mathbb{E}[\Omega(\sigma)] \geq C_{it}$$

where $\Omega(\sigma)$ is the maximum of J symmetric i.i.d. random variables whose distributions are the sum of a standard logistic and a mean-zero normal with standard deviation $\sqrt{1+\sigma^2}$. Since the distribution of C_{it} is constant across cities, a constant fraction of firms δ_t in each city in any given time period will consider moving. Note that the left-hand side is increasing in σ; more firms move in periods when the variance of the common component of city utilities is higher, and fewer move as the distribution of search costs C_{it} shifts leftward.

The number of firms who are born in city j and *move* to city k in period t is

$$M_{jkt} = N \frac{e^{B_j}}{e^{B_0} + \sum_l e^{B_l}} \delta_t \frac{e^{V_{kt}}}{\sum_l e^{V_{lt}}}$$

That is, the number of firms born in j who move to k in period t is equal to the number of firms born in j times the probability a given firm considers moving in period t times the probability it gets its highest utility draw at that time from city k.[10] We therefore have that

$$\frac{M_{kjt}}{M_{jkt}} = \frac{e^{V_{jt}}e^{B_k}}{e^{V_{kt}}e^{B_j}} = \frac{e^{V_{jt}-B_j}}{e^{V_{kt}-B_k}} = \frac{e^{\bar{V}_{jt}}}{e^{\bar{V}_{kt}}}$$

Letting $W_{jt} = e^{\bar{V}_{jt}}$, we have

$$\frac{M_{kjt}}{M_{jkt}} = \frac{W_{jt}}{W_{kt}}$$

That is, in any bilateral comparison, the city that attracts the most net moves is expected to have higher utility. Again, we often have no, or very few, moves between any given pair of cities. However, expanding from two cities to all cities, we can sum over j on both sides to get

$$\sum_j M_{kjt}W_{kt} = \sum_j M_{jkt}W_{jt}$$

and hence

$$\frac{\sum_j M_{jkt}W_{jt}}{\sum_j M_{kjt}} = W_{kt}$$

The denominator is the number of firms born in k that leave, and the numerator is the number that come, weighted by the "utility" of where they come from. If firms from good places come, it's a better signal of quality than if firms from bad places come. If many people come and few leave, it's a better signal of quality than if many come and many leave.

This is simply one linear restriction for each firm. As in Sorkin (2018), the model is overidentified since there are also the pairwise comparisons above (most of which are very noisy and many of which are bilateral zeros). Note that when we compare, for example, New Orleans to Seattle, all the firms that choose between New Orleans and city B, or Seattle and city C, will also give information about the value of New Orleans and Seattle since they form part of a "network" of revealed preference of the relative common value portion of city

[10] In periods $t = 2, 3, 4...$, the fact that some firms have already moved once does not affect this formula. It specifically derives the fraction of firms *born* in j who move to k in period t. The decision problem of a given firm on whether to search a second time is, as derived above, independent from whether it has already moved in the past, and the probability k is maximal if it does so is likewise independent of what city the firm currently resides in.

utility $\bar{V}_t$. This is particularly useful for identifying the relative utility of cities with few total movers, often because they have a small population. For instance, if a small city attracts only one firm, but that firm comes from a city that otherwise loses very few companies, the model puts more weight on the small city being an attractive place rather than one that got idiosyncratically lucky. If the firm it attracts comes from a city that otherwise is fairly unattractive, that one incoming firm may on the other hand be a fairly uninformative signal about how firms on average view the receiving city.

Let us now show how to extract the relative utility vector W from that equality. In matrix form, those linear restrictions can be written $SW = W$ where W is the vector of city common value relative utilities and S is a matrix where $S_{jkt} = \frac{M_{jkt}}{\sum_n M_{jnt}}$. Left to prove is that there exists a matrix W satisfying that equation. If M is strongly connected, meaning that there is a directed path from every city to every other city in the adjacency matrix based on M, then the Perron-Frobenius theorem applies. Perron-Frobenius says that for irreducible non-negative matrices (e.g., strongly connected adjacency matrices), there is a unique largest eigenvalue whose eigenvector is strictly positive. That is, there exists a unique solution to $SW = \lambda W$ where λ is the largest eigenvalue and W is the corresponding eigenvector. It is well known that when you apply Perron-Frobenius to a probability transition matrix, then the biggest eigenvalue is equal to 1, and hence we are done: we have solved for W just by finding the corresponding eigenvector to the first eigenvalue.[11] Given that the eigenvector represents relative values of W, we can convert into city relative common utilities by $\bar{V}_{jt} = \ln(W_{jt})$, using the definition of W.

This method extracts utility nonparametrically, hence in a manner well-suited for the present problem where we do not have good priors for what parametric factors mobile startups care about. In addition, the method is particularly well-suited to data like ours where only a subset of move data is available, but for which the bidirectional flows are always available whenever the unidirectional flow is. The reason is that this estimated common utility

[11] In this discrete choice setting, there is one more fairly simple step to prove the biggest eigenvalue is 1 (see Sorkin (2018), Appendix E).

of a city under our assumptions is independent of N, the number of potential entrepreneurs, δ_t, the fraction of firms that consider moving, and the fraction of firms born in a given city who do not move. Note that since we do not observe firm deaths, within-state moves, or moves to the 15 missing states, we do not actually know what fraction of firms in a given city do not move, so it is essential that our empirical technique does not rely on knowing that figure.

Why are our utility estimates independent of the fraction of firms in a given city who do not move? Mathematically, the estimated utility vector $\bar{V}_t$ is based on an eigenvector whose value is constant regardless of the number of non-movers M_{jjt}.[12] The intuition here is that since we are estimating utility of a city to movers relative to the utility which would rationalize the initial distribution of firms, and since idiosyncratic draws are uncorrelated across cities for a given firm, relative bilateral flows wholly identify utility asymptotically: a city j with positive net flows from a city k is higher utility with certainty as the sample grows large. The overidentifying assumptions we get from having a larger sample of MSAs helps identify relative utility between city pairs even when they have a small number of bilateral flows but a large number of flows to other cities in the network.

One caveat is that the model requires a strongly connected matrix of moves. We restrict analysis to MSAs with at least four firms moving in or moving out, and directly check that the matrix of moves is invertible.[13] This constraint binds particularly for LLCs, which have less mobility than corporations. Since cities outside the strongly connected set by definition have very few moves in or out, 98.9% of all interstate corporation moves to the states in our sample nonetheless are to MSAs within this strongly connected set. In all tables, we denote by "N/A" the utility of cities which are dropped because of this restriction.

[12] Since $\bar{V}$ is completely determined by linear equations of the form $\sum_j M_{kjt}W_{kt} = \sum_j M_{jkt}W_{jt}$, the diagonal element M_{jjt} appears as $M_{jjt}W_{jt}$ on both sides and hence cancels out.

[13] Firms with at least four moves out and no moves in are assigned the utility of the lowest city that is otherwise estimated by the procedure above.

3.3 Model Implications

The model both permits a ranking of city utilities for firms of differing vintages to be estimated, but also provides an interpretation of the stylized empirical facts of entrepreneurial migration. These stylized facts can be divided into three types: which firms move at all, how the decision of where to move varies by firm age, and how the decision of where to move varies by firm size.

Consider first the decision to move at all. There is a fixed cost of moving C_i which must be overcome to make moving worthwhile, even if most firms were in the absence of that cost mismatched with their highest-utility city. Smaller firms, in terms of lifetime expected profitability, will therefore be less likely to move at any given age. Firms whose expected profitability is more variable across cities, operationalized by σ in the model, are on the other hand more likely to move at any given size or age, since when they plan a move, they get the maximum city utility, not the average. A long theoretical and empirical literature has argued that young firms have more variable growth rates and productivity due to the need to learn the best way to run their business (e.g., Jovanovic, 1982). We therefore expect the highest move rates for young firms and those with high expected profits.

Conditional on considering a move, the geographic pattern of migration may vary by firm age. The nursery cities model of Duranton and Puga (2001) combines the insights of Jane Jacobs and Alfred Marshall to argue that young firms benefit from being in an idea-rich, industrially-diverse environment. As firms stabilize their products and business model, they instead are better off being in more specialized cities. If nursery cities help explain entrepreneurial migration, then the idea-rich, diverse cities should have higher utility for young movers than for older ones.[14]

Finally, the idiosyncratic preferences of founders or owners and the direct effect on firm

[14] Note that "double movers" may still be rare in our data even if the nursery cities model holds. The reason is that if very few firms move when very young to San Francisco relative to the number born there, for instance, the great majority of San Francisco-based firms who can consider leaving to a more specialized city when old will be ones born in that city. That is, you need to not just be mismatched in both periods, but also to have low enough moving costs in each period.

profitability can both drive move decisions. For instance, Guzman (2023) argues that there is a causal benefit to relocating to Silicon Valley for a young firm, and shows that, conditional on firm quality, young founders are more likely to move. If city utility is partly personal to the founder (better weather, greater amenities as in Albouy (2016), lower housing costs, etc.) and partly beneficial to the firm's future profits, firms with lower growth intentions and hence lower expected lifetime profitability will, ceteris paribus, be more likely to move to high-amenity cities rather than nursery cities.

4 Measuring Entrepreneurial Migration

Bringing this model to data requires consistent measures of startup bilateral moves for every pair of cities being considered. Measuring this movement of entrepreneurs and their startups across locations is difficult for several reasons. First, in contrast to established companies with set offices and working locations, young entrepreneurs can work at a variety of locations without any of them being common enough to be considered the firm's place of business. For example, an entrepreneur can spend some time at a coffee shop, some time in a co-working space, and some time working while traveling. In this case, the location of the firm itself is unclear. Second, for those firms that establish a location, observing this location choice is challenging because young startups often leave little observable trace of where they are in commonly-used databases. Finally, even if we are able to observe the startups, there is the perpetual concern of startup quality (e.g., Guzman and Stern (2020)): startups are heterogeneous in their underlying potential, most are not growth-oriented, and an approach to studying growth startups independent of their location requires accounting for that orientation at birth.

4.1 Measuring migration through public records

To avoid those issues, we take advantage of the business registration records created when firms are founded. Business registrations are public records created endogenously when a firm is registered as a corporation, partnership, or limited liability company, with the Secretary of State (or Secretary of the Commonwealth) of any U.S. state (or commonwealth).

Taking advantage of the unique institutional setting in the United States, where states are individual jurisdictions and require firms to register in each state in which it does business, we can use the registration process of firms across states to observe the cross-state migrations of startups. Specifically, business registration records require startups to include up to four different addresses of record: the local office in the state of registration, the principal office of the business (i.e., the headquarters), the office of the registered agent (i.e., the lawyer), and the address of the registered directors. While not all addresses are included in all cases, we identify 36 states in which we can identify the principal office of business independently from the local office of business.

We examine startups *that change the principal office of business* in these state datasets to identify headquarter migrations across locations. We identify as a migration any observation for which we can establish three facts: (i) the company with the same name and legal jurisdiction[15] has registered in two different states; (ii) the company has changed the location of principal office from an address located in the origin state to an address located at the destination state; and, (iii), there is a gap of at least three months in the time between when the company was registered in the original (founding) state and the destination.

When do we consider a firm to have moved? If a firm is registered in state A, appears in the business registry of state B at least three months after that original registration date, and has a principal business address (or equivalent) at an address in state B, we consider the firm to have moved from state A to state B. We consider the move date to be the date at which

[15] Note that jurisdiction is not the same as the location of business. All companies have a single state jurisdiction, in which they operate as a local company, while they operate as a *foreign* (to the state) company in other locations.

this firm first registered to do business in state B. There are two reasons for this definition, one practical and one theoretical. On practical grounds, since data on firm registrations does not include the date the actual principal office was moved, we can only use the date the firm first registered in a state which at a later point shows that state as being the location of the principal office. Theoretically, a company which opens an office in a given state, registering there, but which then performs more hiring and other functions until that state is referred to legally as the principal office, even theoretically should have the initial date of registration as the beginning of the eventual migration. Full details of this process, including how it differs from commercial business registries which generally do not identify startups as young as the ones in our dataset, are given in the Online Appendix.

While this approach can be in principle applied to all companies in the business registries, we focus on a smaller sample of companies that show two markers of growth-orientation at founding: registering as a corporation or LLC, and registering under Delaware jurisdiction rather than with their home state. In the process of choosing a jurisdiction for their company, growth-oriented founders benefit from registering the firm in Delaware for several reasons. The Delaware General Corporate Law provides a long canon of decisions that are useful in assessing the predictability of complex contracts. The state has an advanced institutional setup to deal with corporate arbitration including its highly reputed Court of the Chancery. The decisions and legal framework of Delaware are generally regarded as pro-business. These benefits are more useful for startups that hope to grow, especially if they plan to interact with venture capitalists.[16]

However, being in the Delaware jurisdiction also holds extra costs and requires two registrations (one in Delaware and one in the state of operation), imposing costs that a business that expects to be small is likely to deem unnecessary. This creates a natural separating equilibrium, with mostly growth-oriented companies choosing to register in Delaware. Accordingly, while Delaware companies represent only about 4% of all firms, they account

[16]In fact, venture capitalists most often require that portfolio companies are in Delaware because their contracts are specifically written for Delaware corporate law.

for 50% of all publicly listed firms, and over 60% of all VC financing (see Catalini et al., 2019). Delaware firms are also 23 times more likely to achieve an IPO or be acquired than non-Delaware firms (Guzman and Stern, 2020).

In spite of its potential, this approach does bring some limitations. First, an important limitation of our data is that, due to the use of state registries, we are not able to observe migrations of headquarters across MSAs within the same state. Our "city utility" should therefore be interpreted as the utility to non-regional movers, rather than reflecting, for instance, regional competition for firms. While this could lead to a different migration *rate* for larger or smaller states, our empirical approach identifies the relative mover utility of cities using only bilateral moves for each city pair and hence is unaffected by these omissions. Second, our migrations only track the change of legal headquarters, but the way in which companies interact with locations can often be much more nuanced. Companies expand as multi-establishment firms, or work in distributed teams that can include many locations. In this regard, we believe that while we are identifying an important aspect of startup location choice, it is not the only one. Future datasets can improve upon ours, further shedding light on this question. Finally, migration of established startups is only one of the broader set of relocation actions that can happen in entrepreneurship. For example, many individuals might move to locations amenable for startups before becoming entrepreneurs. These relocations will be unobserved in our data. While this is certainly a limitation for the goal of observing all economic migration, we believe it positions the contribution of our data squarely and more clearly on *actual* entrepreneurship at the time it is happening, rather than eventual entrepreneurship.

It is also important to clarify what counts as a startup in our reckoning. A startup is a formal business entity that begins operating for the first time. Mergers that generate a new corporate entity are therefore startups, as are spinouts. In general, it is not obvious whether these types of entities should or should not be called startups, and it is difficult to identify which business registries are spinouts, so we use a conservative definition of startups which includes them. For instance, in 1996, Lucent Technologies was spun out of AT&T, including the famous Bell Labs division. This company was new, and was independent, though it was not "small" in the sense of many startups.[17]

Though business registries appear to be a promising data source for investigating startup behavior, constructing data tracking state-by-state flows from them is not a simple task. Many states do not make full registration data freely available. Records in some states have frequent errors. The firm headquarters location in some cases only lists a lawyer's address, in which case we rely on alternative measures, such as the MSA address of a majority of corporate directors, to identify the firm's metro area. We restrict full details of our matching process to the Online Appendix. However, as noted, our empirical method only requires that if we can observe moves from city A to city B, we can also observe those from B to A. This allows us to simply drop the small number of states whose data practices make it particularly burdensome to observe headquarter locations.[18]

We secured the business registration records of all companies under Delaware jurisdiction registered in 36 U.S. states through the Startup Cartography Project (Andrews et al., 2022). The Startup Cartography Project is a project measuring the founding registration of all companies in the United States outside of Delaware, between 1988 to 2014. From this data, we attempt to extract the local and principal address of office for each firm that also has a Delaware jurisdiction. Using this approach, we excluded 15 states in which we did not think we were able to adequately separate the local address from the headquarters. The states we use represent 82% of the US population and 86% of the 50 biggest metropolitan areas by

[17]As we are interested in growth-oriented startups, we further drop all companies with "Holding" in their name, and all companies with "II", "III", "IV", etc., at the end of their legal name. In our experience, these tend to be financial or real estate holding companies rather than de novo startups.

[18]For a number of firms, the origin state registration has a headquarters address which is updated to the new state after the move. Because we know the date the firm was originally registered, we can nonetheless identify the *state* it was born in. In these cases, we assign birth MSAs probabilistically: if a firm moving to Dallas is known to be born in Massachusetts but the MSA is unknown, and 80% of known births are in Boston, we assign .8 firm moves from Boston to Dallas. Moves are given in rounded numbers in all tables. Full details of this algorithm are available in the Online Appendix.

population. See Online Appendix Figure A2 for a visual display of the included states.[19]

4.2 Summary Statistics

Table 1 presents the summary statistics of all the Delaware-registered corporations in our data. Our dataset includes 181,663 corporations. Of this sample, 0.5% have had an IPO and 2.6% have been acquired.[20] Highlighting the growth orientation of these companies, their probability of positive growth outcomes is more than thirty times higher than that of all new firms, as estimated in Guzman and Stern (2020) at 0.07%. Turning to founding characteristics, 5.8% of the companies have a patent at or around founding and 2.4% of the companies have a trademark. Finally, 3.3% of Delaware-registered corporations move to a new state in our data within 2 years, and 5.6% within 5 years. Accounting for moves to states we do not observe as described in Section 2, our estimated overall migration rate for corporations is 6.6%. We also track 237,307 Delaware-registered LLCs, who are much less likely to be acquired (.4%) or to move (2.8% within five years).

We aggregate this data into information on migration flows on two dimensions: state and Metropolitan Statistical Area (MSA), using the 2013 U.S. Census CBSA definitions. The resulting dataset is a matrix containing the number of movers from each source location to each destination location. In any given year, the modal MSA receives zero high growth startups, and the median MSA receives one.

Table 2 presents the summary statistics of the state and MSA level flows data. Panel A describes the state to state flows. There are 1,260 possible source-destination state pairs (36 home states moving to 35 other states), with an average number of movers between any unidirectional dyad of 3.7 corporations and 4.2 LLCs. Even over our entire 27 year period, 47% of state dyads do not have a single move between them. Panel B describes

[19] We also omit the Trenton, NJ and Augusta, ME firms due to idiosyncrasies in how states record firms in these capital cities.

[20] IPO measures whether the firm joins the NYSE or the NASDAQ as reported by the SDC Global New Issues database. Acquisition is a binary variable equal to 1 if the firm is reported as being fully acquired in the SDC Platinum Mergers and Acquisitions database.

the much sparser MSA to MSA flows. Out of a total of 34,040 MSA unidirectional source-destination pairs, only 5.2% (1,749 pairs) have any movers at all. The average number of movers conditional on having at least one move between MSA pairs is 3.8. This sparseness highlights the value of our empirical method, which uses network properties rather than just bilateral flows to value cities.

Figure 3 shows the distribution of migration rates for startups across their age profiles. We observe a monotonic reduction in the age probability of moving, decreasing steeply initially and then tapering off. Startups have a 2.1% probability of moving in their first year (age 0), followed by 1.2% probability in the second year and 0.9% in the third. By age 5, this probability has reduced to 0.4% and, by age 10, to 0.2%.

Figure 4 documents the declining rate of migration over time, including among the highest-quality firms. To do so, we plot in the top-left panel the five-year migration rate for each yearly cohort of companies born up to 2009. Two patterns emerge. First, there is a secular decline in the migration rates of startups over time going from 6.9% in 1988 to 5.1% in 2010—a 26% drop in magnitude. The fitted line trend is -.0008 and we reject the null that the coefficient is zero (i.e., that there is no decline) at the 1% level using robust standard errors. Second, there is a level of pro-cyclicality around this trend. There are large drops in the migration rate during the years of recession, 1991, 2001, and 2007, and migration rates are relatively higher during the economic boom years. This pattern mirrors a documented secular decline in the inter-state migration rate amongst individuals, as well as other secular drops on business activity more generally (Decker et al., 2014). The top-right, bottom-left and bottom-right panels show this decline in migration holds even if we only look at corporations, or the "highest ex-ante quality" corporations who hold a patent or trademark at founding.

5 Empirical Results

Table 3 shows our primary result. Though our empirical method estimates mover utility for all US MSAs with at least four high-growth startups moving in or out during our 27 year sample, for readability we restrict here to MSAs with a population over 1 million.[21] Column 1 reports the relative utility of movers as estimated from the full matrix of startup location choices using the model in Section 3. The rightmost column gives the same rank if we only look at LLCs. Note an immediate pattern. High-utility cities are dominated by the Sunbelt (Dallas, Phoenix, Austin, San Antonio, Jacksonville, San Diego) and the New South (Charlotte, Nashville, Atlanta, Jacksonville, Raleigh, Birmingham, Richmond, and Tampa). San Jose, Boston, San Francisco, and New York are all below median cities among CBSAs with a population over one million. In the complete list of cities (Appendix Table A2), note that university towns are particularly likely to show low utility for movers relative to founders.

The fact that "startup hubs" do not have particularly high utility to founders is not due to an idiosyncrasy in how we define "high-growth startups", as can be seen by investigating where these firms are born. Appendix Table A3 shows cities by the number of high-growth corporation births per capita. San Jose, Bridgeport, San Francisco, Boulder, Boston, and Durham-Chapel Hill have the highest number, in line with intuition that these are hubs of startup activity (in Bridgeport's case, for financial sector activity). The cities with the lowest number of high-growth corporation births per capita are Biloxi, Youngstown, Buffalo, Corpus Christi, El Paso, Tucson and Rochester, again in line with expectations. Among the cities with high utility for movers, some also birth many startups (Austin) while others are attractive despite not creating a particularly large number of startups given their size (Seattle, Minneapolis).

Figure 5 shows the relationship between startup births per capita and utility for movers graphically. The top-left panel makes clear that there is no relationship between cities that

[21] The listing of all cities by utility can be found in Online Appendix Table A2.

create many startups per capita and those that are attractive to moving startups. However, this finding hides an intriguing lifecycle pattern. In their first year after being founded, or in the first two years, there is a strong *positive* relationship between cities that birth many startups and those that are attractive to movers. Between the third and fifth year after being founded, however, the relationship is precisely the reverse: cities with few births per capita are now the more attractive ones.

Table 4 shows this pattern formally in the first column. The utility of cities to startups moving in their first two years is positively related to the number of startups per capita those cities create, while the opposite pattern holds for later startup moves. To the extent that startups are "mismatched" and must move, they do not move randomly; rather, initially the cities that already had many startups on average benefit from this mobility, whereas as startups become more advanced, they begin to move away from those hubs.

Online Appendix Table A1 constructs the same utility ranking using only LLC moves. Warm-weather "lifestyle" cities loom particularly large: San Diego, Miami, Phoenix, Austin, Los Angeles, and Tampa are all among the top twelve large cities by LLC mover utility. The business centers of the New South - Atlanta, Dallas, Houston, Charlotte - possess much less utility for LLCs than they do for corporations.

What might explain these empirical regularities? Recall that our theoretical model predicts the following facts. First, younger firms move more since the variation across cities matters more to firms with a less-settled business model. Second, firms with more growth intention move more, since they are more likely to find it worth the cost of switching cities. Third, if the Duranton and Puga (2001) "nursery cities" model holds, young firms optimally locate in places with a diverse set of ideas and industries, while they move to lower-cost, more-specialized cities as their business develops. Fourth, if founders consider both pecuniary and non-pecuniary factors, aspects of cities that affect pure economic return should matter more to founders with stronger growth intention. And of course, only firms so "mismatched" with their original city move at all given the cost of doing so.

Online Appendix Table A5 shows that the first two hypotheses hold. The fraction of startups that move is highest the year the firms are founded, and monotonically falls thereafter. However, corporations of any age are much more likely to move than LLCs, those holding IP at birth (in addition to many other measures of growth intention at birth) are as well, and later movers are also much more likely to be acquired or IPO than Delaware-registered firms who either never move or who move when very young. The differences are substantial: of Delaware-registered firms who do not change states in their first five years, 43% are corporations rather than LLCs, while among those who move in their first year, 57% are corporations, and among those moving in year five, 65%.

Columns 2, 3 and 4 in Table 4 test the nursery cities hypothesis, in two ways. First, we measure idea diversity using the four-digit employment HHI of each MSA, where a higher HHI means the city has employment concentrated among fewer sectors. While industrial concentration is strongly negatively associated with the number of startups born per capita, there is no relationship between HHI and utility for startups who move in the first two years after founding, and a positive relationship between industrial concentration and utility for startups who move later. Likewise, while patenting per capita is strongly positively associated with startup births, it is negatively associated with utility for late startups movers. For both measures of "idea diversity", the nursery cities pattern holds.

Columns 5 through 8 in Table 4 examine financial motives for moving by regressing total state-level tax rates as computed by Moretti and Wilson (2017) against startup births and mover utility. While high tail taxes (in this case, 95th percentile income taxes) are not associated with either less entrepreneurship or lower utility for early movers, later movers show a large, negative reaction to these tail taxes. Figure 6 shows this relationship graphically. Online Appendix Table A7 shows that including corporate tax rates makes the negative reaction of late movers to high taxes even more stark: high tail individual tax rates and high corporate tax rates independently repel late-moving startups.

While Figure 6 shows that LLCs are also deterred from moving to cities with high tail taxes, Online Appendix Table A8 shows that the relationship between pecuniary factors and Delaware-registered LLCs is dulled compared to that of corporations. The nursery cities relationships are not statistically significant and not evident even in the point estimates, and when it comes to taxes, LLCs if anything respond more strongly to median tax rates than those at the right tail. Appendix Table A10 regresses city utility on purely non-pecuniary factors such as sunshine and the Albouy (2016) "quality of life" index derived from individual rather than corporation moves. While these factors show no relationship with mover utility for corporations, utility for moving LLCs is strongly associated with sunshine, warmer weather, and higher quality of life. Combined with the tax evidence, this is consistent with the idea that founders with less growth intention, who initially form their ventures as LLCs, react less to financial factors and more to other factors relevant to the personal utility of their founders.

How important are startup moves to the overall number of startups in a city? For cities that generate many startups, net movement is relatively unimportant: San Jose loses a net 25 high-growth startups during a period in which they create almost 9,000. However, startup births are highly skewed, hence startup mobility can be quite important. The median city in startup births per capita in our data, San Antonio, would move ahead of ten more cities in total post-move startups per capita if they had the per capita attractiveness to movers of Austin, and behind seven cities if they had that of New Orleans. Put another way, even though the vast majority of startups don't move and the big startup hubs are driven much more by firm creation than firm mobility, a San Antonio that could attract startups as well as Austin would see roughly 20 percent more age-5 startups than a San Antonio which attracted startups at the rate of New Orleans. That is, while cities like Boston and Mountain View may barely notice that companies like Facebook and Tableau left, a city like Albuquerque or Houston would absolutely notice if they arrived.

Before concluding, let us consider three threats to our empirical approach: that moves are purely idiosyncratic, or that overall net movement is driven by vertical or horizontal sorting.

Consider first idiosyncratic moves. Of course, some startup moves are heavily influenced by the idiosyncratic preferences of founders; for example, Microsoft's relocation to Seattle appears to be partially influenced by the fact that Bill Gates and Paul Allen wanted to be close to their families. The relative weight on city common utility versus firm idiosyncratic factors, and hence the extent to which city fixed characteristics drives startup location choice, can be directly investigated by considering the pair-wise migration rates amongst two cities. Taking the model seriously, if the idiosyncratic factor has zero variance, then all firms who move will go to the same city. In contrast, if only idiosyncratic factors matter, then bilateral flows will be identical in each direction. That is, the hypothesis that moves are idiosyncratic directly implies that $H_0 : E[\frac{Moves\ In_i}{Moves\ Out_i}] = 1$ for any given city. Empirically, this set of hypotheses can be tested with a joint Fisher Exact Chi-squared Test. However, it is straightforward to see that even individual cities have combinations of moves in and moves out that are wildly unlikely to be the result of idiosyncratic movement alone. For example, Dallas has 453 moves in and 215 moves out, violating H_0 at p$<$.00001.

Second, consider the relationship between city utility and an estimate of the vertical quality at birth of firms moving to or from each city. For example, while places with high startup costs such as the Bay Area may on net lose startups, they may tend to shed low quality startups while gaining very high quality ones. Note that our primary sample already restricts only to Delaware-registered corporations at birth, so this robustness check is attempting to handle quality differences within a sample that is already highly selected on quality at birth. To investigate vertical sorting, we replicate the entrepreneurial quality measure of Guzman and Stern (2020), which maps the founding characteristics of startups before moving to estimated probabilities of reaching an equity outcome such as an IPO or acquisition.[22] Online

[22]Specifically, for all non-movers born before 2012, we run a logit model with a binary measure of equity events as the dependent variable, and observables for whether a firm, close to founding and in its birth location, is a corporation, has a short name, is eponymous, has a patent, has a trademark, has both a patent and a trademark, or is estimated to be part of certain industries based on firm name. Predictions from this model report an out of sample ROC score or 0.80. Estimated quality is then the predicted out of sample probability of this model.

Appendix Table A6 shows that firms which move to startup hubs, including those that move to startups hubs in their third to fifth year after being founded, are higher quality than those who move to non-hubs. That said, Online Appendix Table A12 regresses the quality of startups that arrive on the quality of those that leave controlling for the average quality of all firms born in that city and finds, controlling for level of growth startups per capita in a MSA, no relationship between the quality of leavers versus stayers. That is, startup hubs like Silicon Valley do in fact both create and attract high quality startups, but the startups they lose are also disproportionately high quality. In short, we do not find evidence that our primary results are driven by quality-based vertical sorting.

Finally, Appendix Figure A1 shows that our city utilities overall are highly correlated with city utilities estimated using only companies in the health sector, IT sector, services sector, or high tech sector. These industries are estimated as in Guzman and Stern (2020) by predicting industry from a firm's name. In a model of pure horizontal sorting, the rank of *within-industry* utilities should vary. Instead, cross-industry factors cause a strong correlation between the overall city rank and the rank within industry. Of course, we are only able to identify industries in broad classes, and with error, since we do not directly observe industry.

6 Conclusion

Some cities are born lucky: they produce many high-growth startups as a result of their youthful demographics, their technical universities, or spinouts from keystone firms. After birth, however, 6.6% of those high-growth startups will move before they are five years old. Historically, some of the most important startups moved when young: Facebook, Microsoft, Slack, and Tableau are all prominent examples.

We show that the places which create a lot of startups and the ones that are attractive to movers are not the same. We are able to track startups moves across 36 states making up over 82% of the US population using business registration data. This dataset allows us to capture startups before they ever appear in censuses or other public records, and in a way that is neutral to their industry. Although the usual suspects of San Jose, San Francisco, and Boston produce a wildly disproportionate number of high-growth startups per capita, as do university towns, startup moves are not a case of "the rich get richer". While very young startups are more likely to move to cities that birthed many startups, those between two and five years after founding are much more likely to move to low-tax, not-terribly-Bohemian Sunbelt cities. This pattern is most evident for the most growth-oriented firms: those registered as Delaware corporations at birth are particularly likely to shift their headquarters to boring, business-friendly locations, while LLCs, perhaps accounting for non-pecuniary tastes of their founders, move to sunny, high-amenity destinations. And while this general pattern holds over our full sample period, the "attractive cities" to high-quality startups are not set in stone. As can be seen in Online Appendix Table A4, Las Vegas, Nashville, Austin and San Antonio have become relatively more attractive post-2001 compared to the 1990s, while Minneapolis, Richmond, Houston and Denver have become less so.

Our method for estimating startup mover utility is wholly nonparametric and based on revealed preference, using a technique from linear algebra previously applied by Google to identify important websites, and to compensating differentials in labor economics by Sorkin (2018). This technique allows us to compare cities even when they have very few, or even zero, bilateral moves between them, and even when the econometrician has no a priori knowledge of the covariates which startups consider when planning a move.

These results suggest an important focus for spatial entrepreneurship in understanding "startup hubs" as two distinct types of cities: those that create a lot of firms given their population, and those that attract these firms if they choose to leave. It also suggests that college towns and other highly-educated places may not be as advantaged as previously believed. Although they create many startups, those homegrown firms do not create spillovers sufficient to attract more firms from outside. Indeed, quite the opposite. Many university spinouts leave for the types of cities attractive to businesses of all vintages. Studies of spatial entrepreneurship therefore need to carefully separate factors which birth firms and those which affect the post-migration final locations of those startups.

References

John M Abowd, Francis Kramarz, and David N Margolis. High wage workers and high wage firms. *Econometrica*, 67(2):251–333, 1999.

Ufuk Akcigit, Salome Baslandze, and Stefanie Stantcheva. Taxation and the international mobility of inventors. *American Economic Review*, 106(10):2930–81, 2016.

David Albouy. What are cities worth? land rents, local productivity, and the total value of amenities. *Review of Economics and Statistics*, 98(3):477–487, 2016.

RJ Andrews, Catherine Fazio, Jorge Guzman, Yupeng Liu, and Scott Stern. Reprint of the startup cartography project: measuring and mapping entrepreneurial ecosystems. *Research Policy*, 51(9):104581, 2022.

Reiner Braun and Stefan Weik. Foreign venture capital and the exodus of start-ups: Evidence from headquarters relocations. *Working Paper*, 2021.

Guido Buenstorf and Steven Klepper. Heritage and agglomeration: the akron tyre cluster revisited. *The Economic Journal*, 119(537):705–733, 2009.

Christian Catalini, Jorge Guzman, and Scott Stern. Passive versus active growth: Evidence from founder choices and venture capital investment. Technical report, National Bureau of Economic Research, 2019.

Aaron Chatterji, Edward Glaeser, and William Kerr. Clusters of entrepreneurship and innovation. *Innovation policy and the economy*, 14(1):129–166, 2014.

Annamaria Conti and Jorge A Guzman. What is the us comparative advantage in entrepreneurship? evidence from israeli migrantion to the united states. *Review of Economics and Statistics*, 105(3):528–44, 2023.

Michael S Dahl and Olav Sorenson. The embedded entrepreneur. *European management review*, 6(3):172–181, 2009.

Michael S Dahl and Olav Sorenson. Home sweet home: Entrepreneurs' location choices and the performance of their ventures. *Management science*, 58(6):1059–1071, 2012.

Ryan Decker, John Haltiwanger, Ron Jarmin, and Javier Miranda. The role of entrepreneurship in us job creation and economic dynamism. *Journal of Economic Perspectives*, 28(3): 3–24, 2014.

Mercedes Delgado, Michael E Porter, and Scott Stern. Clusters and entrepreneurship. *Journal of economic geography*, 10(4):495–518, 2010.

Gilles Duranton and Diego Puga. Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review*, 91(5):1454–1477, 2001.

William H Frey. U.s. migration still at historically low levels, census shows, 2017.

Edward L Glaeser and William R Kerr. Local industrial conditions and entrepreneurship: how much of the spatial distribution can we explain? *Journal of Economics & Management Strategy*, 18(3):623–663, 2009.

Edward L Glaeser, Sari Pekkala Kerr, and William R Kerr. Entrepreneurship and urban growth: An empirical assessment with historical mines. *Review of Economics and Statistics*, 97(2):498–520, 2015.

Jorge Guzman. Go west young firm: The impact of startup migration on the performance of migrants. *Management Science*, forthcoming, 2023.

Jorge Guzman and Scott Stern. Where is silicon valley? *Science*, 347(6222):606–609, 2015.

Jorge Guzman and Scott Stern. The state of american entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 us states, 1988–2014. *American Economic Journal: Economic Policy*, 12(4):212–43, November 2020. doi: 10.1257/pol.20170498. URL `https://www.aeaweb.org/articles?id=10.1257/pol.20170498`.

John Haltiwanger, Ron S Jarmin, and Javier Miranda. Who creates jobs? small versus large versus young. *Review of Economics and Statistics*, 95(2):347–361, 2013.

Chang-Tai Hsieh and Enrico Moretti. Housing constraints and spatial misallocation. *American Economic Journal: Macroeconomics*, 11(2):1–39, April 2019.

Erik Hurst and Benjamin Wild Pugsley. What do small businesses do? *Brookings Papers on Economic Activity*, page 73, 2011.

Boyan Jovanovic. Selection and the evolution of industry. *Econometrica*, 50(3):649–670, 1982. ISSN 00129682, 14680262. URL `http://www.jstor.org/stable/1912606`.

William R. Kerr and Frederic Robert-Nicoud. Tech clusters. *Journal of Economic Perspectives*, 34(3):50–76, August 2020.

Claudio Michelacci and Olmo Silva. Why so many local entrepreneurs? *The Review of Economics and Statistics*, 89(4):615–633, 2007.

Enrico Moretti and Daniel J Wilson. The effect of state taxes on the geographical location of top earners: evidence from star scientists. *American Economic Review*, 107(7):1858–1903, 2017.

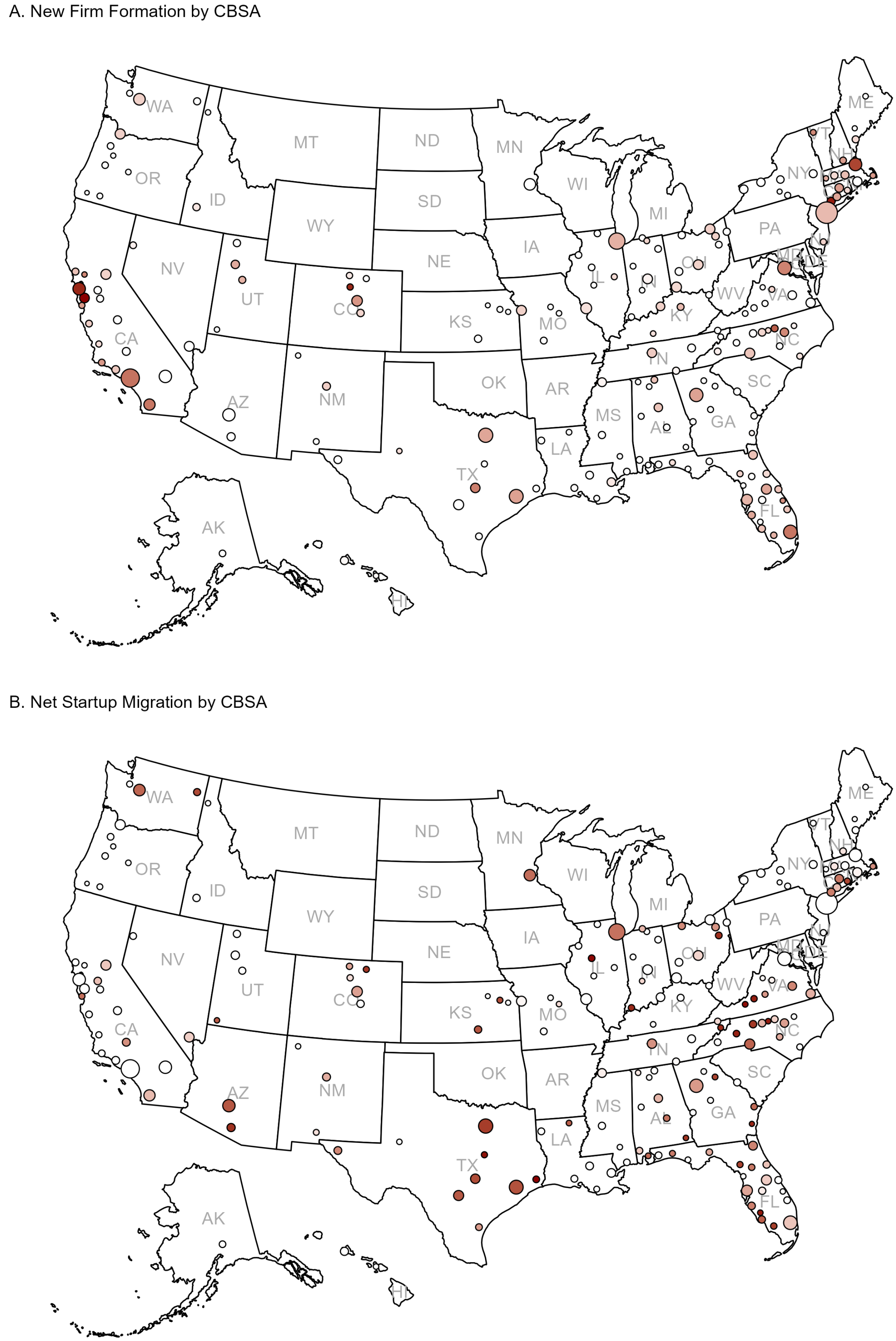
AnnaLee Saxenian. *Regional networks: industrial adaptation in Silicon Valley and route 128*. Citeseer, 1994.

Antoinette Schoar. The divide between subsistence and transformational entrepreneurship. *Innovation policy and the economy*, 10(1):57–81, 2010.

Scott Shane. Why encouraging more people to become entrepreneurs is bad public policy. *Small business economics*, 33(2):141–149, 2009.

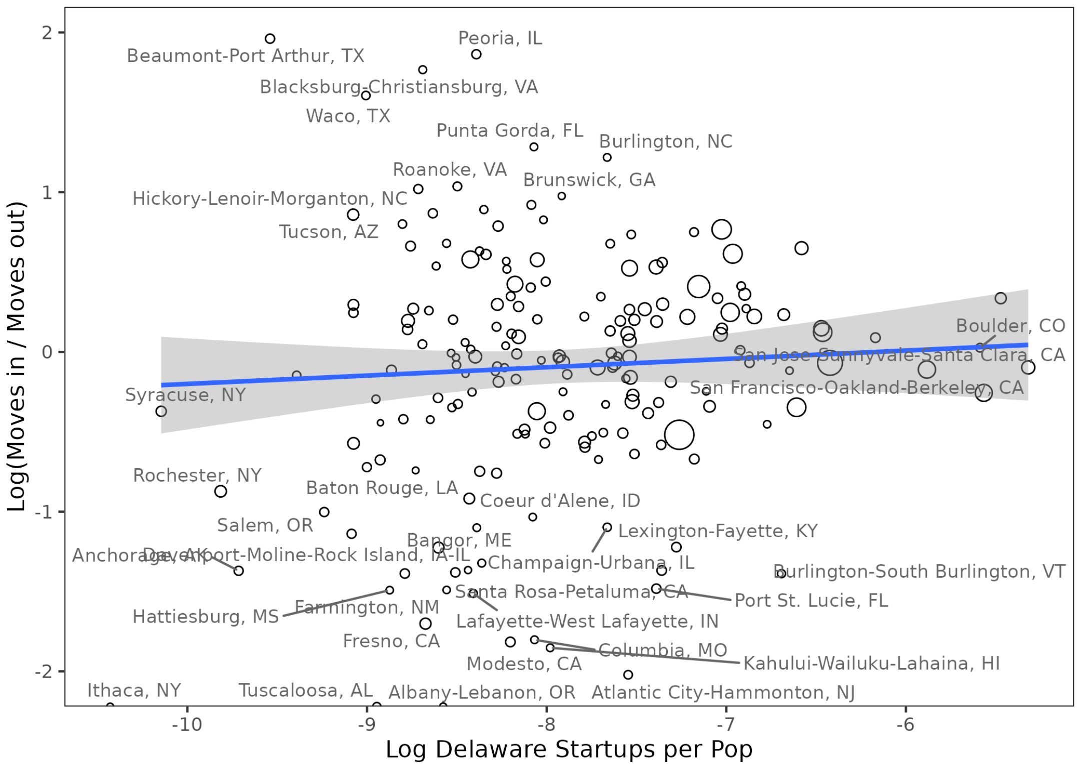
Isaac Sorkin. Ranking firms using revealed preference. *The quarterly journal of economics*, 133(3):1331–1393, 2018.

Figure 1: New Startups and Net Startup Moves by MSA



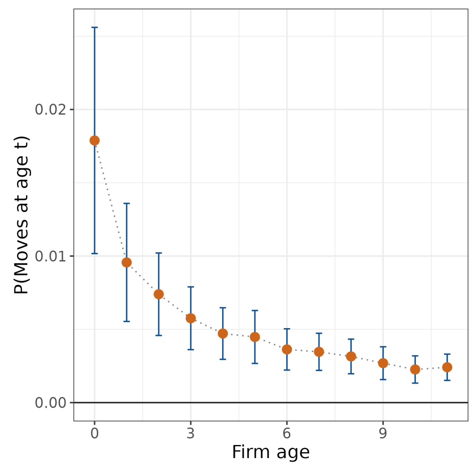
*Notes:*The top map plots the number of startups per capita by MSA, where darker shading signifies more startups, and bubble size signifies MSA population. As in the remainder of the results, "startup" refers to a corporation or LLC registered in Delaware at birth. The bottom map plots startup moves, where the size of the circle is the number of total movers that move into a metropolitan area, and the color of the circle represents the ratio of the moves in over the moves out. Darker cities have a higher number of moves in than moves out, while lighter cities are the opposite.

Figure 2: Estimated Migrant Value of Cities vs Local Ecosystem Strength



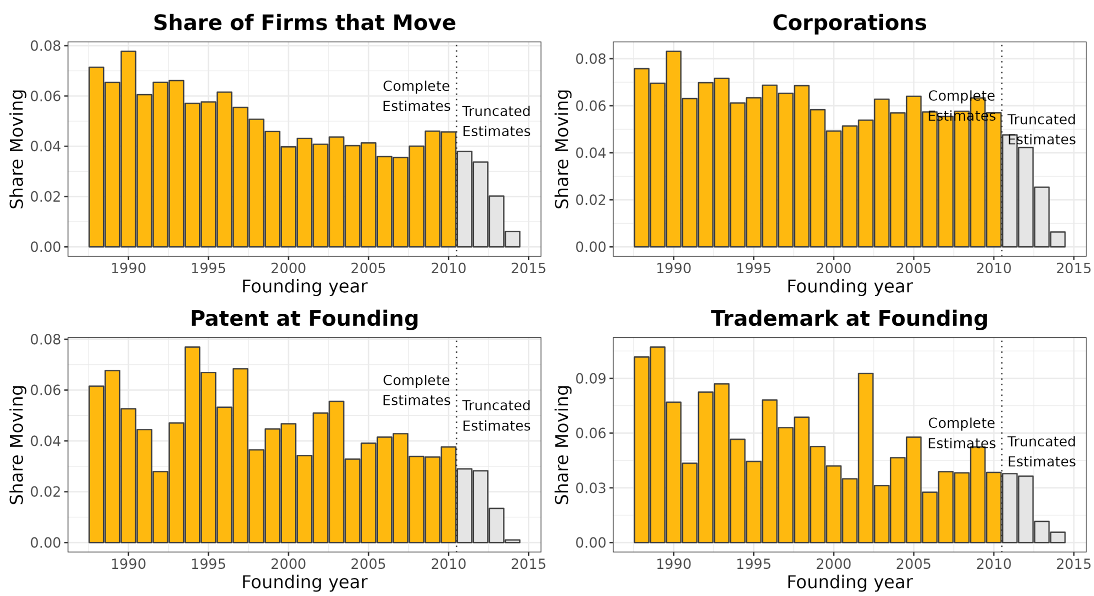
Notes: Bubble size represents city population.

Figure 3: Migration Rate by Age



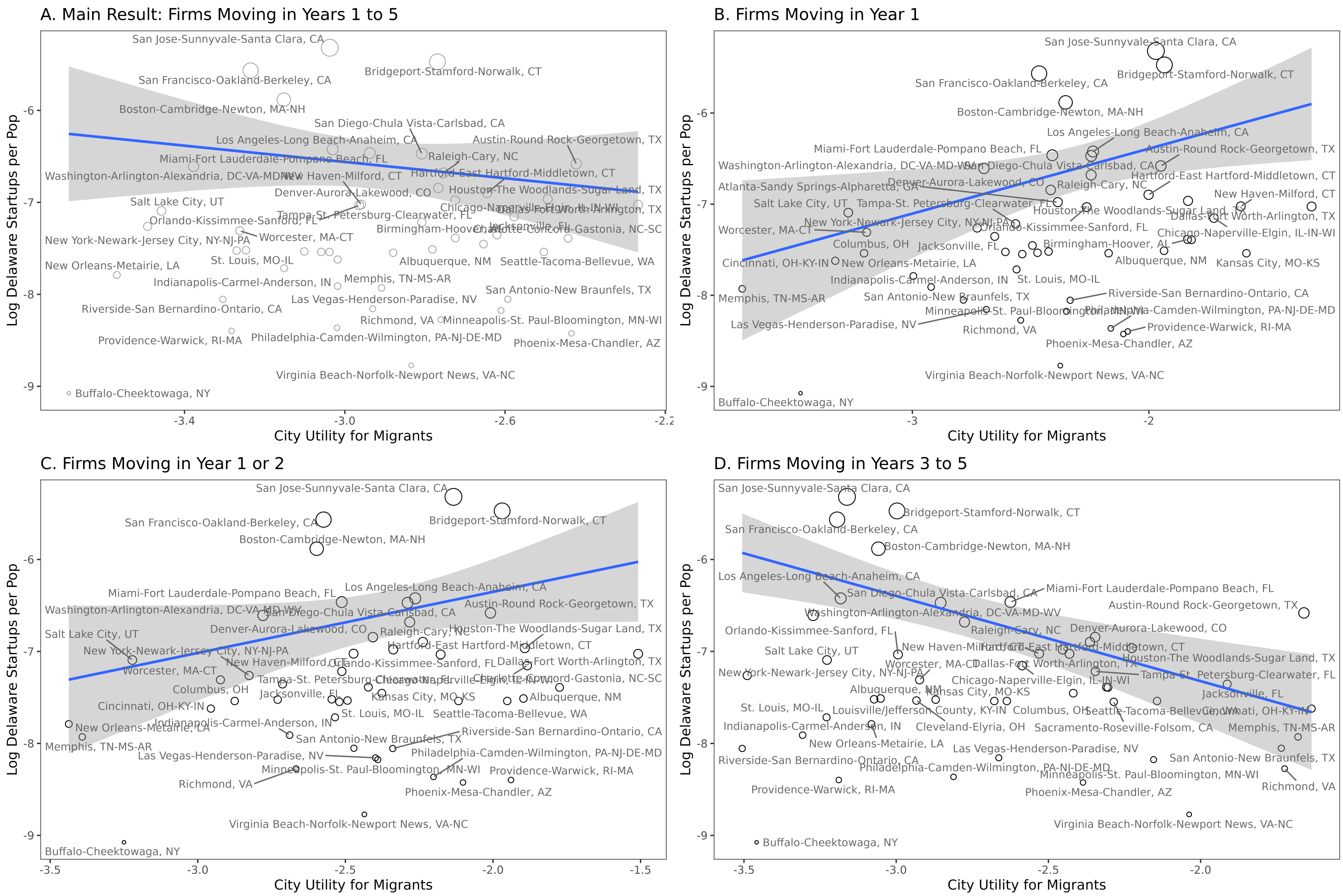
Notes: This figure reports the average unconditional probability of moving by age for startups. Most startups move early, but many also do not survive to be considered in the later periods.

Figure 4: Migration Rate by Founding Year, 1988-2014



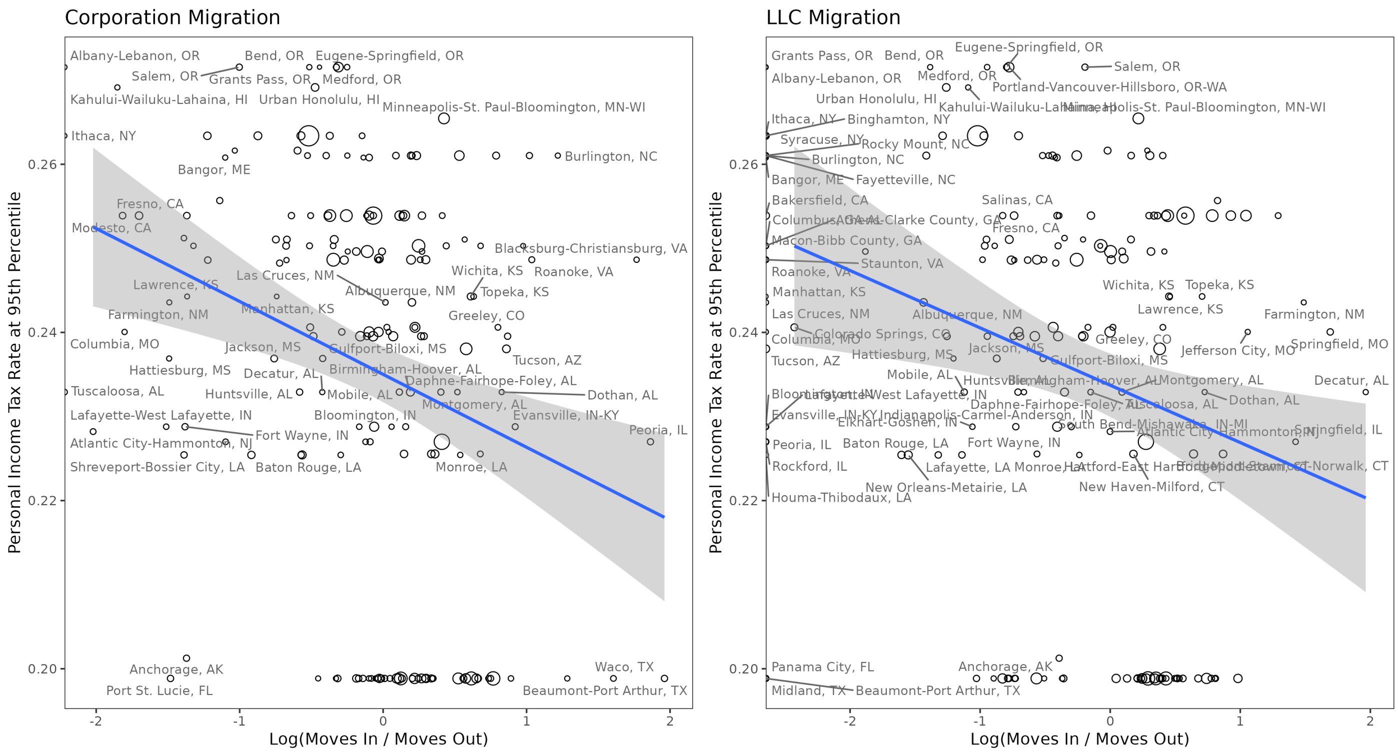
Notes: This figure reports the share of startups by founding year cohort that move within 5 years in our data across states to different CBSAs. Across different subsets of the data, we observe as consistent reduction in the net migration rate of firms in our data, which appear homologous to the observed decline in the cross-state migration of U.S. population.

Figure 5: Migrant City Utility Across Migration Age



Notes: The figure plots the estimated relative city utility for moving corporations based on the age at which they move. Panel A is all movers aged 0-5 years, Panels B through D split these into smaller year ranges. The fitted line is weighted by the ecosystem startup intensity (startups per capita). Bubble indicates startups founded in each city per capita.

Figure 6: Net Migration Rates and Taxes



Notes: This figure compares the net migration rate of firms, estimated as the log of the ratio of in moves over out moves, to the average personal income tax rate at the 95th percentile of income in that state, estimated by Moretti and Wilson (2017). We observe a large negative correlation between both variables.

Table 1: Summary Statistics

Panel A: Corporations (N=181663)

Statistic	Mean	St. Dev.
Incorporation Year	2,001.819	7.470
IPO	0.005	0.071
Acquired	0.026	0.159
Patent	0.058	0.233
Trademark	0.024	0.153
Moves in 2 years	0.033	0.180
Moves in 5 years	0.056	0.231

Panel B: LLCs (N=237307)

Statistic	Mean	St. Dev.
Incorporation Year	2,006.634	5.320
IPO	0.0001	0.010
Acquired	0.004	0.065
Patent	0.015	0.120
Trademark	0.010	0.102
Moves in 2 years	0.018	0.134
Moves in 5 years	0.028	0.166

Panel C: Estimated 5-year U.S. Migration Rates

Corporations	0.066	
LLCs	0.032	

Table 2: Summary Statistics for Migrant Flows Data

Panel A: State to State Migration Flows

Statistic	Mean	St. Dev.	N
Number of Corporation Movers	3.701	10.305	1,260
Number of Corporation Movers Cond. on ≥ 1	6.960	13.309	670
Number of LLC Movers	4.155	11.337	1,260
Number of LLC Movers Cond. on ≥ 1	9.519	15.607	550

Panel B: CBSA to CBSA Migration Flows

Statistic	Mean	St. Dev.	N
Number of Corporation Movers	0.228	1.783	34,040
Number of Corporation Movers Cond. on ≥ 1	3.826	6.927	1,749
Number of LLC Movers	0.153	1.474	34,040
Number of LLC Movers Cond. on ≥ 1	3.689	6.971	1,196

Table 3: Estimated Utility for Large US Cities (Population over 1 million in 2010)

Log Utility	Rank (age: 1-5)	CBSA Name	Moves In	Moves Out	Moves In LLC	Moves Out LLC	LLC Rank (age: 1-5)
-2.2455	1	Dallas-Fort Worth-Arlington, TX	453	215	324	241	16
-2.3842	2	Phoenix-Mesa-Chandler, AZ	94	53	47	32	9
-2.4	3	Austin-Round Rock-Georgetown, TX	166	88	96	74	8
-2.436	4	Charlotte-Concord-Gastonia, NC-SC	108	63	65	83	29
-2.4716	5	Houston-The Woodlands-Sugar Land, TX	376	205	282	184	17
-2.5033	6	Seattle-Tacoma-Bellevue, WA	145	86	43	76	32
-2.5524	7	Chicago-Naperville-Elgin, IL-IN-WI	471	311	341	261	11
-2.5824	8	San Antonio-New Braunfels, TX	45	26	25	20	25
-2.5872	9	Minneapolis-St. Paul-Bloomington, MN-WI	90	59	82	65	18
-2.6072	10	Jacksonville, FL	48	35	49	19	1
-2.6117	11	Nashville-Davidson–Murfreesboro–Franklin, TN	96	72	86	61	10
-2.6395	12	Hartford-East Hartford-Middletown, CT	89	63	29	15	6
-2.708	13	Atlanta-Sandy Springs-Alpharetta, GA	363	286	217	239	26
-2.7352	14	Richmond, VA	26	19	22	23	23
-2.739	15	Raleigh-Cary, NC	98	77	33	24	14
-2.7569	16	Denver-Aurora-Lakewood, CO	237	191	114	177	30
-2.77	17	Birmingham-Hoover, AL	51	42	36	51	33
-2.7925	18	Tampa-St. Petersburg-Clearwater, FL	95	78	88	42	4
-2.7928	19	San Diego-Chula Vista-Carlsbad, CA	153	134	217	77	2
-2.8196	20	Virginia Beach-Norfolk-Newport News, VA-NC	19	16	9	16	35
-2.8666	21	Memphis, TN-MS-AR	35	35	43	41	22
-2.8958	22	Sacramento-Roseville-Folsom, CA	32	28	38	15	3
-2.898	23	Las Vegas-Henderson-Paradise, NV	62	56	33	78	39
-2.9264	24	Miami-Fort Lauderdale-Pompano Beach, FL	349	314	339	239	12
-2.9466	25	Orlando-Kissimmee-Sanford, FL	75	68	73	58	20
-2.9866	26	Cincinnati, OH-KY-IN	52	55	24	43	36
-2.9909	27	Columbus, OH	52	49	27	42	38
-3.0023	28	Indianapolis-Carmel-Anderson, IN	47	49	31	47	27
-3.0143	29	Los Angeles-Long Beach-Anaheim, CA	507	544	663	374	7
-3.0493	30	San Jose-Sunnyvale-Santa Clara, CA	213	238	53	35	15
-3.0505	31	Kansas City, MO-KS	74	78	18	36	43
-3.0929	32	Cleveland-Elyria, OH	45	52	39	50	31
-3.1366	33	Boston-Cambridge-Newton, MA-NH	487	548	253	253	24
-3.1437	34	St. Louis, MO-IL	80	90	8	9	19
-3.2156	35	San Francisco-Oakland-Berkeley, CA	336	433	242	154	13
-3.2365	36	Louisville/Jefferson County, KY-IN	43	58	21	45	41
-3.2478	37	Portland-Vancouver-Hillsboro, OR-WA	100	134	46	100	37
-3.2753	38	Providence-Warwick, RI-MA	12	14	23	21	21
-3.2799	39	Riverside-San Bernardino-Ontario, CA	27	38	23	10	5
-3.3593	40	Washington-Arlington-Alexandria, DC-VA-MD-WV	257	362	140	181	28
-3.4623	41	New York-Newark-Jersey City, NY-NJ-PA	615	1038	263	731	42
-3.4623	42	Salt Lake City, UT	52	72	22	47	40
-3.5586	43	New Orleans-Metairie, LA	35	63	14	66	45
-3.6558	44	Buffalo-Cheektowaga, NY	11	19	1	4	44
-3.8411	45	Rochester, NY	5	11	2	4	34

Table 4: What Predicts City Utility?

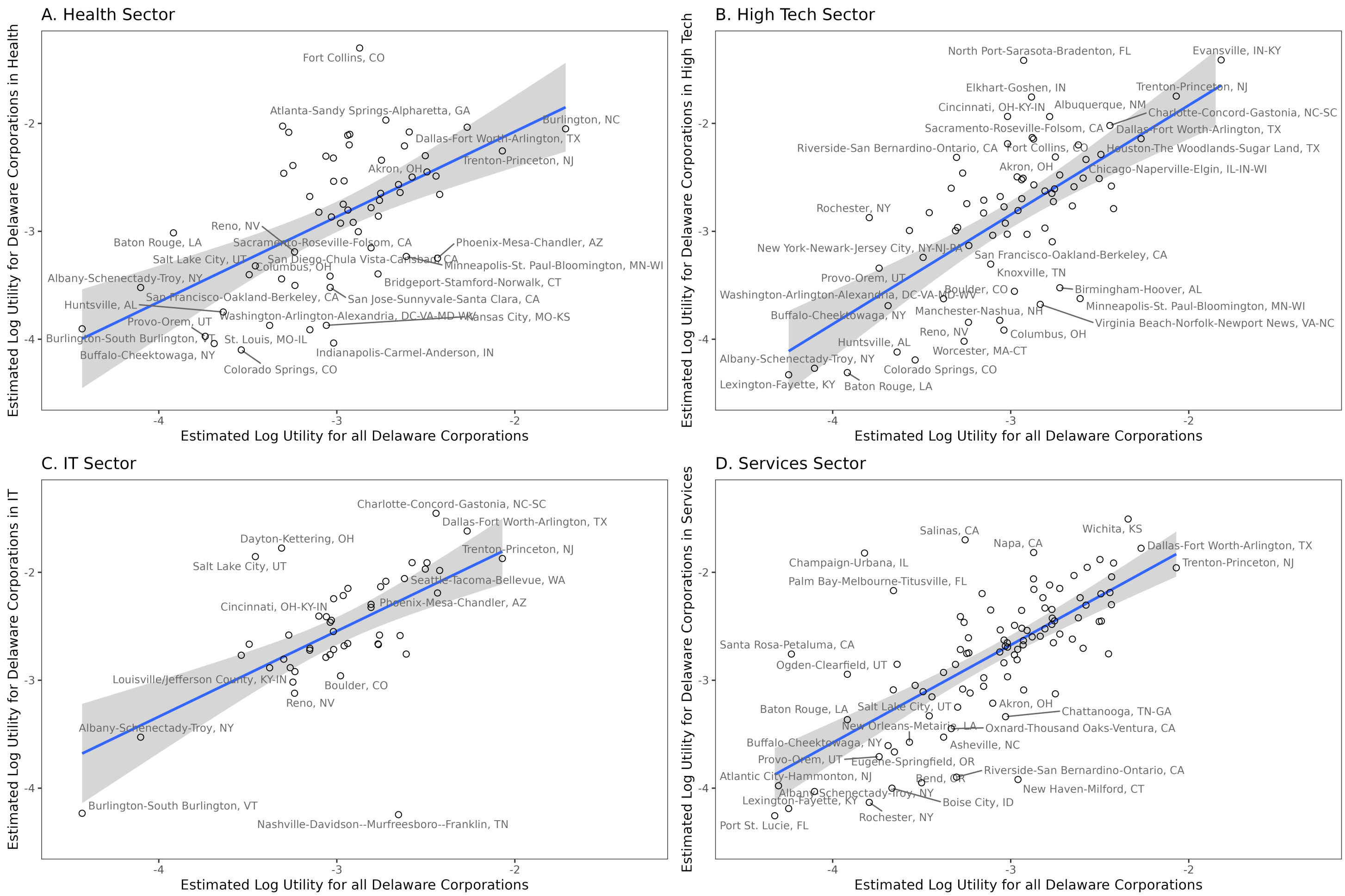
	Dependent variable:							
	Baseline	**Nursery Cities**			**Income Taxes**			
	Migrant City Utility	City Entrepreneurship	*Migrant* City Utility	*Migrant* City Utility	City Entrepreneurship	City Entrepreneurship	*Migrant* City Utility	*Migrant* City Utility
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth Startups per Capita	0.183** (0.066)							
Growth Startups per Capita × Later Movers (Years 3-5)	−0.315*** (0.090)							
Industry Concentration (HHI)		−0.108** (0.051)	−0.051 (0.036)					
Industry Concentration (HHI) × Later Movers (Years 3-5)			0.095* (0.051)					
Patenting per Capita		0.503*** (0.067)		0.049 (0.052)				
Patenting per Capita × Later Movers (Years 3-5)				−0.171* (0.088)				
Personal Income Tax (95th)					4.145 (3.591)		−2.979 (2.512)	
Personal Income Tax (95th) × Later Movers (Years 3-5)							−8.751** (3.717)	
Personal Income Tax (50th)						−11.212* (5.946)		−6.412* (3.469)
Personal Income Tax (50th) × Later Movers (Years 3-5)								−1.521 (5.546)
Observations	138	136	136	138	138	138	138	138
R^2	0.198	0.401	0.150	0.151	0.011	0.038	0.271	0.167

OLS regressions.

City utility is our estimated measure from the underlying graph of moves across cities in the United States. Columns 1-3 use the utility estimated through the moves of corporations registered under Delaware jurisdiction (but domiciled anywhere in the U.S.). Columns 4-6 use the utility estimated through the moves of LLCs registered under Delaware jurisdiction. Personal income tax estimates are taken from Moretti and Wilson (2017), who estimate state-level taxes for all U.S. at different points of the income distribution. Robust standard errors in parenthesis. Significance denoted as *p<0.1; **p<0.05; ***p<0.01

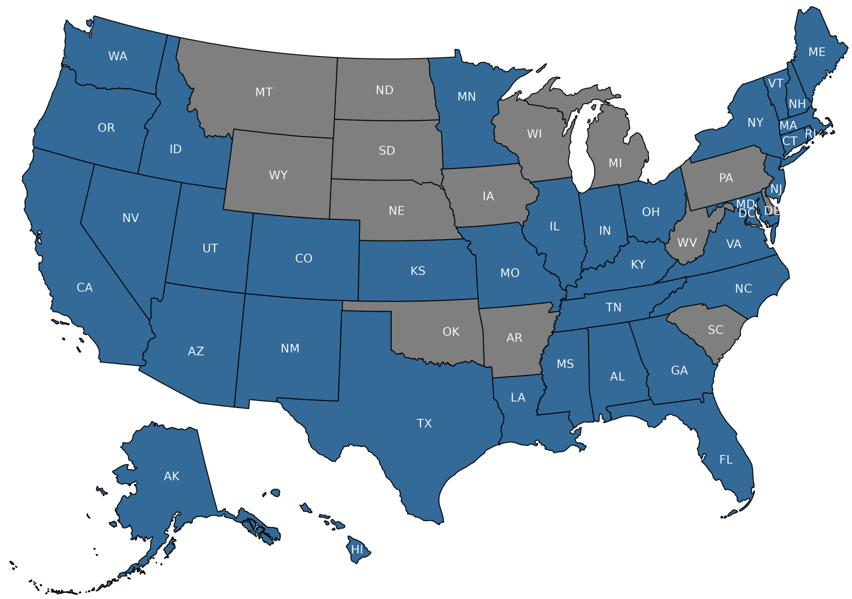
Appendix

Figure A1: Utility By Different Industries



Notes: We report the relationship between the estimated utility of all migrant Delaware corporations, and the utility estimates using only Delaware corporations with a name associated to a specific sector. To extract firms associated to specific sectors, we replicate the measures used in Guzman and Stern (2020) who use a different dataset of firms with tagged industries and then look for words in the firm name that are overarchingly associated with each industry. We focus on four broad industry groups: Healthcare, High Tech, IT, and Services.

Figure A2: 36 Jurisdictions Included in Dataset (82% of US Population)



*Notes:*This map represents the states whose business registrations are included in our data. Grey states are not included in our data.

Table A1: Estimated Utility for Large US Cities Based on LLCs (Population over 1 million in 2010).

Log Utility	CBSA	CBSA Name	LLC Moves In	LLC Moves Out	2010 Pop.	LLC Rank	Log Utility LLC
-2.607	27260	Jacksonville, FL	49	19	1,345,596	1	-1.76
-2.793	41740	San Diego-Chula Vista-Carlsbad, CA	217	77	3,095,313	2	-1.817
-2.896	40900	Sacramento-Roseville-Folsom, CA	38	15	2,149,127	3	-1.885
-2.793	45300	Tampa-St. Petersburg-Clearwater, FL	88	42	2,783,243	4	-1.959
-3.28	40140	Riverside-San Bernardino-Ontario, CA	23	10	4,224,851	5	-1.965
-2.639	25540	Hartford-East Hartford-Middletown, CT	29	15	1,212,381	6	-2.012
-3.014	31080	Los Angeles-Long Beach-Anaheim, CA	663	374	12,828,837	7	-2.227
-2.4	12420	Austin-Round Rock-Georgetown, TX	96	74	1,716,289	8	-2.302
-2.384	38060	Phoenix-Mesa-Chandler, AZ	47	32	4,192,887	9	-2.309
-2.612	34980	Nashville-Davidson–Murfreesboro–Franklin, TN	86	61	1,670,890	10	-2.334
-2.552	16980	Chicago-Naperville-Elgin, IL-IN-WI	341	261	9,461,105	11	-2.365
-2.926	33100	Miami-Fort Lauderdale-Pompano Beach, FL	339	239	5,564,635	12	-2.366
-3.216	41860	San Francisco-Oakland-Berkeley, CA	242	154	4,335,391	13	-2.374
-2.739	39580	Raleigh-Cary, NC	33	24	1,130,490	14	-2.383
-3.049	41940	San Jose-Sunnyvale-Santa Clara, CA	53	35	1,836,911	15	-2.392
-2.245	19100	Dallas-Fort Worth-Arlington, TX	324	241	6,426,214	16	-2.404
-2.472	26420	Houston-The Woodlands-Sugar Land, TX	282	184	5,920,416	17	-2.407
-2.587	33460	Minneapolis-St. Paul-Bloomington, MN-WI	82	65	3,348,859	18	-2.437
-3.144	41180	St. Louis, MO-IL	8	9	2,787,701	19	-2.437
-2.947	36740	Orlando-Kissimmee-Sanford, FL	73	58	2,134,411	20	-2.472
-3.275	39300	Providence-Warwick, RI-MA	23	21	1,600,852	21	-2.521
-2.867	32820	Memphis, TN-MS-AR	43	41	1,324,829	22	-2.554
-2.735	40060	Richmond, VA	22	23	1,208,101	23	-2.691
-3.137	14460	Boston-Cambridge-Newton, MA-NH	253	253	4,552,402	24	-2.696
-2.582	41700	San Antonio-New Braunfels, TX	25	20	2,142,508	25	-2.699
-2.708	12060	Atlanta-Sandy Springs-Alpharetta, GA	217	239	5,286,728	26	-2.795
-3.002	26900	Indianapolis-Carmel-Anderson, IN	31	47	1,887,877	27	-2.842
-3.359	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	140	181	5,636,232	28	-2.878
-2.436	16740	Charlotte-Concord-Gastonia, NC-SC	65	83	2,217,012	29	-2.943
-2.757	19740	Denver-Aurora-Lakewood, CO	114	177	2,543,482	30	-2.966
-3.093	17460	Cleveland-Elyria, OH	39	50	2,077,240	31	-2.972
-2.503	42660	Seattle-Tacoma-Bellevue, WA	43	76	3,439,809	32	-3.13
-2.77	13820	Birmingham-Hoover, AL	36	51	1,128,047	33	-3.131
-3.841	40380	Rochester, NY	2	4	1,079,671	34	-3.136
-2.82	47260	Virginia Beach-Norfolk-Newport News, VA-NC	9	16	1,676,822	35	-3.171
-2.987	17140	Cincinnati, OH-KY-IN	24	43	2,114,580	36	-3.281
-3.248	38900	Portland-Vancouver-Hillsboro, OR-WA	46	100	2,226,009	37	-3.324
-2.991	18140	Columbus, OH	27	42	1,901,974	38	-3.345
-2.898	29820	Las Vegas-Henderson-Paradise, NV	33	78	1,951,269	39	-3.41
-3.462	41620	Salt Lake City, UT	22	47	1,087,873	40	-3.418
-3.236	31140	Louisville/Jefferson County, KY-IN	21	45	1,235,708	41	-3.47
-3.462	35620	New York-Newark-Jersey City, NY-NJ-PA	263	731	19,567,410	42	-3.557
-3.051	28140	Kansas City, MO-KS	18	36	2,009,342	43	-3.614
-3.656	15380	Buffalo-Cheektowaga, NY	1	4	1,135,509	44	-3.755
-3.559	35380	New Orleans-Metairie, LA	14	66	1,189,866	45	-3.941

Table A2: Estimated Utility. Full List.

Log Utility	Rank	CBSA	CBSA Name	Moves In	Moves Out	2010 Pop.	LLC Rank	Log Utility LLC
-1.065	1	37900	Peoria, IL	12	2	379,186	NA	
-1.33	2	13980	Blacksburg-Christiansburg, VA	7	1	178,237	NA	
-1.444	3	13140	Beaumont-Port Arthur, TX	5	1	403,190	NA	
-1.546	4	39460	Punta Gorda, FL	4	1	159,978	NA	
-1.605	5	47380	Waco, TX	4	1	252,772	NA	
-1.705	6	15500	Burlington, NC	13	4	151,131	NA	
-1.784	7	21780	Evansville, IN-KY	12	5	311,552	122	-5.063
-1.807	8	40220	Roanoke, VA	8	3	308,707	NA	
-2.045	9	15940	Canton-Massillon, OH	7	3	404,422	NA	
-2.14	10	44420	Staunton, VA	2	2	118,502	NA	
-2.144	11	25860	Hickory-Lenoir-Morganton, NC	7	3	365,497	NA	
-2.153	12	27740	Johnson City, TN	6	2	198,716	NA	
-2.172	13	49180	Winston-Salem, NC	12	6	640,595	108	-3.693
-2.175	14	24540	Greeley, CO	4	2	252,825	NA	
-2.2	15	15260	Brunswick, GA	4	1	112,370	29	-2.33
-2.21	16	34940	Naples-Marco Island, FL	11	5	321,520	25	-2.304
-2.221	17	46060	Tucson, AZ	13	6	980,263	NA	
-2.241	18	20020	Dothan, AL	6	3	145,639	NA	
-2.245	19	19100	Dallas-Fort Worth-Arlington, TX	453	215	6,426,214	39	-2.404
-2.322	20	48620	Wichita, KS	19	10	630,919	23	-2.299
-2.349	21	33740	Monroe, LA	5	3	176,441	96	-3.438
-2.353	22	23540	Gainesville, FL	9	4	264,275	52	-2.614
-2.384	23	38060	Phoenix-Mesa-Chandler, AZ	94	53	4,192,887	27	-2.309
-2.4	24	12420	Austin-Round Rock-Georgetown, TX	166	88	1,716,289	24	-2.302
-2.403	25	42340	Savannah, GA	10	6	347,611	86	-3.297
-2.41	26	37860	Pensacola-Ferry Pass-Brent, FL	5	6	448,991	8	-1.856
-2.411	27	19300	Daphne-Fairhope-Foley, AL	3	2	182,265	NA	
-2.436	28	16740	Charlotte-Concord-Gastonia, NC-SC	108	63	2,217,012	69	-2.943
-2.441	29	19340	Davenport-Moline-Rock Island, IA-IL	1	3	379,690	NA	
-2.46	30	45820	Topeka, KS	8	4	233,870	12	-1.981
-2.472	31	26420	Houston-The Woodlands-Sugar Land, TX	376	205	5,920,416	40	-2.407
-2.476	32	42100	Santa Cruz-Watsonville, CA	9	6	262,382	NA	
-2.483	33	15980	Cape Coral-Fort Myers, FL	21	12	618,754	17	-2.224
-2.503	34	42660	Seattle-Tacoma-Bellevue, WA	145	86	3,439,809	76	-3.13
-2.542	35	33860	Montgomery, AL	12	8	374,536	53	-2.65
-2.552	36	16980	Chicago-Naperville-Elgin, IL-IN-WI	471	311	9,461,105	34	-2.365
-2.568	37	31340	Lynchburg, VA	4	3	252,634	NA	
-2.582	38	41700	San Antonio-New Braunfels, TX	45	26	2,142,508	56	-2.699
-2.587	39	33660	Mobile, AL	7	6	412,992	114	-3.844
-2.587	40	33460	Minneapolis-St. Paul-Bloomington, MN-WI	90	59	3,348,859	41	-2.437
-2.607	41	27260	Jacksonville, FL	48	35	1,345,596	4	-1.76
-2.612	42	34980	Nashville-Davidson–Murfreesboro–Franklin, TN	96	72	1,670,890	30	-2.334
-2.62	43	12700	Barnstable Town, MA	11	9	215,888	123	-5.063
-2.639	44	35980	Norwich-New London, CT	6	4	274,055	NA	
-2.639	45	25540	Hartford-East Hartford-Middletown, CT	89	63	1,212,381	15	-2.012
-2.644	46	18880	Crestview-Fort Walton Beach-Destin, FL	5	3	235,865	26	-2.307
-2.644	47	27620	Jefferson City, MO	4	4	149,807	13	-1.983
-2.648	48	12020	Athens-Clarke County, GA	3	1	192,541	NA	
-2.676	49	36100	Ocala, FL	3	2	331,298	NA	
-2.702	50	41100	St. George, UT	3	2	138,115	NA	
-2.708	51	12060	Atlanta-Sandy Springs-Alpharetta, GA	363	286	5,286,728	62	-2.795
-2.72	52	44700	Stockton, CA	3	3	685,306	NA	
-2.735	53	40060	Richmond, VA	26	19	1,208,101	54	-2.691
-2.739	54	39580	Raleigh-Cary, NC	98	77	1,130,490	37	-2.383
-2.746	55	42200	Santa Maria-Santa Barbara, CA	11	12	423,895	20	-2.265
-2.753	56	10420	Akron, OH	22	17	703,200	61	-2.791
-2.757	57	19740	Denver-Aurora-Lakewood, CO	237	191	2,543,482	70	-2.966
-2.758	58	14860	Bridgeport-Stamford-Norwalk, CT	242	174	916,829	14	-2.01
-2.765	59	40420	Rockford, IL	4	4	349,431	NA	
-2.766	60	10740	Albuquerque, NM	51	42	887,077	110	-3.715
-2.77	61	13820	Birmingham-Hoover, AL	51	42	1,128,047	77	-3.131
-2.778	62	18580	Corpus Christi, TX	3	2	428,185	NA	
-2.793	63	45300	Tampa-St. Petersburg-Clearwater, FL	95	78	2,783,243	10	-1.959
-2.793	64	41740	San Diego-Chula Vista-Carlsbad, CA	153	134	3,095,313	6	-1.817
-2.804	65	22180	Fayetteville, NC	4	3	366,383	NA	
-2.804	66	21340	El Paso, TX	6	4	804,123	31	-2.344
-2.82	67	47260	Virginia Beach-Norfolk-Newport News, VA-NC	19	16	1,676,822	80	-3.171
-2.847	68	22660	Fort Collins, CO	8	6	299,630	63	-2.814
-2.85	69	44060	Spokane-Spokane Valley, WA	4	2	527,753	57	-2.746
-2.866	70	43780	South Bend-Mishawaka, IN-MI	5	4	319,224	58	-2.749
-2.867	71	32820	Memphis, TN-MS-AR	35	35	1,324,829	50	-2.554
-2.869	72	34900	Napa, CA	7	8	136,484	1	-1.549
-2.87	73	24660	Greensboro-High Point, NC	26	22	723,801	73	-3.07
-2.873	74	12540	Bakersfield, CA	4	3	839,631	NA	
-2.875	75	31420	Macon-Bibb County, GA	2	3	232,293	NA	
-2.891	76	21140	Elkhart-Goshen, IN	5	6	197,559	NA	
-2.896	77	40900	Sacramento-Roseville-Folsom, CA	32	28	2,149,127	9	-1.885
-2.898	78	29820	Las Vegas-Henderson-Paradise, NV	62	56	1,951,269	92	-3.41
-2.907	79	35840	North Port-Sarasota-Bradenton, FL	28	20	702,281	16	-2.145
-2.917	80	40580	Rocky Mount, NC	3	4	152,392	NA	
-2.917	81	29740	Las Cruces, NM	4	4	209,233	NA	
-2.921	82	44140	Springfield, MA	11	11	621,570	22	-2.296
-2.926	83	33100	Miami-Fort Lauderdale-Pompano Beach, FL	349	314	5,564,635	35	-2.366
-2.936	84	20500	Durham-Chapel Hill, NC	55	52	504,357	49	-2.55
-2.947	85	36740	Orlando-Kissimmee-Sanford, FL	75	68	2,134,411	43	-2.472

-2.949	86	35300	New Haven-Milford, CT	37	33	862,477	59	-2.776
-2.957	87	45780	Toledo, OH	12	9	610,001	91	-3.377
-2.96	88	14500	Boulder, CO	82	79	294,567	60	-2.785
-2.973	89	45220	Tallahassee, FL	6	6	367,413	19	-2.257
-2.987	90	17140	Cincinnati, OH-KY-IN	52	55	2,114,580	85	-3.281
-2.988	91	37460	Panama City, FL	2	2	184,715	NA	
-2.99	92	16860	Chattanooga, TN-GA	14	14	528,143	95	-3.418
-2.991	93	18140	Columbus, OH	52	49	1,901,974	88	-3.345
-3.002	94	26900	Indianapolis-Carmel-Anderson, IN	47	49	1,887,877	64	-2.842
-3.01	95	38340	Pittsfield, MA	2	3	131,219	7	-1.847
-3.014	96	31080	Los Angeles-Long Beach-Anaheim, CA	507	544	12,828,837	18	-2.227
-3.025	97	31700	Manchester-Nashua, NH	32	31	400,721	109	-3.7
-3.049	98	41940	San Jose-Sunnyvale-Santa Clara, CA	213	238	1,836,911	38	-2.392
-3.051	99	28140	Kansas City, MO-KS	74	78	2,009,342	104	-3.614
-3.074	100	14740	Bremerton-Silverdale-Port Orchard, WA	3	3	251,133	NA	
-3.074	101	28940	Knoxville, TN	17	20	837,571	33	-2.365
-3.084	102	49660	Youngstown-Warren-Boardman, OH-PA	4	4	565,773	105	-3.655
-3.086	103	28700	Kingsport-Bristol, TN-VA	3	4	309,544	NA	
-3.093	104	17460	Cleveland-Elyria, OH	45	52	2,077,240	71	-2.972
-3.12	105	30340	Lewiston-Auburn, ME	3	3	107,702	NA	
-3.125	106	38860	Portland-South Portland, ME	22	25	514,098	74	-3.084
-3.137	107	14460	Boston-Cambridge-Newton, MA-NH	487	548	4,552,402	55	-2.696
-3.141	108	29180	Lafayette, LA	10	18	466,750	107	-3.69
-3.144	109	41180	St. Louis, MO-IL	80	90	2,787,701	42	-2.437
-3.155	110	13780	Binghamton, NY	2	2	251,725	NA	
-3.173	111	44100	Springfield, IL	3	3	210,170	NA	
-3.203	112	29460	Lakeland-Winter Haven, FL	5	5	602,095	66	-2.902
-3.212	113	19430	Dayton-Kettering, OH	9	15	799,232	113	-3.769
-3.212	114	39900	Reno, NV	17	19	425,417	100	-3.504
-3.216	115	41860	San Francisco-Oakland-Berkeley, CA	336	433	4,335,391	36	-2.374
-3.228	116	41500	Salinas, CA	4	8	415,057	NA	
-3.236	117	31140	Louisville/Jefferson County, KY-IN	43	58	1,235,708	98	-3.47
-3.243	118	19660	Deltona-Daytona Beach-Ormond Beach, FL	10	10	590,289	21	-2.272
-3.248	119	38900	Portland-Vancouver-Hillsboro, OR-WA	100	134	2,226,009	87	-3.324
-3.253	120	25060	Gulfport-Biloxi, MS	7	11	370,702	84	-3.232
-3.264	121	49340	Worcester, MA-CT	23	28	916,980	32	-2.359
-3.274	122	16820	Charlottesville, VA	7	7	218,705	103	-3.61
-3.275	123	39300	Providence-Warwick, RI-MA	12	14	1,600,852	47	-2.521
-3.28	124	40140	Riverside-San Bernardino-Ontario, CA	27	38	4,224,851	11	-1.965
-3.294	125	14540	Bowling Green, KY	3	6	158,599	72	-3.007
-3.333	126	26380	Houma-Thibodaux, LA	2	3	208,178	124	-5.063
-3.338	127	37100	Oxnard-Thousand Oaks-Ventura, CA	13	19	823,318	68	-2.935
-3.357	128	11700	Asheville, NC	7	10	424,858	28	-2.313
-3.359	129	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	257	362	5,636,232	65	-2.878
-3.364	130	31740	Manhattan, KS	2	4	92,719	NA	
-3.37	131	42680	Sebastian-Vero Beach, FL	3	5	138,028	3	-1.622
-3.428	132	46520	Urban Honolulu, HI	16	26	953,207	111	-3.751
-3.431	133	17980	Columbus, GA-AL	2	3	294,865	125	-5.063
-3.462	134	35620	New York-Newark-Jersey City, NY-NJ-PA	615	1038	19,567,410	101	-3.557
-3.462	135	41620	Salt Lake City, UT	52	72	1,087,873	94	-3.418
-3.478	136	13460	Bend, OR	5	8	157,733	106	-3.668
-3.481	137	24420	Grants Pass, OR	2	3	82,713	NA	
-3.512	138	17820	Colorado Springs, CO	16	27	645,613	121	-4.644
-3.526	139	19460	Decatur, AL	2	3	153,829	NA	
-3.559	140	35380	New Orleans-Metairie, LA	35	63	1,189,866	117	-3.941
-3.623	141	21660	Eugene-Springfield, OR	7	10	351,715	81	-3.213
-3.624	142	27140	Jackson, MS	13	28	567,122	102	-3.601
-3.631	143	14020	Bloomington, IN	3	3	159,549	NA	
-3.632	144	26580	Huntington-Ashland, WV-KY-OH	2	4	364,908	NA	
-3.639	145	45060	Syracuse, NY	2	3	662,577	NA	
-3.642	146	26620	Huntsville, AL	9	19	417,593	97	-3.462
-3.652	147	14260	Boise City, ID	18	33	616,561	46	-2.51
-3.656	148	15380	Buffalo-Cheektowaga, NY	11	19	1,135,509	112	-3.755
-3.659	149	42020	San Luis Obispo-Paso Robles, CA	3	5	269,637	2	-1.556
-3.665	150	37340	Palm Bay-Melbourne-Titusville, FL	10	15	543,376	48	-2.524
-3.669	151	44180	Springfield, MO	4	5	436,712	NA	
-3.732	152	39340	Provo-Orem, UT	22	43	526,810	93	-3.416
-3.767	153	32780	Medford, OR	3	4	203,206	NA	
-3.781	154	12260	Augusta-Richmond County, GA-SC	2	4	564,873	NA	
-3.799	155	16580	Champaign-Urbana, IL	3	9	231,891	NA	
-3.841	156	40380	Rochester, NY	5	11	1,079,671	78	-3.136
-3.843	157	33260	Midland, TX	2	3	141,671	126	-5.063
-3.856	158	17660	Coeur d'Alene, ID	2	6	138,494	5	-1.816
-3.902	159	12940	Baton Rouge, LA	9	25	802,484	120	-4.34
-3.905	160	36260	Ogden-Clearfield, UT	5	11	597,159	44	-2.49
-3.938	161	26140	Homosassa Springs, FL	2	2	141,236	NA	
-3.941	162	41420	Salem, OR	2	5	390,738	82	-3.215
-3.947	163	23060	Fort Wayne, IN	2	8	416,257	83	-3.225
-4.037	164	48900	Wilmington, NC	3	7	254,884	99	-3.498
-4.12	165	10580	Albany-Schenectady-Troy, NY	8	29	870,716	115	-3.86
-4.149	166	29940	Lawrence, KS	1	4	110,826	NA	
-4.203	167	12620	Bangor, ME	1	3	153,923	NA	
-4.216	168	42220	Santa Rosa-Petaluma, CA	3	12	483,878	45	-2.501
-4.225	169	30460	Lexington-Fayette, KY	10	34	472,099	90	-3.372
-4.228	170	23580	Gainesville, GA	1	4	179,684	NA	
-4.297	171	38940	Port St. Lucie, FL	3	13	424,107	67	-2.926
-4.359	172	15540	Burlington-South Burlington, VT	12	48	211,261	79	-3.155
-4.487	173	17860	Columbia, MO	1	5	162,642	NA	
-4.522	174	29200	Lafayette-West Lafayette, IN	1	5	201,789	NA	

-4.696	175	25620	Hattiesburg, MS	1	4	142,842	118	-4.083
-4.796	176	11260	Anchorage, AK	2	8	380,821	75	-3.088
-4.837	177	43340	Shreveport-Bossier City, LA	2	8	439,811	119	-4.116
-4.983	178	22140	Farmington, NM	1	4	130,044	NA	
-5.017	179	12100	Atlantic City-Hammonton, NJ	1	8	274,549	51	-2.575
-5.16	180	33700	Modesto, CA	1	6	514,453	NA	
-5.373	181	10540	Albany-Lebanon, OR	0	6	116,672	NA	
-5.373	182	23420	Fresno, CA	0	5	930,450	89	-3.357
-5.373	183	27060	Ithaca, NY	0	7	101,564	NA	
-5.373	184	27980	Kahului-Wailuku-Lahaina, HI	1	6	154,924	116	-3.891
-5.373	185	46220	Tuscaloosa, AL	0	4	230,162	NA	

Table A3: Number of new Delaware corporations and LLCs (firm births) by city.

CBSA	2010 Pop.	CBSA Name	Corporations	LLCs	Corps / Pop	LLCs / Pop
41940	1,836,911	San Jose-Sunnyvale-Santa Clara, CA	8,996	4,187	4.8974	2.2794
14860	916,829	Bridgeport-Stamford-Norwalk, CT	3,854	6,428	4.2036	7.0111
41860	4,335,391	San Francisco-Oakland-Berkeley, CA	16,580	18,748	3.8243	4.3244
14500	294,567	Boulder, CO	1,103	685	3.7445	2.3254
14460	4,552,402	Boston-Cambridge-Newton, MA-NH	12,685	15,571	2.7864	3.4204
20500	504,357	Durham-Chapel Hill, NC	1,055	587	2.0918	1.1639
31080	12,828,837	Los Angeles-Long Beach-Anaheim, CA	20,842	43,382	1.6246	3.3816
33100	5,564,635	Miami-Fort Lauderdale-Pompano Beach, FL	8,678	12,503	1.5595	2.2469
41740	3,095,313	San Diego-Chula Vista-Carlsbad, CA	4,793	8,445	1.5485	2.7283
12420	1,716,289	Austin-Round Rock-Georgetown, TX	2,380	3,431	1.3867	1.9991
47900	5,636,232	Washington-Arlington-Alexandria, DC-VA-MD-WV	7,603	5,278	1.349	0.9364
34900	136,484	Napa, CA	177	400	1.2969	2.9307
39580	1,130,490	Raleigh-Cary, NC	1,420	852	1.2561	0.7537
15540	211,261	Burlington-South Burlington, VT	262	143	1.2402	0.6769
42680	138,028	Sebastian-Vero Beach, FL	158	150	1.1447	1.0867
19740	2,543,482	Denver-Aurora-Lakewood, CO	2,711	3,478	1.0659	1.3674
42200	423,895	Santa Maria-Santa Barbara, CA	440	846	1.038	1.9958
12700	215,888	Barnstable Town, MA	220	294	1.019	1.3618
25540	1,212,381	Hartford-East Hartford-Middletown, CT	1,225	845	1.0104	0.697
42100	262,382	Santa Cruz-Watsonville, CA	260	111	0.9909	0.423
31700	400,721	Manchester-Nashua, NH	395	163	0.9857	0.4068
26420	5,920,416	Houston-The Woodlands-Sugar Land, TX	5,598	8,298	0.9455	1.4016
12060	5,286,728	Atlanta-Sandy Springs-Alpharetta, GA	4,928	5,139	0.9321	0.9721
35300	862,477	New Haven-Milford, CT	768	439	0.8905	0.509
19100	6,426,214	Dallas-Fort Worth-Arlington, TX	5,712	10,878	0.8889	1.6928
36740	2,134,411	Orlando-Kissimmee-Sanford, FL	1,884	2,868	0.8827	1.3437
35840	702,281	North Port-Sarasota-Bradenton, FL	610	647	0.8686	0.9213
41620	1,087,873	Salt Lake City, UT	904	947	0.831	0.8705
38340	131,219	Pittsfield, MA	107	193	0.8154	1.4708
16980	9,461,105	Chicago-Naperville-Elgin, IL-IN-WI	7,400	14,257	0.7821	1.5069
39340	526,810	Provo-Orem, UT	402	376	0.7631	0.7137
34940	321,520	Naples-Marco Island, FL	245	406	0.762	1.2628
45300	2,783,243	Tampa-St. Petersburg-Clearwater, FL	2,044	2,603	0.7344	0.9352
35620	19,567,410	New York-Newark-Jersey City, NY-NJ-PA	13,738	14,370	0.7021	0.7344
30460	472,099	Lexington-Fayette, KY	326	300	0.6905	0.6355
49340	916,980	Worcester, MA-CT	614	533	0.6696	0.5813
27260	1,345,596	Jacksonville, FL	861	993	0.6399	0.738
15980	618,754	Cape Coral-Fort Myers, FL	395	508	0.6384	0.821
42220	483,878	Santa Rosa-Petaluma, CA	308	425	0.6365	0.8783
26620	417,593	Huntsville, AL	265	260	0.6346	0.6226
37340	543,376	Palm Bay-Melbourne-Titusville, FL	340	277	0.6257	0.5098
13820	1,128,047	Birmingham-Hoover, AL	698	1,898	0.6188	1.6826
38940	424,107	Port St. Lucie, FL	262	259	0.6178	0.6107
16740	2,217,012	Charlotte-Concord-Gastonia, NC-SC	1,368	2,430	0.617	1.0961
37100	823,318	Oxnard-Thousand Oaks-Ventura, CA	486	461	0.5903	0.5599
34980	1,670,890	Nashville-Davidson–Murfreesboro–Franklin, TN	968	1,575	0.5793	0.9426
41500	415,057	Salinas, CA	227	299	0.5469	0.7204
10740	887,077	Albuquerque, NM	485	85	0.5467	0.0958
31140	1,235,708	Louisville/Jefferson County, KY-IN	670	795	0.5422	0.6434
38900	2,226,009	Portland-Vancouver-Hillsboro, OR-WA	1,202	1,383	0.54	0.6213
23540	264,275	Gainesville, FL	142	134	0.5373	0.507
17460	2,077,240	Cleveland-Elyria, OH	1,111	1,257	0.5348	0.6051
42660	3,439,809	Seattle-Tacoma-Bellevue, WA	1,831	1,285	0.5323	0.3736
18140	1,901,974	Columbus, OH	1,012	875	0.5321	0.46
28140	2,009,342	Kansas City, MO-KS	1,069	551	0.532	0.2742
10420	703,200	Akron, OH	374	211	0.5319	0.3001
12100	274,549	Atlantic City-Hammonton, NJ	145	169	0.5281	0.6156
40900	2,149,127	Sacramento-Roseville-Folsom, CA	1,133	1,445	0.5272	0.6724
21140	197,559	Elkhart-Goshen, IN	103	57	0.5214	0.2885
17820	645,613	Colorado Springs, CO	331	208	0.5127	0.3222
24660	723,801	Greensboro-High Point, NC	366	332	0.5057	0.4587
16820	218,705	Charlottesville, VA	109	236	0.4984	1.0791
17140	2,114,580	Cincinnati, OH-KY-IN	1,036	863	0.4899	0.4081
38860	514,098	Portland-South Portland, ME	249	298	0.4843	0.5797
44140	621,570	Springfield, MA	299	300	0.481	0.4826
35980	274,055	Norwich-New London, CT	131	86	0.478	0.3138
19660	590,289	Deltona-Daytona Beach-Ormond Beach, FL	282	333	0.4777	0.5641
16580	231,891	Champaign-Urbana, IL	109	65	0.47	0.2803
15500	151,131	Burlington, NC	71	23	0.4698	0.1522
33260	141,671	Midland, TX	66	225	0.4659	1.5882
42020	269,637	San Luis Obispo-Paso Robles, CA	124	222	0.4599	0.8233
18880	235,865	Crestview-Fort Walton Beach-Destin, FL	107	159	0.4536	0.6741
14540	158,599	Bowling Green, KY	71	82	0.4477	0.517
41180	2,787,701	St. Louis, MO-IL	1,242	239	0.4455	0.0857
48900	254,884	Wilmington, NC	110	91	0.4316	0.357
14260	616,561	Boise City, ID	256	278	0.4152	0.4509
35380	1,189,866	New Orleans-Metairie, LA	493	401	0.4143	0.337
22660	299,630	Fort Collins, CO	124	110	0.4138	0.3671
11700	424,858	Asheville, NC	161	110	0.379	0.2589
39900	425,417	Reno, NV	160	177	0.3761	0.4161
40580	152,392	Rocky Mount, NC	56	42	0.3675	0.2756
26900	1,887,877	Indianapolis-Carmel-Anderson, IN	693	713	0.3671	0.3777
15260	112,370	Brunswick, GA	41	33	0.3649	0.2937
32820	1,324,829	Memphis, TN-MS-AR	477	904	0.36	0.6824
16860	528,143	Chattanooga, TN-GA	189	286	0.3579	0.5415

27980	154,924	Kahului-Wailuku-Lahaina, HI	53	91	0.3421	0.5874
46520	953,207	Urban Honolulu, HI	326	537	0.342	0.5634
42340	347,611	Savannah, GA	116	91	0.3337	0.2618
29180	466,750	Lafayette, LA	155	90	0.3321	0.1928
20020	145,639	Dothan, AL	48	48	0.3296	0.3296
26140	141,236	Homosassa Springs, FL	46	53	0.3257	0.3753
45220	367,413	Tallahassee, FL	117	141	0.3184	0.3838
41700	2,142,508	San Antonio-New Braunfels, TX	682	750	0.3183	0.3501
40140	4,224,851	Riverside-San Bernardino-Ontario, CA	1,342	1,527	0.3176	0.3614
17860	162,642	Columbia, MO	51	6	0.3136	0.0369
39460	159,978	Punta Gorda, FL	50	35	0.3125	0.2188
17660	138,494	Coeur d'Alene, ID	43	38	0.3105	0.2744
21780	311,552	Evansville, IN-KY	96	75	0.3081	0.2407
33860	374,536	Montgomery, AL	115	314	0.307	0.8384
13460	157,733	Bend, OR	47	87	0.298	0.5516
19430	799,232	Dayton-Kettering, OH	237	164	0.2965	0.2052
29820	1,951,269	Las Vegas-Henderson-Paradise, NV	560	725	0.287	0.3716
45780	610,001	Toledo, OH	175	242	0.2869	0.3967
17980	294,865	Columbus, GA-AL	84	106	0.2849	0.3595
29460	602,095	Lakeland-Winter Haven, FL	171	175	0.284	0.2907
37860	448,991	Pensacola-Ferry Pass-Brent, FL	127	110	0.2829	0.245
33460	3,348,859	Minneapolis-St. Paul-Bloomington, MN-WI	942	3,250	0.2813	0.9705
33660	412,992	Mobile, AL	114	108	0.276	0.2615
36100	331,298	Ocala, FL	91	86	0.2747	0.2596
33700	514,453	Modesto, CA	141	118	0.2741	0.2294
19300	182,265	Daphne-Fairhope-Foley, AL	49	50	0.2688	0.2743
41100	138,115	St. George, UT	37	31	0.2679	0.2245
27620	149,807	Jefferson City, MO	40	38	0.267	0.2537
37460	184,715	Panama City, FL	49	54	0.2653	0.2923
28940	837,571	Knoxville, TN	215	261	0.2567	0.3116
49180	640,595	Winston-Salem, NC	164	125	0.256	0.1951
40060	1,208,101	Richmond, VA	308	570	0.2549	0.4718
40420	349,431	Rockford, IL	89	74	0.2547	0.2118
27140	567,122	Jackson, MS	144	142	0.2539	0.2504
43780	319,224	South Bend-Mishawaka, IN-MI	81	59	0.2537	0.1848
44100	210,170	Springfield, IL	53	47	0.2522	0.2236
48620	630,919	Wichita, KS	151	120	0.2393	0.1902
27740	198,716	Johnson City, TN	47	42	0.2365	0.2114
23580	179,684	Gainesville, GA	42	37	0.2337	0.2059
36260	597,159	Ogden-Clearfield, UT	138	145	0.2311	0.2428
45820	233,870	Topeka, KS	54	308	0.2309	1.317
12620	153,923	Bangor, ME	35	28	0.2274	0.1819
37900	379,186	Peoria, IL	86	55	0.2268	0.145
39300	1,600,852	Providence-Warwick, RI-MA	361	405	0.2255	0.253
29200	201,789	Lafayette-West Lafayette, IN	45	40	0.223	0.1982
32780	203,206	Medford, OR	45	48	0.2215	0.2362
29740	209,233	Las Cruces, NM	46	12	0.2199	0.0574
38060	4,192,887	Phoenix-Mesa-Chandler, AZ	920	882	0.2194	0.2104
12940	802,484	Baton Rouge, LA	175	163	0.2181	0.2031
29940	110,826	Lawrence, KS	24	11	0.2166	0.0993
30340	107,702	Lewiston-Auburn, ME	23	20	0.2136	0.1857
14020	159,549	Bloomington, IN	34	40	0.2131	0.2507
21660	351,715	Eugene-Springfield, OR	72	104	0.2047	0.2957
40220	308,707	Roanoke, VA	63	33	0.2041	0.1069
14740	251,133	Bremerton-Silverdale-Port Orchard, WA	51	31	0.2031	0.1234
44420	118,502	Staunton, VA	24	12	0.2025	0.1013
23060	416,257	Fort Wayne, IN	84	122	0.2018	0.2931
22180	366,383	Fayetteville, NC	73	54	0.1992	0.1474
31420	232,293	Macon-Bibb County, GA	46	42	0.198	0.1808
12020	192,541	Athens-Clarke County, GA	37	42	0.1922	0.2181
22140	130,044	Farmington, NM	25	3	0.1922	0.0231
10540	116,672	Albany-Lebanon, OR	22	27	0.1886	0.2314
10580	870,716	Albany-Schenectady-Troy, NY	160	266	0.1838	0.3055
44180	436,712	Springfield, MO	80	16	0.1832	0.0366
33740	176,441	Monroe, LA	32	20	0.1814	0.1134
15940	404,422	Canton-Massillon, OH	72	50	0.178	0.1236
19460	153,829	Decatur, AL	27	25	0.1755	0.1625
31340	252,634	Lynchburg, VA	44	23	0.1742	0.091
23420	930,450	Fresno, CA	159	274	0.1709	0.2945
13980	178,237	Blacksburg-Christiansburg, VA	30	10	0.1683	0.0561
28700	309,544	Kingsport-Bristol, TN-VA	52	53	0.168	0.1712
25860	365,497	Hickory-Lenoir-Morganton, NC	60	69	0.1642	0.1888
31740	92,719	Manhattan, KS	15	2	0.1618	0.0216
12540	839,631	Bakersfield, CA	134	140	0.1596	0.1667
44060	527,753	Spokane-Spokane Valley, WA	83	57	0.1573	0.108
47260	1,676,822	Virginia Beach-Norfolk-Newport News, VA-NC	260	349	0.1551	0.2081
44700	685,306	Stockton, CA	106	170	0.1547	0.2481
43340	439,811	Shreveport-Bossier City, LA	67	76	0.1523	0.1728
25060	370,702	Gulfport-Biloxi, MS	56	37	0.1511	0.0998
24540	252,825	Greeley, CO	38	31	0.1503	0.1226
49660	565,773	Youngstown-Warren-Boardman, OH-PA	80	47	0.1414	0.0831
25620	142,842	Hattiesburg, MS	20	30	0.14	0.21
24420	82,713	Grants Pass, OR	11	14	0.133	0.1693
12260	564,873	Augusta-Richmond County, GA-SC	75	42	0.1328	0.0744
46220	230,162	Tuscaloosa, AL	30	59	0.1303	0.2563
26380	208,178	Houma-Thibodaux, LA	27	19	0.1297	0.0913
26580	364,908	Huntington-Ashland, WV-KY-OH	45	30	0.1233	0.0822
47380	252,772	Waco, TX	31	39	0.1226	0.1543
15380	1,135,509	Buffalo-Cheektowaga, NY	130	46	0.1145	0.0405

18580	428,185	Corpus Christi, TX	49	49	0.1144	0.1144
21340	804,123	El Paso, TX	92	226	0.1144	0.2811
46060	980,263	Tucson, AZ	112	92	0.1143	0.0939
19340	379,690	Davenport-Moline-Rock Island, IA-IL	43	42	0.1133	0.1106
41420	390,738	Salem, OR	38	56	0.0973	0.1433
13780	251,725	Binghamton, NY	21	3	0.0834	0.0119
13140	403,190	Beaumont-Port Arthur, TX	29	25	0.0719	0.062
11260	380,821	Anchorage, AK	23	79	0.0604	0.2074
40380	1,079,671	Rochester, NY	59	42	0.0546	0.0389
45060	662,577	Syracuse, NY	26	26	0.0392	0.0392
27060	101,564	Ithaca, NY	3	6	0.0295	0.0591

Table A4: Estimated Utility Before and After 2001

CBSA	CBSA Name	Rank 1988-2001	Log Utility 1988-2001	Rank 2002-2015	Log Utility 2002-2015	2010 Pop.
33460	Minneapolis-St. Paul-Bloomington, MN-WI	1	-1.9262	36	-3.0842	3,348,859
38060	Phoenix-Mesa-Chandler, AZ	2	-2.2819	10	-2.4936	4,192,887
19100	Dallas-Fort Worth-Arlington, TX	3	-2.3107	2	-2.269	6,426,214
26420	Houston-The Woodlands-Sugar Land, TX	4	-2.4337	17	-2.697	5,920,416
13820	Birmingham-Hoover, AL	5	-2.437	42	-3.3728	1,128,047
16740	Charlotte-Concord-Gastonia, NC-SC	6	-2.4726	5	-2.3897	2,217,012
27260	Jacksonville, FL	7	-2.5551	20	-2.7311	1,345,596
42660	Seattle-Tacoma-Bellevue, WA	8	-2.5588	7	-2.443	3,439,809
12420	Austin-Round Rock-Georgetown, TX	9	-2.5902	3	-2.2703	1,716,289
40060	Richmond, VA	10	-2.6473	23	-2.7795	1,208,101
16980	Chicago-Naperville-Elgin, IL-IN-WI	11	-2.6939	8	-2.4478	9,461,105
25540	Hartford-East Hartford-Middletown, CT	12	-2.7258	12	-2.5434	1,212,381
39580	Raleigh-Cary, NC	13	-2.741	25	-2.8148	1,130,490
19740	Denver-Aurora-Lakewood, CO	14	-2.7469	26	-2.8554	2,543,482
12060	Atlanta-Sandy Springs-Alpharetta, GA	15	-2.7548	19	-2.7289	5,286,728
34980	Nashville-Davidson–Murfreesboro–Franklin, TN	16	-2.7946	6	-2.4395	1,670,890
40900	Sacramento-Roseville-Folsom, CA	17	-2.8319	24	-2.8087	2,149,127
41700	San Antonio-New Braunfels, TX	18	-2.8731	1	-2.2407	2,142,508
45300	Tampa-St. Petersburg-Clearwater, FL	19	-2.8799	21	-2.7554	2,783,243
33100	Miami-Fort Lauderdale-Pompano Beach, FL	20	-2.8864	34	-3.0475	5,564,635
39300	Providence-Warwick, RI-MA	21	-2.9569	45	-3.5449	1,600,852
41940	San Jose-Sunnyvale-Santa Clara, CA	22	-3.0083	32	-3.0196	1,836,911
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	23	-3.0425	29	-2.9675	5,965,343
41740	San Diego-Chula Vista-Carlsbad, CA	24	-3.0455	13	-2.5813	3,095,313
26900	Indianapolis-Carmel-Anderson, IN	25	-3.0854	39	-3.1449	1,887,877
36740	Orlando-Kissimmee-Sanford, FL	26	-3.1364	18	-2.7127	2,134,411
17460	Cleveland-Elyria, OH	27	-3.1628	40	-3.1828	2,077,240
14460	Boston-Cambridge-Newton, MA-NH	28	-3.1989	38	-3.1268	4,552,402
31080	Los Angeles-Long Beach-Anaheim, CA	29	-3.2004	28	-2.9034	12,828,837
28140	Kansas City, MO-KS	30	-3.2846	15	-2.6864	2,009,342
17140	Cincinnati, OH-KY-IN	31	-3.3161	16	-2.6879	2,114,580
47260	Virginia Beach-Norfolk-Newport News, VA-NC	32	-3.3195	9	-2.4791	1,676,822
32820	Memphis, TN-MS-AR	33	-3.3248	4	-2.3439	1,324,829
41180	St. Louis, MO-IL	34	-3.3349	27	-2.8741	2,787,701
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	35	-3.3666	43	-3.3733	5,636,232
18140	Columbus, OH	36	-3.3711	14	-2.6254	1,901,974
29820	Las Vegas-Henderson-Paradise, NV	37	-3.3853	11	-2.5171	1,951,269
41860	San Francisco-Oakland-Berkeley, CA	38	-3.4039	35	-3.0725	4,335,391
31140	Louisville/Jefferson County, KY-IN	39	-3.4439	33	-3.0238	1,235,708
38900	Portland-Vancouver-Hillsboro, OR-WA	40	-3.508	31	-2.9896	2,226,009
35620	New York-Newark-Jersey City, NY-NJ-PA	41	-3.5265	44	-3.4603	19,567,410
15380	Buffalo-Cheektowaga, NY	42	-3.5812	46	-4.6435	1,135,509
35380	New Orleans-Metairie, LA	43	-3.6426	41	-3.3637	1,189,866
41620	Salt Lake City, UT	44	-3.9013	30	-2.9786	1,087,873
40140	Riverside-San Bernardino-Ontario, CA	45	-3.9093	22	-2.7746	4,224,851
40380	Rochester, NY	46	-4.6001	37	-3.1016	1,079,671

Table A5: Summary Statistics of Firms Across Mover Age

Year of Migration	*Count*	*Corporation*	*Patent Application at Founding*	*Patent Assignment at Founding*	*Trademark at Founding*	*High Tech*	*Short Name*	*Eponymous*	*Patent Application in 6 Years*	*Patent Assignment in 6 Years*	*Trademark in 6 Years*	*Acquired*	*IPO*
Did not move	400645	0.427	0.029	0.022	0.016	0.066	0.469	0.074	0.47	0.617	0.068	0.013	0.002
1	6256	0.574	0.018	0.015	0.013	0.078	0.477	0.03	1.221	1.328	0.14	0.03	0.005
2	4296	0.609	0.026	0.02	0.018	0.085	0.528	0.035	1.328	1.554	0.161	0.038	0.009
3	2981	0.628	0.033	0.024	0.019	0.087	0.543	0.027	2.539	2.946	0.162	0.033	0.011
4	2124	0.636	0.039	0.028	0.018	0.099	0.532	0.027	1.541	2.014	0.198	0.041	0.011
5	1606	0.65	0.033	0.026	0.014	0.098	0.554	0.025	1.62	1.607	0.162	0.039	0.015
T-Tests													
Years 3-5 vs 1-2		-6.236***	-5.161***	-3.719***	-1.163	-2.915***	-5.69***	2.054**	-1.85*	-2.192**	-3.373***	-1.194	-3.427***
Years 1-5 vs Did not move		-47.343***	1.693*	1.009	0.112	-8.947***	-11.76***	32.447***	-6.092***	-6.484***	-25.38***	-15.764***	-9.699***

Table A6: Summary Statistics of Firms Hubs vs Non Hubs

category	*Count*	*Corporation*	*Patent Application at Founding*	*Patent Assignment at Founding*	*Trademark at Founding*	*High Tech*	*Short Name*	*Eponymous*
Born in Startup Hub	106073.00	0.48	0.05	0.03	0.02	0.08	0.53	0.08
Born outside Startup Hub	294572.00	0.41	0.02	0.02	0.01	0.06	0.45	0.07
Moved to Hub: 0-2	2060.00	0.66	0.04	0.03	0.02	0.09	0.57	0.03
Moved to Hub: 3-5	1248.00	0.69	0.05	0.04	0.02	0.12	0.60	0.02
Moved to Non Hub: 0-2	8492.00	0.57	0.02	0.01	0.01	0.08	0.48	0.03
Moved to Non Hub: 3-5	5463.00	0.62	0.03	0.02	0.02	0.09	0.53	0.03

Notes: Startup hubs are defined as the top 5 MSAs in the data in terms of venture capital: San Francisco-Oakland-Berkley, CA MSA; San Jose-Sunnyvale-Santa Clara, CA MSA; Boston-Cambridge-Newton, MA-NH MSA; Austin-Round Rock-Georgetown, TX MSA; and New York-Newark-Jersey City, NY-NJ-PA MSA.

Table A7: Corporate Taxes and Estimated City Utility

	Dependent variable:				
	Baseline	*Corporate Taxes*			
	City Entrepreneurship	City Utility	City Utility	City Utility	City Utility
	(1)	(2)	(3)	(4)	(5)
Corporate Income Taxes	20.543^{***}	-5.606^{*}	0.857	-1.570	4.892
	(4.734)	(2.987)	(3.496)	(4.029)	(3.269)
Corporate Income Taxes × Later Movers (Years 3-5)			-12.925^{**}		-12.925^{***}
			(4.440)		(3.801)
Personal Income Tax at 95th Percentile				-6.567^{**}	-6.567^{**}
				(3.202)	(2.193)
Observations	138	138	138	138	138
R^2	0.230	0.053	0.243	0.115	0.305

City utility is our estimated measure from the underlying graph of moves across cities in the United States. Corporate tax estimates are taken from Moretti and Wilson (2017), who estimate state-level taxes for all U.S. at different points of the income distribution. Robust standard errors in parenthesis. Significance denoted as $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A8: Predictors of City Utility : LLC data

	Dependent variable:							
	Baseline	**Nursery Cities**			**Income Taxes**			
	Migrant City Utility	City Entrepreneurship	*Migrant* City Utility	*Migrant* City Utility	City Entrepreneurship	City Entrepreneurship	*Migrant* City Utility	*Migrant* City Utility
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth Startups per Capita	0.359*** (0.079)							
Growth Startups per Capita × Later Movers (Years 3-5)	0.010 (0.128)							
Industry Concentration (HHI)		−0.087 (0.054)	−0.056 (0.051)					
Industry Concentration (HHI) × Later Movers (Years 3-5)			0.017 (0.076)					
Patenting per Capita		0.493*** (0.064)		0.094 (0.066)				
Patenting per Capita × Later Movers (Years 3-5)				0.198 (0.126)				
Personal Income Tax (95th)					5.136 (3.527)		−5.012* (2.867)	
Personal Income Tax (95th) × Later Movers (Years 3-5)							−4.846 (6.466)	
Personal Income Tax (50th)						−9.569 (5.893)		−14.905*** (4.230)
Personal Income Tax (50th) × Later Movers (Years 3-5)								−6.103 (8.466)
Observations	118	118	118	118	118	118	118	118
R^2	0.289	0.399	0.140	0.207	0.019	0.030	0.181	0.258

OLS regression with city utility as the dependent variable. City utility is our estimated measure from the underlying graph of moves across cities in the United States. Columns 1-3 use the utility estimated through the moves of corporations registered under Delaware jurisdiction (but domiciled anywhere in the U.S.). Columns 4-6 use the utility estimated through the moves of LLCs registered under Delaware jurisdiction. Personal income tax estimates are taken from Moretti and Wilson (2017), who estimate state-level taxes for all U.S. at different points of the income distribution. Robust standard errors in parenthesis. Significance denoted as *p<0.1; **p<0.05; ***p<0.01

Table A9: Distance and migration rates. Dep. Var. log(migrants+1).

Model:	(1)	(2)	(3)
Variables			
Constant	-0.0333		
	(0.0348)		
Log10(Distance)	0.0087	-0.0003	-0.0115**
	(0.0060)	(0.0050)	(0.0057)
Fixed-effects			
Source CBSA FE		Yes	Yes
Dest CBSA FE			Yes
Fit statistics			
Observations	424,452	424,452	424,452
R^2	3.49×10^{-5}	0.03527	0.06494
Within R^2		2.91×10^{-8}	4.35×10^{-5}

Clustered (Source CBSA FE & Dest CBSA FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The impact of distance on the migration counts across locations conditional on region fixed-effects is statistcally positive but not economically meaningful. The range of the Log10(Distance) variable is from 4.5 to 7. Going from the closest to the furthest pair only increases mgiration rates by 0.03%.

Table A10: Amenities: Do Local Amenties Correlate to Estimated City Utility?

	Corporations				LLCs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cooling Degree Days /1000	0.0203				-0.0352			
	(0.0958)				(0.0978)			
Heating Degree Days /1000	0.0350				-0.1502*			
	(0.0860)				(0.0811)			
Sunshine Percentage	0.5300				1.6837**			
	(0.8106)				(0.6494)			
Inverse Dist. from Water	0.0131				0.1701**			
	(0.0682)				(0.0781)			
Latitude	-0.0295				0.0531			
	(0.0373)				(0.0326)			
Average Home Value		-0.0714				0.2274**		
		(0.0690)				(0.0892)		
Quality of Life Index			-1.4970				3.0219*	
			(1.0807)				(1.5449)	
Bohemia				-0.4037				0.8907*
				(0.4042)				(0.5090)
Num.Obs.	185	185	185	185	126	126	126	126
Log.Lik.	-215.899	-218.685	-218.194	-218.567	-139.059	-142.924	-143.765	-144.640
F	0.838	1.070	1.919	0.998	4.260	6.499	3.826	3.062

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Summary Statistics for Metropolitan Areas

Statistic	Mean	St. Dev.	N
Population	978,560.467	1,935,880.581	185
Log(HHI)	−24.272	2.353	184
Patents per Thousand Pop	0.006	0.009	185
Income Tax			
Income Tax at 50th Perc.	0.107	0.016	185
Income Tax at 95th Perc.	0.236	0.023	185
Startup Cartography Project			
Delaware Corporations	952.568	2,699.156	185
Delaware LLCs	1,238.449	4,181.380	185

Table A12: How Does the Estimated Quality of Movers that Leave and Arrive to a City Correlate?

	log(Avg. In Mover Quality)		
	log(move_in_quality)		
	(1)	(2)	(3)
log(Avg. Out Mover Quality)	0.412***	0.102	0.114
	(0.102)	(0.076)	(0.081)
Log(Delaware Startups Per Capita)		0.808***	0.840***
		(0.078)	(0.077)
Observations	182	182	182
R^2	0.103	0.468	0.489

OLS regression. Average quality estimated by replicating the measure of Guzman and Stern (2020) in the data. Specifically, for all non-movers born before 2012, we run a logit model with a binary measure of equity events as the dependent variable, and observables for whether a firm, close to founding and in its birth location, is a corporation, has a short name, is eponymous, has a patent, has a trademark, has both a patent and a trademark, and five industry characteristics based on firm name. Predictions from this model report an out of sample ROC score or 0.80. Estimated quality is the predicted out of sample probability of this model.We average this value for all movers in and out of a city, and firms born in a city that do not move. Robust standard errors in parenthesis. Column (3) is weighted by the total movers in or out of each city. Significance denoted as *p<0.1; **p<0.05; ***p<0.01

Appendix B

Data Appendix To: Entrepreneurial Migration

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(Columbia University)

1 Introduction

This appendix overviews the construction and development of the data in our paper *Entrepreneurial Migration*. The appendix is divided into four sections. First, we cover the conceptual goal and need for measuring entrepreneurial migration. Then, we outline the key challenges in doing so, particularly around firm heterogeneity, defining migration, and observability. Then, we explain the data — business registration records for Delaware registered companies — and the overall approach to constructing our dataset. We also review the key summary statistics of the full set of firms. Finally, we compare our data to other potential datasets. Abridged fragments of this appendix are also included in the main text.

2 Why Measure Migration of High Growth Startups?

The importance of understanding the role of location on startup performance has been of interest at least since Marshall (Marshall, 1890; Jacobs, 1970; Saxenian, 1994; Glaeser, Kerr, & Kerr, 2015). A growing literature documents a number of localized economic benefits for regions that have more startups,, the most important one being economic growth (Glaeser, Kerr, & Ponzetto, 2010). Over the last decade, an important formalization of this relationship has emphasized that it is one group of startups in particular — high growth startups — that account for the bulk of this economic impact (Schoar, 2010; Guzman & Stern, 2020). High growth startups are firms that have a disproportionate likelihood of growth. In particular, a number of studies have documented that this growth intent is reflected in founding choices entrepreneurs take in the early stages of their business activities (Guzman & Stern, 2020).

In direct contrast to the importance of the location where firms locate is the possibility of migration. While most startups are born and develop in the city where their founders lived prior to founding (Michelacci & Silva, 2007), this pattern is not universal. Anecdotes abound of good entrepreneurs who chose to start a company in one location only to see it grow in a different one. For example, while Marc Andreesen had all the initial ideas and training for what would become Netscape at the University of Illinois Urbana-Champaign, he moved to California to build the company itself. Similarly, Bill Gates and Paul Allen wrote the original Microsoft programs while Gates was a student at Harvard, but they eventually grew the company in the Seattle area after an interlude in New Mexico. The impact of these entrepreneurial migrations on their destination regions has been substantial. A series of policies has emerged to motivate high talent entrepreneurs to move to a region with the goal of replicating some version of this story, the most notable of these being Startup Chile. Other policies, most notably in Israel, instead encourage entrepreneurs to 'move out' of their home region to a richer destination with the goal that the spillovers from future growth benefit back into the region (Conti & Guzman, 2023).

Yet, whether migration of high growth startups actually happens, and what are the characteristics that drive it, appear so far unexplored.

Understanding the economic phenomenon of entrepreneurial migration poses a number of both conceptual and measurement challenges. Migration has been studied substantially in economic theory (e.g. Roback) as a choice problem over some maximization function for either people or firms. Absent principal-agent issues, this maximization should be over the weighted utility of the equity-holders of the firm. Yet, because entrepreneurs also tend to be the managers, the maximization cannot simply be done on the role of location on increasing firm value, but also on the utility costs for managers to relocate to one of these regions, independent of the startup. For example, relocating might require being away from loved ones, losing an additional personal income source (e.g. the income of a spouse), or simply living in a location that is not personally desirable. Furthermore, these same personal connections also constitute valuable local relationships, that in and of themselves are likely to impact firm performance.

To date, a series of studies has emerged understand the differences between personal connections and locational benefits as drivers to startup firm performance (Dahl & Sorenson, 2012; Michelacci & Silva, 2007; Guzman, 2023), as well as how changes in the 'appeal' of a city influence would-be migrants on their choice of hiring a manager or moving themselves (Kulchina, 2014). However, a systematic measurement of entrepreneurial migration for high growth startups does not yet exist, leaving many critical questions unanswered.

3 The Difficulty in Measuring Startup Migration

Measuring entrepreneurial migration itself represents a few unique challenges, including accounting for firm quality, observing firms in their original location, and observing the migration of the firms in a timely fashion. We review each in turn.

Accounting for firm quality in migration is particularly important. One reason is the growing sense of importance assessed in the literature to the significant heterogeneity in firm potential (Schoar, 2010; Guzman & Stern, 2020) – with a few 'high growth' firms accounting for the majority of the economic impact of entrepreneurship. Understanding the migration patterns of all firms might explain little about economic growth, while finding the few firms that do have the potential to grow might be much more informative. A second, equally important, reason is that the motivations for migration, or the behaviors that lead to them, might be different across the entrepreneurship of high growth and non high growth startups. Recent evidence finds ample variation on the personality of high growth entrepreneurs versus other types of actors (Kerr, Kerr, & Xu, 2017), and studies on the motivations of these shows that it is not only profit or productivity that defines their choices (Guzman, Oh, & Sen, 2020). In short, a clear focus on measurement of high growth startups is critical to understand the phenomenon of entrepreneurial migration and its performance.

The remaining concerns reflect challenges in the observability of entrepreneurial migrations. Because some founders move before starting a company, while other migrants might become entrepreneurs only years after arriving in an entrepreneurial region (Saxenian, 2007), there is no obvious breakpoint on which to define a migration as 'entrepreneurial'. A different, narrower approach, and the one we focus on in this paper, focuses on simply studying the migration of newly born startups. The unique advantage of using this definition is that it circumvents vexing questions about how location influences the choice of entrepreneurial entry. That is, if individuals migrate before becoming entrepreneurs, would they have been entrepreneurs before migrating?

Finally, there remains a question of how to observe the changes in the location of firms. That is, restricting 'entrepreneurial migration' to mean a firm that moves its headquarters to a new location, the problem involves defining "firm", "headquarters", and tracking these moves in a consistent way. We take advantage of institutional details in the United States that allow this tracking.

4 Data

Our analysis is focused on the founding and geographic reallocation of companies registered under Delaware jurisdiction. These are not companies headquartered in Delaware — they are headquartered across the United States. Instead, being under Delaware jurisdiction reflects the fact that when a firm is founded it has the freedom to choose where to register.[1] This choice of jurisdiction is consequential to a large number of corporate legal aspects of the firm, including labor disputes, shareholder disputes, and the legality and enforceability of certain contracts. Since the early twentieth century, two broad choices of jurisdiction have emerged for new U.S. firms.

[1]This feature of multiple jurisdictions appears to be an unusual feature of the United States. In most other countries, corporate law is overarchingly similar across all regions of the country.

Most startups (about 96%) initially register under only the local jurisdiction of their own state. There are several benefits to registering in the local jurisdiction, including a simplicity in translating between corporate law and the local law, and the need to pay for only one registration. In general, being in the local jurisdiction is simply cheaper.

A few companies (most of the remaining 4%), however, choose instead to register under Delaware jurisdiction and then operate as a foreign (out of state) company in the state in which they are headquartered. This process is more expensive, as it requires more legal work to maintain both registrations, and the firms need to pay fees to both states. However, it also creates certain benefits that accrue particularly well to entrepreneurs that intend to scale the company. First, corporate law is mostly case-based in the United States, and Delaware is the state with the largest canon of corporate law. This means that precedent on the enforceability of different clauses and contracts has been tested and developed in detail. Venture capitalists, for example, are usually reluctant to extend contracts to firms in other jurisdictions due to the uncertainty of knowing whether and how a contract would hold. Second, Delaware Corporate Law is commonly taught in law schools nationwide. Finally, Delaware has a reputation for fairness in dealing with corporate disputes, through its specialized Court of the Chancery. Together, these benefits have become significant for many firms in the United States, and are particularly valuable for those firms that intend to be large. The additional costs of Delaware registration create a separating equilibrium of sorts: firms with high growth intention choose Delaware, while the rest choose the local law (Catalini, Guzman, & Stern, 2019). Accordingly, while Delaware represents less than 0.5% of the U.S. population, over half of all U.S. publicly listed firms are registered here. In empirical estimates, firms registered in Delaware at founding are over 45 times more likely to achieve an equity growth outcome (such as an IPO or acquisition) (Guzman & Stern, 2020).

We obtained data on all the Delaware jurisdiction firms registered between 1988 and 2014 in each of these states through the Startup Cartography Project (Fazio, Guzman, Liu, & Stern, 2022). The Startup Cartography Project (SCP) is a project focused on the measurement of firm formation through business registration across time and location.

The data included the name of each company, the registered address of the principal office, and the date in which it registered in each state. We also obtained all observables used in the SCP to measure entrepreneurial quality – an estimate of the founding potential of companies based on the predicted probability of growth based on founding characteristics.

To track the migration of Delaware firms in their location choices, we take advantage of unique institutional rules in state-level corporate laws, requiring firms to register in every state in which they engage in meaningful business activity.[2] These registrations are required to use exactly the same official firm name, down to the comma, in each state where they do business. Because firms register in a state only at the time of entering the state, we can use the registration date to assess when a firm expands location to another state. In most cases, this is a subsidiary expansion while the headquarters of the company remain in the home location. Yet, sometimes, it will represent (or will eventually become) an entrepreneurial migration — i.e. the relocation of the company headquarters.

Differentiating between these two modes of expansion is difficult as it would require a firm to state separately the location of the principal office and the location of the state-based office. Through a manual check of the information in each state, we identified 35 U.S. states, and the District of Columbia, in which the process of registration distinctly requires firms to separately document the local state office and the principal office through one of two modes: either requiring the primary corporate address explicitly in the registration form, or by requesting the address of the president, CEO, or main manager of the firm. In the latter case, we assume that if the majority of officers live in the same MSA, then the corporate headquarters is located in that MSA. These 36 jurisdictions form the basis of our analysis.[3]

Specifically, we use primary corporate addresses in most states. In AL, AZ, RI, MN, FL, GA, NM, firms often list their Delaware registration address or the address of a local

[2]Broadly, this occurs when a firm has hired employees in a state, opened a bank account, or is renting an office.

[3]Our states are Alaska, Alabama, Arizona, California, Colorado, Connecticut, DC, Florida, Georgia, Hawaii, Idaho, Illinois, Indiana, Kansas, Kentucky, Louisiana, Massachusetts, Maine, Minnesota, Missouri, Mississippi, North Carolina, New Hampshire, New Jersey, Nevada, New York, Ohio, Oregon, Rhode Island, Tennessee, Texas, Utah, Virginia, Vermont, Washington, and West Virginia.

corporate agent as their "headquarters address". If a corporation is registered in Delaware, is in one of those states, and has Delaware as their headquarters or an agent address as their mailing address, we consider it headquartered in an MSA only if at least one director address is local. In Texas, many corporations use a lawyer address as their headquarters location. We therefore use the majority of director addresses to identify the MSA of the firm. In Maine, hand-checking shows that the "Additional Addresses" is most likely to include the actual firm address, hence we use that field rather than the business address field.

In all states, if the registered headquarters address has the name of a registering agent in the address field ("National Registered Agents", "CT Corporation", "Corporate Service Corporation", "The Corporation Trust", "Corporation Service Company", "c/o" or "Prentice Hall") or has a commonly-repeated address (generally a lawyer address), we only consider it local to that MSA if at least one director is in the state. Note that we still only consider the firm local if the agent or lawyer address is in the state in question, and the firm to have registered in that state.

Using this information, we matched the Delaware-registered companies across each state in our sample. To do this, we tracked the initial state registration date of each firm in each state, as well as the registered zip code (either of the "primary" company address, or the broader MSA in the case of states where director addresses were used). Using this data, we operationalize a measure of migration through the following algorithm:

1. The first state in which the firm is registered is the founding state.

2. If a firm name is registered in Delaware in year X, and that same name had been registered in another state in a prior year, we treat the firm's year of birth as the earliest registration date. This pattern often occurs prior to mergers or other legal changes involving firms that were not actually Delaware-registered-at-birth.

3. If a firm changes its principal office to another state, and the destination MSA does not include the source state, we consider this a migration.

4. The date in which it first registers in the destination state is the migration date.

This allows us to track well the relocation of startup companies across state-lines. In our main analysis, a startup migration is a firm that moves within five years of the first time they appear in our data. We drop all moves within 3 months of the initial founding date as these tend to conflate moves with firms who register in many states on founding. For instance, a restaurant chain that spins out one of its brands as an independent firm will be registered in many states nearly simultaneously. The fact that one state processes the registration a few days before another does not mean that the firm was "founded" in the earlier state.

4.1 Examples of Movers

Figures B1 and B2 provide tangible examples of migrations and the associated business registration records.

Figure B1 presents the *California* business registration records for two MIT startups founded in 2010, Ginger.io and Sociometric Solutions (later Humanyze). Both startups were founded at the MIT Media Lab by Ph.D. students of Professor Alex (Sandy) Pentland based on work done during their dissertations. Both startups focused on the application of analytics to handheld devices to understand social dynamics. However, Ginger.io decided to move early on to Silicon Valley, while Sociometric did not. Accordingly, Ginger.io shows a business registration with a Principal Executive Office in Silicon Valley. We also see the address of the Chief Executive Office (which is often used as validation in the measurement) is also in Silicon Valley. In contrast, Sociometric Solutions shows a Principal Executive Office in Boston, and a CEO office in Boston. The only address in California is the Address of Principal Office in California, indicating that Sociometric Solutions's role in California is only a satellite office. In this case, Ginger.io would be considered a migration, but Sociometric Solutions would not.

We use the time of initial registration at the destination as the migration date. To guarantee the firm was established in the origin region first, I require that the time elapsed between registration in the origin state and destination is at least three months. Furthermore, I exclude all migrations where the origin state is also part of the destination MSA to avoid cross-state migrations within the same metro area. Finally, I focus only on migrations within the first two years of founding, the early stages of the firm, to allow time to experience outcomes after founding.

In Figure B2 we instead show the information of the *Washington* registration for a California based company, Tableau Software. Three elements are appreciable in this setup. First, the address of the principal office for Tableau is now 2517 East Helen Street, Seattle, WA, which suggests the company has moved into the state. Interestingly, this address is a residential address, and the CEO, Christian Chabot, initially ran the business from his home. Second, in the list of offices, two of the officers have addresses in Washington state. However, not all officers do: Pat Hanrahan, the Chief Technology Officer (and also a Stanford faculty member), is still located in California. In this case, we would consider this a migration given that both the majority of directors is in the destination state, and the address of the firm is in the destination state.

5 Drawbacks and Risks of Measurement Approach

Our approach does come with several drawbacks and potential risks. We review each of the main ones in turn.

The timing of migration. In the process of migration, timing is important. Our data does not allow us to know precisely the date a company changes the official main location for a company. Indeed, this "precise date" is not particularly well-defined. A Seattle-based startup may open an office in Phoenix in 2007, slowly move various corporate tasks to that office in 2008, then begin referring to Phoenix as its "headquarters" publicly in 2009. However, for the analyst it is not conceptually obvious when the headquarters "move" began. We therefore define the date of a move as the first date a firm registers business in any state where it eventually refers to that state as housing its "principal address".

We believe this is a relatively minor concern because it does not affect *who* we code as migrants, nor *where* do they move to, but only *when* they move. The timing of migration itself is not a main area of analysis in our paper.

Relocation within states. The strength of our data is in identifying migration across state lines to different MSAs. Our data, however, does not allow us to track migrations within the same state such as moving from San Diego, CA to San Francisco, CA or from Rochester, NY to New York City. Although restricting to cross-state migrations limits the total number of HQ moves, it does not bias the results of our utility-based approach. Recall that the utility-based approach depends on the relative number of moves between cities, and omitting within-state moves means the omitted moves are bi-directional for any city pair. Note also that when tracking MSA moves, we also drop moves if the firm moves from one MSA to a different state which also makes up the origin MSA. For instance, the New York City MSA includes zip codes in New Jersey, so a New York City firm that moved to New Jersey will not be counted as a cross-state move in our data. This is due to issues with interpolating origin MSAs when only the state of origin can be observed, as noted below. Again, this omission does not bias our results.

What (and who) moves? Another limitation of our data is that it does not allow us to go into the organizational structure of each migration beyond the relocation of headquarters. Naturally, some firms will not move fully and might leave someone in the original location, or might choose other work arrangements. Future datasets would do well to improve upon this margin.

Definition of a startup. We define startup, as discussed, to mean a new business entity. Spinouts and subsidiaries of existing firms, which may be quite large at "founding", therefore count as startups. Hand-investigation of the data suggests that the vast majority of data points are "true startups", meaning small, de novo firms. That said, utility estimates for some cities are affected by this distinction. For example, Peoria, Illinois is the highest utility small city, based largely on having 12 startups move in while only 2 move out. Many of these 12 moves are the result of agricultural acquisitions, whereby a novel corporate entity was created to help facilitate the sale, and the headquarters was then integrated into Peoria the next year. Moves of this type are, however, quite rare in the data at large.

6 Industry Classification

While the bulk of our analysis does not depend on firm industry, we do incorporate heterogeneity on industry in some robustness tests (such as Appendix Figure A1). The business registration data does not have industry codes. We use a name-based algorithm to incorporate industry in our data. Building on the same implementation in (Andrews, Fazio, Guzman, Liu, & Stern, 2022) and (Guzman & Stern, 2020), our broader approach (including the industry categorization used here and elsewhere) proceeds as follows.

We create four measures based on how the firm name reflects the industry or sector that the firm within which the firm is operating. To do so, we take advantage of two features of the US Cluster Mapping Project (Delgado, Porter, and Stern, 2016), which categorizes industries into (a) whether that industry is primarily local (demand is primarily within the region) versus traded (demand is across regions) and (b) among traded industries, a set of 51 traded clusters of industries that share complementarities and linkages. We augment the classification scheme from the US Cluster Mapping Project with the complete list of firm names and industry classifications contained in Reference USA, a business directory containing more than 10 million firm names and industry codes for companies across the United States. Using a random sample of 1.5 million Reference USA records, we create two indices for every word ever used in a firm name. The first of these indices measures the degree of localness, and is defined as the relative incidence of that word in firm names that are in local versus non-local industries. We then define a list of Top Local Words, defined as those words that are (a) within the top quartile of this distribution and (b) have an overall rate of incidence greater than 0.01% within the population of firms in local industries (see Guzman and Stern, (2015, Table S10) for the complete list). Finally, we define local to be equal to one for firms that have at least one of the Top Local Words in their name, and zero otherwise. We then undertake a similar exercise for the degree to which a firm name is associated with a traded name. It is important to note that there are firms which we cannot associate either with traded or local and thus leave out as a third category. Just more than 19% of firms have local names, though only 5% of firms for whom growth equals one, and while 54% of firms are associated with the traded sector, 59% of firms for whom growth equals one do.

We additionally examine the type of traded cluster a firm is associated with, focusing in particular on whether the firm is in a high-technology cluster or a cluster associated with resource intensive industries. For our high technology cluster group (Traded High Technology), we draw on firm names from industries include in ten USCMP clusters: Aerospace Vehicles, Analytical Instruments, Biopharmaceuticals, Downstream Chemical, Information Technology, Medical Devices, Metalworking Technology, Plastics, Production Technology and Heavy Machinery, and Upstream Chemical. From 1988 to 2008, while only 5% firms are associated with high technology, this rate increases to 16% within firms that achieve our growth outcome. For our resource intensive cluster group, we draw on firms names from fourteen USCMP clusters: Agricultural Inputs and Services, Coal Mining, Downstream Metal Products, Electric Power Generation and Transmission, Fishing and Fishing Products, Food Processing and Manufacturing, Jewelry and Precious Metals, Lighting and Electrical Equipment, Livestock Processing, Metal Mining, Nonmetal Mining, Oil and Gas Production and Transportation, Tobacco, Upstream Metal Manufacturing. While 14% of firms are associated with resource intensive industries, and 13% amongst growth firms.

Finally, we also repeat the same procedure to find firms associated with more narrow sets of clusters that have a closer linkage to growth entrepreneurship in the United States. We specifically focus on firms associated with Biotechnology, E-Commerce, Information Technology, Medical Devices and Semiconductors. It is important to note that these definitions are not exclusive and our algorithm could associate firms with more than one industry group. For Biotechnology (Biotechnology Sector), we use firm names associated with the US CMP Biopharmaceuticals cluster. While only 0.19% of firms are associated with Biotechnology, this number increases to 2.2% amongst growth firms. For E-commerce (E-Commerce Sector) we focus on firms associated with the Electronic and Catalog Shopping sub-cluster within the Distribution and Electronic Commerce cluster. And while 5% of all firms are associated with e-commerce, the rate is 9.3% for growth firms. For Information Technology (IT Sector), we focus on firms related to the USCMP cluster Information Technology and Analytical Instruments. 2.4% of all firms in our sample are associated with IT, and 12% of all growth firms are identified as IT-related. For Medical Devices (Medical Dev. Sector), we focus on firms associated with the Medical Devices cluster. We find that while 3% of all firms are in medical devices, this number increases to 9.6% within growth firms. Finally, for Semiconductors (Semiconductor Sector), we focus on the sub-cluster of Semiconductors within the Information Technology and Analytical Instruments cluster. Though only 0.04% of all firms are associated with semiconductors, 0.5% of growth firms are.

References

Andrews, R., Fazio, C., Guzman, J., Liu, Y., & Stern, S. (2022). Reprint of the startup cartography project: measuring and mapping entrepreneurial ecosystems. *Research Policy*, *51*(9), 104581.

Catalini, C., Guzman, J., & Stern, S. (2019). *Passive versus active growth: Evidence from founder choices and venture capital investment* (Tech. Rep.). National Bureau of Economic Research.

Conti, A., & Guzman, J. A. (2023). What is the us comparative advantage in entrepreneurship? evidence from israeli migrantion to the united states. *Review of Economics and Statistics*, *105*(3), 528-44.

Dahl, M. S., & Sorenson, O. (2012). Home sweet home: Entrepreneurs' location choices and the performance of their ventures. *Management science*, *58*(6), 1059–1071.

Fazio, C., Guzman, J., Liu, Y., & Stern, S. (2022). Reprint of "the startup cartography project: measuring and mapping entrepreneurial ecosystems". *Research Policy*, *51*(9), 104581.

Glaeser, E. L., Kerr, S. P., & Kerr, W. R. (2015). Entrepreneurship and urban growth: An empirical assessment with historical mines. *Review of Economics and Statistics*, *97*(2), 498–520.

Glaeser, E. L., Kerr, W. R., & Ponzetto, G. A. (2010). Clusters of entrepreneurship. *Journal of urban economics*, *67*(1), 150–168.

Guzman, J. (2023). Go west young firm: The impact of startup migration on the performance of migrants. *Management Science*, *forthcoming*.

Guzman, J., Oh, J. J., & Sen, A. (2020). What motivates innovative entrepreneurs? evidence from a global field experiment. *Management Science*, *66*(10), 4808–4819.

Guzman, J., & Stern, S. (2020, November). The state of american entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 us states, 1988–2014. *American Economic Journal: Economic Policy*, *12*(4), 212-43. Retrieved from `https://www.aeaweb.org/articles?id=10.1257/pol.20170498` doi: 10.1257/pol.20170498

Jacobs, J. (1970). *The economy of cities*. Penguin Random House.

Kerr, S. P., Kerr, W. R., & Xu, T. (2017). Personality traits of entrepreneurs: A review of recent literature.

Kulchina, E. (2014). Media coverage and location choice. *Strategic Management Journal*, *35*(4), 596–605.

Marshall, A. (1890). *The principles of economics*. McMaster University Archive for the History of Economic Thought.

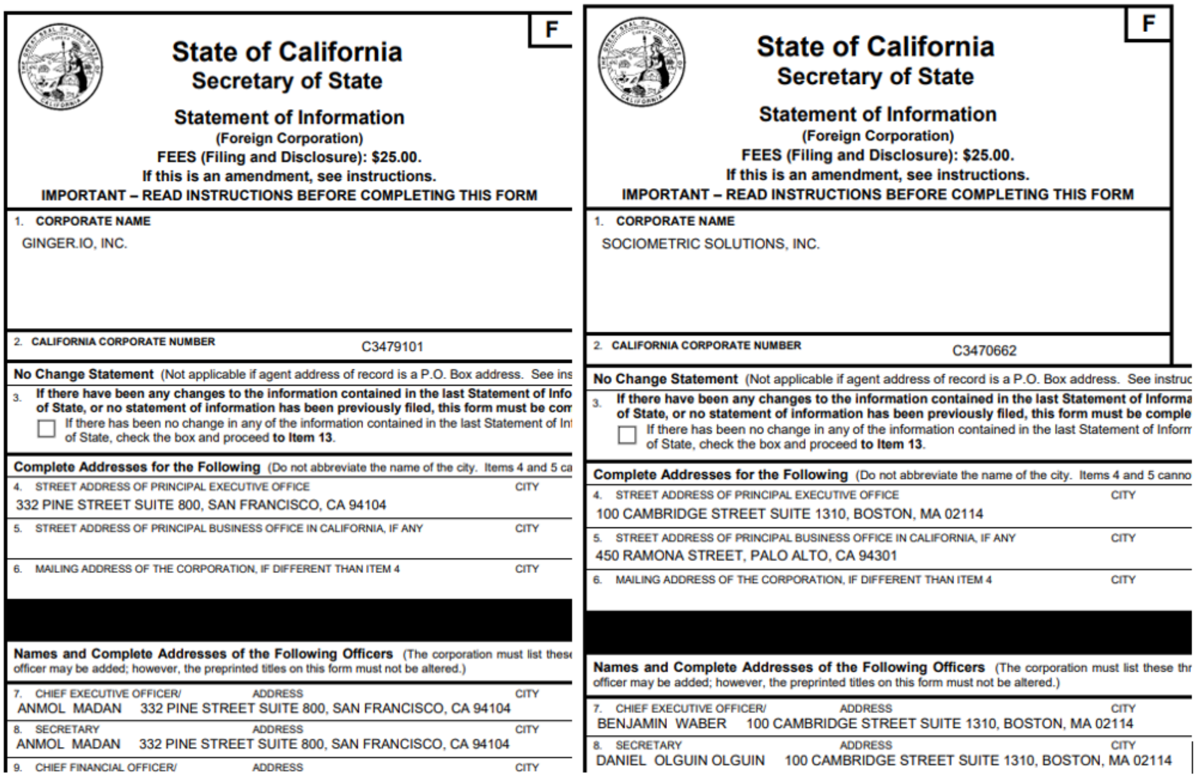
Michelacci, C., & Silva, O. (2007). Why so many local entrepreneurs? *The Review of Economics and Statistics*, *89*(4), 615–633.

Saxenian, A. (1994). *Regional advantage: Culture and competition in silicon valley and route 128*. Harvard University Press.

Saxenian, A. (2007). *The new argonauts: Regional advantage in a global economy*. Harvard University Press.

Schoar, A. (2010). The divide between subsistence and transformational entrepreneurship. *Innovation policy and the economy*, *10*(1), 57–81.

Figure B1: Comparison of Business Registration Records for two Massachusetts Firms. Ginger.io (a migrant to Silicon Valley) and Sociometric Solutions (a non-migrant).



F

State of California
Secretary of State

Statement of Information
(Foreign Corporation)
FEES (Filing and Disclosure): $25.00.
If this is an amendment, see instructions.
IMPORTANT – READ INSTRUCTIONS BEFORE COMPLETING THIS FORM

1. CORPORATE NAME
GINGER.IO, INC.

2. CALIFORNIA CORPORATE NUMBER C3479101

No Change Statement (Not applicable if agent address of record is a P.O. Box address. See ins

3. If there have been any changes to the information contained in the last Statement of Info of State, or no statement of information has been previously filed, this form must be com
If there has been no change in any of the information contained in the last Statement of In of State, check the box and proceed to Item 13.

Complete Addresses for the Following (Do not abbreviate the name of the city. Items 4 and 5 ca

4. STREET ADDRESS OF PRINCIPAL EXECUTIVE OFFICE CITY
332 PINE STREET SUITE 800, SAN FRANCISCO, CA 94104

5. STREET ADDRESS OF PRINCIPAL BUSINESS OFFICE IN CALIFORNIA, IF ANY CITY

6. MAILING ADDRESS OF THE CORPORATION, IF DIFFERENT THAN ITEM 4 CITY

[redacted]

Names and Complete Addresses of the Following Officers (The corporation must list these officer may be added; however, the preprinted titles on this form must not be altered.)

7. CHIEF EXECUTIVE OFFICER/ ADDRESS CITY
ANMOL MADAN 332 PINE STREET SUITE 800, SAN FRANCISCO, CA 94104

8. SECRETARY ADDRESS CITY
ANMOL MADAN 332 PINE STREET SUITE 800, SAN FRANCISCO, CA 94104

9. CHIEF FINANCIAL OFFICER/ ADDRESS CITY

F

State of California
Secretary of State

Statement of Information
(Foreign Corporation)
FEES (Filing and Disclosure): $25.00.
If this is an amendment, see instructions.
IMPORTANT – READ INSTRUCTIONS BEFORE COMPLETING THIS FORM

1. CORPORATE NAME
SOCIOMETRIC SOLUTIONS, INC.

2. CALIFORNIA CORPORATE NUMBER C3470662

No Change Statement (Not applicable if agent address of record is a P.O. Box address. See instruc

3. If there have been any changes to the information contained in the last Statement of Informa of State, or no statement of information has been previously filed, this form must be comple
If there has been no change in any of the information contained in the last Statement of Inform of State, check the box and proceed to Item 13.

Complete Addresses for the Following (Do not abbreviate the name of the city. Items 4 and 5 canno

4. STREET ADDRESS OF PRINCIPAL EXECUTIVE OFFICE CITY
100 CAMBRIDGE STREET SUITE 1310, BOSTON, MA 02114

5. STREET ADDRESS OF PRINCIPAL BUSINESS OFFICE IN CALIFORNIA, IF ANY CITY
450 RAMONA STREET, PALO ALTO, CA 94301

6. MAILING ADDRESS OF THE CORPORATION, IF DIFFERENT THAN ITEM 4 CITY

[redacted]

Names and Complete Addresses of the Following Officers (The corporation must list these thr officer may be added; however, the preprinted titles on this form must not be altered.)

7. CHIEF EXECUTIVE OFFICER/ ADDRESS CITY
BENJAMIN WABER 100 CAMBRIDGE STREET SUITE 1310, BOSTON, MA 02114

8. SECRETARY ADDRESS CITY
DANIEL OLGUIN OLGUIN 100 CAMBRIDGE STREET SUITE 1310, BOSTON, MA 02114

Notes: An example of the business registration record of two Massachusetts companies founded in 2010 by PhD students at MIT. Ginger.io moved to California, and shows both the address of the principal executive and the address of the chief executive in California. Sociometric Solutions did not move to California, but did open a branch. Correspondingly, the principal office and chief executive are still in Massachusetts, and only the address of the office in California has a California address.

Figure B2

10/19/2004 497169
$216.00 Check #241
Tracking ID: 795909
Doc No: 497169-001

STATE OF WASHINGTON
SECRETARY OF STATE

CERTIFICATE OF AUTHORITY
FOREIGN PROFIT CORPORATION

(Per Chapter 23B.15 RCW)

FEE: $175

EXPEDITED (24-HOUR) SERVICE AVAILABLE – $20 PER ENTITY INCLUDE FEE AND WRITE "EXPEDITE" IN BOLD LETTERS ON OUTSIDE OF ENVELOPE

- Please PRINT or TYPE in black ink
- Sign, date and return original AND ONE COPY to:

CORPORATIONS DIVISION
801 CAPITOL WAY SOUTH • PO BOX 40234
OLYMPIA, WA 98504-0234

- BE SURE TO INCLUDE FILING FEE. Checks should be made payable to "Secretary of State"

FILED
SECRETARY OF STATE
OCT 19 2004
STATE OF WASHINGTON

FOR OFFICE USE ONLY
FILED: / /
UBI: 602-438-440
CORPORATION NUMBER:

IMPORTANT! Person to contact about this filing: THOMAS E. WALKER JR
Daytime Phone Number (with area code): (650) 678 9698

NAME OF CORPORATION (As Recorded in the State/Country of Incorporation): TABLEAU SOFTWARE, INC
ORIGINALLY INCORPORATED IN: State/Country DE ON: Date 7/19/04

NOTE: If the name listed above is unavailable in Washington state or does not meet the requirements of 23B.15 RCW, please provide the name the corporation adopts for use in Washington State. You must also attach a Board of Directors Resolution approving the use of an alternate name.

NAME THE CORPORATION ADOPTS FOR USE IN WASHINGTON STATE:
APPROVED BY DIRECTORS ☐ Resolution Attached

PRINCIPAL OFFICE ADDRESS OF CORPORATION *(Street Address Required - Please Do Not Use PO Box)*
Address 2517 East Helen Street
City SEATTLE State or Country WA ZIP or Postal Code 98112

EFFECTIVE DATE OF CERTIFICATE OF AUTHORITY *(Specified effective date may be up to 90 days AFTER receipt of the document by the Secretary of State)*
☐ Specific Date: ______ ☒ Upon filing by the Secretary of State

PERIOD OF DURATION *(Check one only)*
☒ Perpetual
☐ ______ Years *(indicate number of years)*

DATE CORPORATION BEGAN DOING BUSINESS IN WASHINGTON STATE
Date 07/19/2004

CERTIFICATE OF EXISTENCE
☒ Attached is an original Certificate of Existence, issued no more than 60 days prior to this application, duly authenticated by the Secretary of State or other official having custody of corporate records in the state or country of incorporation.

NAME AND ADDRESS OF WASHINGTON STATE REGISTERED AGENT
Name CHRISTIAN CHABOT
Street Address *(Required)* 2517 East Helen Street City Seattle State WA ZIP 98112
PO Box *(Optional – Must be in same city as street address)* ______ ZIP *(If different than street ZIP)* ______

I consent to serve as Registered Agent in the State of Washington for the above named corporation. I understand it will be my responsibility to accept Service of Process on behalf of the corporation; to forward mail to the corporation; and to immediately notify the Office of the Secretary of State if I resign or change the Registered Office Address.

Signature of Agent: [signature]
Printed Name: CHRISTIAN CHABOT
Date: 10/18/2004

NAMES AND ADDRESSES OF ALL CURRENT OFFICERS AND DIRECTORS *(If necessary, attach additional names and addresses)*
Name See ATTACHED
Address ______ City ______ State ______ ZIP ______

SIGNATURE OF OFFICER OR CHAIRPERSON
This document is hereby executed under penalties of perjury, and is, to the best of my knowledge, true and correct.

Signature of Officer/Chairperson: [signature]
Printed Name: CHRISTIAN CHABOT
Title: CEO
Date: 10/18/2004

FOR OFFICE USE ONLY

CORPORATIONS INFORMATION AND ASSISTANCE – 360/753-7115 (TDD – 360/753-1485)

010-001 (9/00)

TABLEAU
SOFTWARE

List of Officers

Christian Chabot
Chief Executive Officer
2517 E Helen Street
Seattle, WA 98112

Pat Hanrahan
Chief Technology Officer
40 Minoca Road
Portola Valley, CA 94028

Chris Stolte
Vice President
4035 49th Avenue SW
Seattle, WA 98116

NO DIRECTORS AT THIS TIME

Delaware

The First State

I, HARRIET SMITH WINDSOR, SECRETARY OF STATE OF THE STATE OF DELAWARE, DO HEREBY CERTIFY "TABLEAU SOFTWARE, INC." IS DULY INCORPORATED UNDER THE LAWS OF THE STATE OF DELAWARE AND IS IN GOOD STANDING AND HAS A LEGAL CORPORATE EXISTENCE SO FAR AS THE RECORDS OF THIS OFFICE SHOW, AS OF THE FOURTEENTH DAY OF OCTOBER, A.D. 2004.

AND I DO HEREBY FURTHER CERTIFY THAT THE FRANCHISE TAXES HAVE NOT BEEN ASSESSED TO DATE.

Harriet Smith Windsor

Harriet Smith Windsor, Secretary of State

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AUTHENTICATION: 3412603

DATE: 10-14-04