Go West Young Firm: The Benefits of Startup Relocation to Silicon Valley

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Abstract

I study the benefits to entrepreneurial migration, focused on firms moving to Silicon Valley. Using a machine learning estimator and panel data, I find moving to Silicon Valley leads to higher startup performance on equity outcomes, financing, patenting, products, and revenue. These results are robust to a stringent coefficient stability test, and show no evidence of pre-trends. The benefits are partially driven by knowledge spillovers, and sensitive to capital market conditions during migration. Despite the benefits to migration, most startups do not move. A simple analysis suggests this may be due to the personal costs of moving for founders themselves.

*I am thankful to Scott Stern, Pierre Azoulay, Christian Catalini, and Olenka Kacperczyk for their advice and support on this project. I also thank Kevin Bryan, Bo Cowgill, JP Eggers, Cathy Fazio, Joshua Gans, Deepak Hedge, David Hsu, Bill Kerr, Daniel Keum, Ramana Nanda, Rob Seamans, Dan Wang, and Sam Zyontz. This project was done with support of the Kauffman Foundation, the Jean Hammond (1986) and Michael Krasner (1974) Entrepreneurship Fund at MIT, and the Edward B. Roberts (1957) Entrepreneurship Fund at MIT. Email: jag2367@columbia.edu

1 Introduction

Silicon Valley is the quintessential high productivity economic cluster of the innovation economy (Guzman & Stern, 2015; Saxenian, 1994; W. Kerr & Kominers, 2014). It accounts for 16 percent of U.S. patenting (Forman, Goldfarb, & Greenstein, 2016), 44 percent of venture capital investment (Andes, Trujillo, & Marchio, 2016), high inventor productivity (Moretti, 2019), and some of the highest personal income per capita (of Economic Analysis, 2019). Accordingly, it looms large in entrepreneurship studies of locational advantages (Saxenian, 1994; Stuart & Sorenson, 2003b), and is at the center of the global productivity growth created by the information economy.

One area where palpable interest has emerged is the possibility of startup relocation to Silicon Valley. For example, Hsieh and Moretti (2019) estimate that high housing costs in San Jose, San Francisco, and New York alone cost the United States 3.7 percent of annual GDP due to misallocation, and Moretti (2019) estimates that the productivity of star software inventors raises by 22 percent when they move to Silicon Valley. In an in depth study of biotechnology startups, Stuart and Sorenson (2003b) find that there are significant differences between the spatial distribution of founding rates and the distribution of sucess, suggesting misallocation. For entrepreneurs and technologists, whether migration to Silicon Valley leads to higher startup performance appears to be an area of persistent concern.[1] Cosidering geography more generally, the persistent outsized performance of a few entrepreneurial clusters has been a matter of consistent inquiry in academic research,[2] leading to a natural question of whether and how can firms benefit by relocating to them.

However, notwithstanding the outsized performance of Silicon Valley, the benefits of

[1] Consider, for example, https://www.startupgrind.com/blog/should-you-move-your-startup-to-silicon-valley/, or https://medium.com/lombardstreet-io/why-you-might-want-to-move-your-startup-to-silicon-valley-95921efff06.

[2] A few central mechanisms proposed for the outsize performance of clusters include culture (Saxenian, 1994; Florida, 2002), distance and infrastructure (W. Kerr & Kominers, 2014; Agrawal, Galasso, & Oettl, 2017; Belenzon & Schankerman, 2013), built space and serendipitous interaction (M. Roche, Oettl, & Catalini, 2020; M. P. Roche, 2019), financial liquidity (Stuart & Sorenson, 2003a; Chen, Gompers, Kovner, & Lerner, 2010), Marshallian agglomerations (Chatterji, Glaeser, & Kerr, 2014; Delgado, Porter, & Stern, 2010; Andrews, Fazio, Guzman, Liu, & Stern, 2020), laws, regulations, and political borders (Marx, Strumsky, & Fleming, 2009; Singh & Marx, 2013), and immigration (Balsmeier, Fleming, Marx, & Shin, 2020; W. Kerr, 2008).

migration to it are not obvious. As emphasized since Marshall (1890), startups result from ideas optimized to a certain birth region, which may make them be a bad fit in other locations, even if these locations appear higher productivity on average. As well, entrepreneurs rely significantly on their social networks for hiring, financing, and growth (Sorenson, 2018; Uzzi, 1999), and they are likely to have a stronger social network at home than at the destination region (Michelacci & Silva, 2007; Dahl & Sorenson, 2012). Do high growth startups that move to Silicon Valley experience higher performance? If they do, what may preclude other entrepreneurs from moving as well?

In this paper, I present original evidence on this question by studying how does relocating to Silicon Valley influence the performance of high growth startups, vis-à-vis the counterfactual of staying at a firm's home location. To do so, I study a large sample of Delaware jurisdiction firms (which overarchingly represent high quality startups (Guzman & Stern, 2020)) that relocate their headquarters from outside California into Silicon Valley.[3] Using a high-dimensional machine learning estimator and startup fixed-effects models, I find that moving to Silicon Valley leads to higher startup performance on equity outcomes, financing, patenting, products, and revenue. These results are robust to a stringent coefficient stability test that builds on Oster (2019), and a test of the benefits over time that allows ruling out that unobserved time-specific productivity shocks drive selection into migration. A micro-geography analysis suggests the benefits are partially driven by knowledge spillovers within Silicon Valley, and heterogeneity across time shows that financial outcomes (equity sale and venture capital) are sensitive to timing of migration, but other benefits are not.

Even though there are substantial benefits of moving to Silicon Valley, most startups do not move. The final piece of the paper highlights one possibile explanation for this missallocation: that entrepreneurs, who are fundamentally maximizing their own utility, face further migration costs in their personal wealth (or utility), outside the productivity of their firm. This allows spatial equilibrium in utility even when there is not one in the

[3]These are not startups founded in Delaware, but instead all states in the United States. Delaware is simply the legal jurisdiction under which the firm works. Empirically, firms that register in Delaware are over 40 times more likely to achieve an IPO or a high value acquisition. The benefits of Delaware are documented in Guzman and Stern (2015, 2020); Guzman (2020), among others.

allocation of productive firms.

These results contribute to several areas of entrepreneurship research. First, they speak to the way in which entrepreneurs gather resources and grow their firms, providing evidence on whether they are able to do so in locations outside of their home. Prior work has emphasized that entrepreneurs rely significantly on their social networks to activate necessary resources (Sorenson, 2018; Stuart & Sorenson, 2003b, 2003a; Saxenian, 1994), as well as the important role of personal history and preferences in determining location choices (Michelacci & Silva, 2007; Rosenthal & Strange, 2012). The present paper adds nuance to that picture by finding that some firms do move and, at least within this sample, eventually do better. In panel regressions, results show that while differences in financing and innovation take several years to evidence themselves for migrants, they are ultimately large. Still, consistent with the importance of personal preferences and history, most startups face signficant costs to move and choose to stay at home. Future work could build from these results to better consider variation across firms to understand who benefits from migration, and variation across locations to learn where these migrations are profitable.

Second, this paper contributes to reseach on the determinants of entrepreneurial ecosystems. While a long literature has sought to understand how do different local ecosystems create different types of firms (Chatterji et al., 2014; Delgado et al., 2010; Marx et al., 2009), there is much less work studying the firms that move to an ecosystem from outside of it.[4] This is perhaps suprising, since the popular press has often emphasized the tremendous importance of some entrepreneurial migrants, such as Shockley Semiconductor, Amazon, Microsoft, Netscape, Facebook, or Dropbox, for their destination regions, and conversely a loss for their original region of birth. Recognizing and studying the fundamental interplay between the migration of startups and the growth of the ecosystem is an important area for future work.

Fianlly, at a policy level, these results also speak to the types of policies that can support entrepreneurship driven regional growth. The evidence in this paper shows that a

[4]These results also speak, even if less directly, to work on international migration and entrepreneurship, including its relationship to regional growth (Saxenian, 2006; W. Kerr, 2008), and how it shapes startup performance (Denor & Singer, 2011; Conti & Guzman, 2019).

startup surrounded by additional resources appears able to transform some of these into productive outcomes without requiring long-term local embeddedness. There are a range of common policy interventions focused around this idea, including industrial expansions through 'Big Push' (Murphy, Shleifer, & Vishny, 1989), SBIR matching programs (Lanahan & Feldman, 2015), subsidies to the migration of entrepeneurs such as Startup Chile (Gonzalez-Uribe & Leatherbee, 2018), and the National Science Foundation I-Corps cluster-building program. Even though it is important to be patient in developing an ecosystem (Lerner, 2012), the evidence in this paper suggests targetted policies that simply increase available resources hold promise.

The remainder of this paper is structured as follows. Section 2 covers the data construction, including how migration is measured, and some summary statistics of the main migration rates and differences in outcomes. Section 3 is the empirical approach. Section 4 presents all results. Secton 5 concludes by discussing the implications of these results for economic theory, policy, and entrepreneurs and managers themselves.

2 Data

The data is built from business registration records from 26 U.S. states, representing 70% of U.S. GDP, from 1988 to 2014.[5] This data was retrieved during the first phase of the broader effort of the Startup Cartography Project (Andrews et al., 2020). Business registration records 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).

To focus this study on startups with high growth intention, I select on the subset of startups that register under Delaware jurisdiction. These are not firms headquartered in Delaware. They operate in every state but have chosen to be established under Delaware Corporate Law rather than the regime of their home state. There are some significant benefits to registering in Delaware. The Delaware General Corporate Law is the best under-

[5]A map of all states in the data is included in Appendix Figure A1.

stood corporate law in the U.S., with a long cannon of decisions that are useful in creating predictable contracts even in cases of significant complexity. The state of Delaware also has an advanced institutional setup to deal with corporate arbitration including its highly reputed Court of the Chancery. Furthermore, the decisions and legal framework of Delaware are generally regarded as pro-business. These benefits are significantly more useful for startups that will be large or for startups interacting with investors, including venture capitalists.[6] On the other hand, registering under Delaware jurisdiction also carries extra costs since it requires maintaining two registrations (one in Delaware and one in the state of operation). This imposes extra fees that a business that expects to be small is likely to prefer not spend.[7] This creates a natural separating equilibrium, with growth-oriented companies choosing to register in Delaware but the bulk of firms registering locally. While Delaware companies represent only about 4% of all firms, they account for over half of all publicly listed firms, and over 60% of all VC financing (see Catalini, Guzman, & Stern, 2019), and Delaware-founded startups are 23 times more likely to achieve an IPO or be acquired than non-Delaware ones (Guzman & Stern, 2017, 2020).

The complete dataset contains the registration of 488,960 new Delaware firms observed in their home state. I enhance business registration data by using a name-matching algorithm[8] to merge business registrations with five other datasets: (i) three types of intellectual property filings from the U.S. Patent and Trademark Office (trademark applications, patent applications, and patent assignments), (ii) all new IPOs in the U.S. from the SDC New Issues database, (iii) all U.S. M&A activity reported in the SDC Mergers and Acquisitions database, (iv) venture capital activity from ThompsonReuters VentureXpert, and (v) annual estimates of sales from Infogroup USA annual files.

Firm Observables at Founding. The first step is to characterize the firm at founding, in their home state. I build a large number of measures to eventually feed to the a ma-

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

[7] On average, these fees amount to a few thousand dollars per year.

[8] The matching approach builds on the existing approaches of W. Kerr and Fu (2008) and Balasubramanian and Sivadasan (2009). Further details are available on the Supplementary Materials of Guzman and Stern (2015, 2020), as well as Andrews et al. (2020).

chine learning algorithm. As explained by Belloni, Chernozhukov, and Hansen (2014), the goal here is to be as flexible as possible and create many variables. We can later allow the variable selection procedure (double LASSO) to keep only those measures that best predict treatment or outcomes. In the empirical analysis, the machine learning algorithm is trained with a 50% training data that is excluded form the estimation precluding any concern of overfitting.

From business registration I create 2 binary measures indicating whether a firm is a corporation and whether it is an LLC. Building on existing evidence that firm name length predicts performance (e.g., Green & Jame, 2013), I create 12 measures of firm name length, including a continuous measure of the number of words in the firm name, the square of the number of words, and 10 binary indicators for whether the name is exactly 1 through 10 words long. I create industry measures by using the approach of Guzman and Stern (2015, 2020), which uses a large sample of firms with NAICS codes to create a name-based algorithm that allows categorizing firms in to different economic clusters from the U.S. Cluster Mapping Project (Delgado, Porter, & Stern, 2014). There are 13 binary measures following this approach, one for each of the following groups: Agriculture and Food, Automotive, Chemicals, Clothing, Consumer Apparel, Distribution and Shipping, Energy, High Technology, Local Industries, Mining, Paper and Plastic, Publishing, and Services. I also create 5 more measures for names associated with specific high tech industries that have accounted for a meaningful share of high growth entrepreneurship in this time period: IT, Biotechnology, E-Commerce, Medical Devices, and Semiconductors. Finally, I create six measures from intellectual property filings. Three indicate whether the firm applies for a patent in their first year, has a patent assigned (from a prior inventor) in their first year, or files for a trademark in their first year. The other three indicate whether the firm applies for more than one patent, is assigned more than one patent, or applies for more than one trademark in their first year.

This leads to a total of 38 measures observable at the time of firm founding, which can be combined in 703 ways in two-way in interactions, for a total of 741 observable measures at founding.

Measures of Regional Entrepreneurial Quality. To measure the quality of the entrepreneurial ecosystem, I use the public datasets provided through the Startup Cartography Project (see Andrews et al., 2020).

Measures of Firm Performance. I develop six outcome measures based on the firms observed performance six years after founding. *IPO* and *Acquisition* are two binary variables equal to 1 if the firm has an IPO or an acquisition within six years. The key outcome of interest, *Equity Growth*, is simply the union of these two variables. It is equal to 1 if a firm achieves an IPO or an acquisition and zero otherwise. Though rare, equity growth represents a highly desirable outcome for entrepreneurs with high growth intention (the sale of their company), and closely matches the anecdotal incentives sought by many high growth founders. *Follow-on Patent* is equal to 1 if the firm files or acquires (is assigned) one or more patents, excluding the first year window used for at-founding observables. *Follow-on Trademark* is equal to 1 if the firm files one or more trademarks, excluding the first year window.[9] *Venture Capital*, is equal to 1 if the firm receives venture capital. And *High Sales* is equal to 1 if the firm achieves $1 million or more in sales six years after founding (as reported by Infogroup USA).

Measuring Migration. To track migration, I use the fact that companies need to register not only in the state in which they are founded, but also in every state in which they rent real estate, hire people, or set up a local bank account. These registrations include at least the name of the firm, the date of registration, the address of the firm's local office within the state, and the address of the principal office (headquarters). Because Delaware corporate law specifically requires companies to name themselves sufficiently different from one another, and because (except for rare cases) companies must register with their true name in each state, the matching across registries is very simple and allows high confidence that two registrations of a Delaware jurisdiction firm under the same name, in two different states, represent the same firm.

[9]For migrant firms, patent and trademark outcomes are only included if the patent is assigned to a firm in the destination state, to avoid potential biases ocurring through innovative activity ocurring at home.

I operationalize migration through three conditions: (1) The first state in which the firm registers is assumed to be the birth state, and its registration date the date of founding; (2) if a firm then registers in a second state with its principal office in this new state, this is considered a migration as long as the firm lived in the birth state for at least 3 months; (3) the date of registration in the destination state is the migration date. This limits the analysis to migration of registered firms across states, but with an ability to see the specific destination address (and hence also the destination MSA). Focusing on cross-state migrations allows me to generally abstract away from migrations within the same economic region.

I develop two measures documenting migration. *Migrant (Anywhere)* is equal to 1 if the firm moves to any destination within the first two years after founding, and *Migrant to Silicon Valley* is equal to 1 if a firm moves to Silicon Valley in the first two years after founding. Silicon Valley is defined as the union of the San Jose-Sunnyvale-Santa Clara, CA MSA and the San Francisco-Oakland-Hayward, CA MSA.

Table 1 shows summary statistics for some of the key variables. Figure 1 shows the incidence of migration and the differences in firm outcomes comparing migrants to non-migrants. Though only 4.2% of startups move across states in the first two years, these firms account for 10.2% of equity growth outcomes, 6.5% of firms with venture capital financing, and 7.5% of firms with patenting, six years later. The difference is even more stark when we look at migrants to Silicon Valley. The migrants account for only 0.25% of all firms, but they represent 2.9% of firms that achieve an equity growth event, 2.5% of all VC funded firms, and 1.75% of all patenting firms.

The over-representation of migrants on success outcomes is quite significant, but these simple statistics also quickly raise concerns about selection bias. The next section explains the econometric methodology.

3 Econometric Framework

The econometric framework is divided in three sections. An approach to measure the quality of companies at founding, the cross-sectional specification, including the coefficient stability test that builds from the machine learning estimates, and the panel specification.

3.1 Estimating Entrepreneurial Quality

To estimate startup quality around founding (and before moving), I implement the 'entrepreneurial quality' approach covered in Guzman and Stern (2015), Guzman and Stern (2020), and other related work. This approach combines three interrelated insights. First, as the challenges to reach a growth outcome as a sole proprietorship are formidable, a practical requirement for any entrepreneur to achieve growth is business registration (as a corporation, partnership, or limited liability company). This practical requirement allows forming a quasi-population of entrepreneurs 'at risk' of growth at a similar (and foundational) stage of the entrepreneurial process. Second, it is possible to distinguish among business registrants by observing choices the founders make at or close to the time of registration informed by their own ambitions and expectations for the firm. Examples of these choices include whether the founders name the firm after themselves (eponymy), whether the firm is organized in order to facilitate equity financing (e.g., registering as a corporation or in Delaware), and whether the firm seeks intellectual property protection (e.g., a patent or trademark). Third, one can leverage the fact that, though rare, it is possible to observe meaningful growth outcomes for some firms (e.g., those that achieve an IPO or high-value acquisition).

Combining these insights, we can consider a firm fully characterized by many (even infinite) founding observables Z_i. Entrepreneurial quality is defined as simply the relationship between a specific growth outcomes g_i and these founding startup characteristics. Specifically, for a firm i and a growth outcome g_i quality is

$$\theta_i = P(g_i|Z_i) \tag{1}$$

Given a subset of observed founding characteristics $Z'_i \in Z_i$, an imperfect empirical estimate of quality can then be estimated as the *predicted* out of sample probability of measured founding characteristics on performance—i.e. $\hat{\theta}_i = \hat{P}(g_i|Z'_i)$.

The approach of the present paper is to use machine learning on high-dimensional data and firm fixed-effects as two complementary approaches to account for a large number of Z'_i. The empirical fit of the machine learning model is evaluated though the ROC score.[10] In my setting, the ROC score represents an answer to the following problem: if two random startups, one which achieved growth and one which did not, are fed to the machine learning predictive model from (1), what is the probability that this model will score the growth startup higher than the non-growth startup? A fully uninformative classifier will have an ROC score of 0.5, while a perfect classifier will have an ROC score of 1. *Fit* is defined as the share of the distribution between 0.5 and 1 that is covered by the ROC score. This can also be usefully interpreted as the share of variation in outcomes accounted for by the predictive model, a fact that will be later used in the coefficient stability tests.

$$Fit = (1 - ROC)/.5 \tag{2}$$

In the empirical portion of this paper, this machine learning predictive model is estimated only on firms that do not migrate, allowing the prediction to be interpreted as the expected performance of a firm if it stayed at home.

3.2 Cross Sectional Approach using High-Dimensional Data and Machine Learning

Consider many firms, indexed by i, all born outside Silicon Valley. The firms are fully characterized by a high-dimensional (even infinite) number of observables Z_i. The firm's performance Y_i can be determined by two structural functions of these observables, g_1 for

[10] ROC stands for Receiver-Operating-Characteristic, a name that is a remnant of the early application of this measure to radar signal processing during World War II. It is formally defined as the area-under-the-curve of a model's true positive rate compared to the false positive rate at all possible probability thresholds.

the performance in Silicon Valley and g_0 for the performance at home, and two additively separable error terms U_{i1} and U_{i0}.

$$Y_i = \begin{cases} Y_i(1) = g_1(Z_i) + U_{i1} & \text{if located in Silicon Valley} \\ Y_i(0) = g_0(Z_i) + U_{i0} & \text{if located outside Silicon Valley} \end{cases}$$

The goal is to estimate the treatment effect on the treated.

$$\Delta = E[\frac{Y_i(1) - Y_i(0)}{\theta}|S_i = 1] \tag{3}$$

The econometric challenge is that we do not observe $Y_i(0)$ (nor g_0) for those who move, and therefore cannot estimate Δ directly. The goal of index models is to use some set of observables $X_i \in Z_i$ to estimate a function $\hat{g}_0(X_i)$ such that $\hat{g}_0(X_i) \approx g_0(Z_i)$. If the errors terms can be assumed to be mean-zero (i.e. $E[U_{i1} - U_{i0}|D_i, X_i] = 0$) then Δ is identified.[11] [12] This paper implements the 'double-LASSO' approach, which takes advantage of a high dimensional number of observables Z_i' to estimate these counterfactuals. Specifically, building on (Belloni et al., 2014), it offers and tests the key assumption that a large number of observables can characterize relatively well non-migrant performance.

A central assumption is therefore that the predicted value of performance from observables $\hat{g}_0(Z_i')$ is close enough to the true value of underlying firm expected performance at home. This is itself testable. To do so, building on Altonji, Elder, and Taber (2005) and Oster (2019), we look at the stability of the coefficients as follow-on information is added. The Oster approach considers whether adding additional observables z_i to Z_i' that are ex-

[11] Critically, this depends on how good the observables X_i are. The recent boom in IT infrastructure generally called 'Big Data' has created a substantial number of measures that can be included in X_i, which computer scientists and econometricians have embraced with the hope that can enable us to estimate a better $\hat{g}_0$ and reduce this bias. The new methods developed (generally falling under the label 'machine learning') take advantage of these measures.

[12] One particularly important that becomes more salient in machine learning is the risk of lack of common support. Though easily defendible in low-dimensional regressions, common support (also called covariate overlap) can often fail when high dimensional, an issue most recently highlighted by D'Amour, Ding, Feller, Lei, and Sekhon (2017). To achieve common support, a machine learning approach must rely on a variable regularization technique to guarantee overlap. I use the 'double LASSO' approach developed by Belloni et al. (2014) for variable regularization in this paper.

pected to be meaningful for migration (e.g., home state information) increases the information captured in the regression (i.e. increases the R^2) and changes the coefficient of interest. The relative importance of remaining unobservables can then be backed out under two key assumptions. First, we must assume that unobservables are not more correlated to the outcome than the observables z_i. This assumption is maintained in this paper. Specifically, I compare the coefficient stability from a regression with and without state-of-birth by year fixed effects. Because the location of birth is shown to influence who moves, and should also impact mover performance, the fixed effects should be highly correlated with selection to move (a fact also shown empirically).

Second, one must also make assumptions about how big can the unobservables be based on the R^2 of the model. Oster proposes using 1.3 times the R^2 of the observational model. In this paper I relax this assumption and instead consider how large would the unobservables have to be if all remaining variation was taken into account—i.e., if $Fit = 1$. This allows more confidence on the estimate and the stringency of the test.

3.3 Panel Data Regressions

The second econometric approach takes advantage of the panel structure of the data. Considering the fact that not all migrants move at the same time, I set up a panel that includes age and firm fixed effects and compares the benefits of peformance for early movers compared to other movers that have not yet moved. That is, for each migrant firm i, moving at age m, of age t, I run OLS regressions of the form

$$Y_{i,m,t,\tau} = \lambda_i + \gamma_t + \rho_m + \boldsymbol{\beta_\tau'} \boldsymbol{M_{i,\tau}} + \epsilon_{i,t,m,\tau}$$

where $\boldsymbol{M_{i,\tau}}$ is a vector of individual indicators for each value of τ, defined as the difference between the age at migration and t. λ_i is a firm fixed effect, γ_t is an age fixed effect, ρ_m is a fixed effect for age at migration, $Y_{i,m,t,\tau}$ is an outcome measure, and $\epsilon_{i,t,m,\tau}$ is white noise.[13] The coefficients of interest are the vector $\boldsymbol{\beta_\tau}$, which represent the differences in

[13] This approach has commonly been used in urban economics to study the effect of location on per-

the performance of migrants after migration (or before if $\tau < 0$), once fixed firm differences (λ_i) and mean age differences (γ_t) are accounted for. To take advantage of additional time-periods to better observe differences, while keeping close to the early stages of the firm, I change the dataset to consider the first five years of the firm at the semester level, allowing τ to range from -11 to +11.

4 Results

4.1 Entrepreneurial Quality Estimates

I estimate entrepreneurial quality through a random forest (Breiman, 2001) and predict the likelihood of *Equity Growth* from firm observables at founding. There are too many observable measures available to include (741 in total). I use the variable regularization method double-LASSO Belloni et al. (2014), to guarantee that the estimator has common support.[14] The random forest model predicts *Equity Growth* from *LASSO Controls* on a 50% random sub-sample of non-migrants. The predicted estimates can be interpreted as the probability of success when the firm stays at home. Table A1 reports two simple logit models to highlight some interesting relationships of core variables.

The ROC score for the random forest model is 0.86 in the training sample, and 0.85 in the holdout (non training) sample. The holdout ROC graph is plotted in Figure 2A. The out of sample ROC of 0.85 implies a *Fit* of 0.7—70% of the variation in outcomes is accounted for by the model.

Figure 2B reports the predictive performance of this model through an out of sample 10-fold cross validation procedure. It plots the distribution of firms that achieve growth out of sample across 5% groups of the predicted quality distribution. The top 5% of the out of sample quality distribution accounts for 43% of all growth firms, and the top 10% for 59%.

sonal productivity (e.g. Glaeser & Maré, 2001).

[14] *LASSO Controls* is the set of 91 variables selected. Besides being used in a random forest, these variables can also be used as controls directly in an OLS regression, providing a secondary estimating approach.

Together, these results suggest a high level of out of sample predictive performance for the machine learning model. All follow-on analyses in this paper are performed only on the holdout sample.

4.2 Selection into Migration

Figure 3 shows the selection into migration. Panel A is a binned scatterplot of firm quality and the average rate of migration for each bin. The relationship between migration rates and estimated startup quality is positive, better firms are more likely to migrate. Panel B is the binned scatterplot of birth state estimated startup quality and the average rate of migration. The fit is negative, firms are more likely to leave low quality regions. Panel C plots, within a year, the share of all movers that move to a destination state and the estimated startup quality of that state in that year. The fit is once again positive. Conditional on migration, firms are more likely to move to higher quality states.

These relationships are sharpened in Table 3, which presents a linear probability model with *Migrant (Anywhere)* as the dependent variable, controlling for year, state, and state-year pair fixed-effects. The preferred specification is Column 3, it suggest that increasing firm quality by one log-point (about two thirds of a standard deviation) leads to an increase in the likelihood of migration of 1.2%. Given a mean migration rate of 3.3% (in the full sample), this is a 36% change from the baseline.

4.3 Migration and Startup Performance: Machine Learning Estimates

We now proceed to the centerpiece of this paper, estimating the impact of migration on startup performance.

Figure 4A reports graphically the change in odds of *Equity Growth* when comparing migrants and non-migrants in several statistical models. The odds are estimated by running a linear probability model of *Equity Growth* with migration as the independent variable, and then dividing the coefficient by the expected performance had the firm not moved (its estimated entrepreneurial quality). The regression tables are available in Appendix Table A2. Standard errors are clustered by founding state.

The top portion of Figure 4A reports the increase in odds from migration to Silicon Valley. The first estimate is the naïve estimate: the coefficient of a regression without any controls, divided by the sample mean of the outcome. The naïve estimate is 8.3. The three models below the naïve model perform a series of improvements that reflect common changes that we would expect to see in a low-dimensional selection on observables approach—adding state fixed-effects, or state-year pair fixed effects, and controlling for firms that have intellectual property or venture capital before moving. The estimated effect is very similar to the naïve estimate. The last three rows move away from the classic selection on observables and instead use high dimensional methods as presented in Section 2. The differences are significant and the odds of equity growth drops by half (though it is still meaningful). The preferred estimate is a model controlling for entrepreneurial quality and state-year fixed effects (in green). The result suggests migration to Silicon Valley increases the odds of *Equity Growth* by 4.1X.

The two bottom portions of Figure 4A report differences in performance for migrations to other destinations (excluding Silicon Valley) and for all migrants. The effects are lower but still positive and economically meaningful. Moving to other destinations suggests an increase of 2.3X the odds of success. In both cases, the naïve estimate substantially overestimates the benefit of migration.

Figures 4B and 4C report a series of heterogeneity analyses. Figure 4B reports the estimates of the role of migration across a series of sub-samples—only firms with a patent, only firms with a trademark, only corporations, only firms with venture capital investment, and only firms with a name associated with high tech. There is variation in the coefficients, and the precision within each sample. However, the point estimate of the change in odds is always positive, with values between 2 and 4, and never statistically different from the main effect.

Figure 4C shows the effect of migration on the performance of startups across the quality distribution using a kernel regression with an Epanechnikov kernel and a bandwidth of 0.05. The results suggest increasing returns of migration for estimated entrepreneurial quality, with the bottom 40% having no perceivable benefit from migration and the benefit increasing as the estimator moves up the distribution.

Together, these results suggest a persistent positive benefit of migration on the performance of startups, which is particularly high for movers to Silicon Valley, and highlights at least a 2X overestimate of the effect of migration when using common controls, compared to the machine learning method used here.

Other Outcomes. I expand the analysis to other outcomes in Figure 5, by studying the effect of migration to Silicon Valley on the odds of patenting, trademarks (a proxy for commercialization), venture capital financing, and sales. The econometric models are equivalent to those in Figure 4A, a different random forest is run for each outcome variable to estimate the expected performance for migrants if they had stayed at home. The ROC scores of these random forest models range from 0.70 (sales) to 0.95 (patenting). The increase in odds from migration implied by the naïve model is much higher than the preferred model in all cases, in some cases being three times as much. The benefits of migration are all positive but do vary by outcome, they are higher for increases in venture capital financing, and sales, than for patenting and trademarks.

4.3.1 Robustness Tests for Ommitted Variables

Next, I consider two robustness tests to assess ommitted variable bias: whether the machine learning approach has captured enough variation at founding, and whether other unobservables can creep in and bias the main estimates in the time between firm founding and migration.

The first potential ommitted variable bias stems from failing to account for some important unobservables at founding. Section 3 overviews an implementation of the coefficient stability test in Oster (2019), that takes advantage of the value of FIT to consider how much information is left to be explained in the data.[15] In Table 4, I report estimates

[15] As explained in Section 3, the method relies on using the increase in R^2 and change in coefficient between a first and a second regression can be used to assess the necessary size of follow-on unobservables to make the effect go away, under the assumption that the unobservables are as related to performance as

using this approach comparing a model without state-year fixed effects to a model with state-year fixed effects, and report two scenarios: the size of unobservables needed for the coefficient to become zero, and for the 95% confidence interval to include zero (even if the coefficient is positive). Unobservables need to be at least 25 times larger than observables for migrants to Silicon Valley for the confidence interval to include zero, and 36 times for the point estimate to be zero. This is much higher than the 30% of variation available according to the ROC score. The ample difference between these two suggests that there is not enough unobservable variation left to make the results zero or even close to it.

The second potential ommitted variable is the possibility of productivity shocks after founding. If firms are matched well at founding, but diverge after founding due to unobservable shocks that correlate with both migration and performance, then the likelihood of having received such a shock should increase mechanically with firm age. One conclusion of it is we would expect a positive bias to 'creep in' for firms that move at an older age—i.e., the benefit of migration would be correctly estimated for firms who move close to birth, but estimates for later movers would include both the benefit of migration and some upward bias from unobserved shocks. In Figure 6 I report separate estimates of the treatment effect of migration for migrants that move at each semester of age, from semesters 1 through 4. Consistent with the idea that productivity shocks are not changing the propensity to move, the effect is similar across all four semesters.

4.4 Migration and Startup Performance: Fixed-Effects Regressions

We proceed now to a second analysis on the effect of migration on firm performance that does not rely on machine learning, but instead on using the timing of migration in a panel format. To do so, I study the impact of migration on the performance of startups under a panel structure with semester level observations, and include firm fixed effects, semester of age fixed-effects, and age at migration fixed effects, to study how does the the performance of migrant startups of the same age, but who move at different times, differ. The empirical

the added observables in the second regression.

model is reported in 3.3.

Figure 7 plots the coefficients of this regression for four outcomes—the number of patent applications, trademark applications, venture capital dollars raised (in millions), and equity growth—from five years before moving to five years after moving, taking advantage of variation in the timing of the move. The figure also reports a 'baseline' measure for each outcome, which is the mean value of the outcome variable for a matched set of firms of the same estimated entrepreneurial quality, born in the same location and year, that do not move.

Three take-aways are apparent. First, there is no significantly different value in any of the pre-trends in the data. For three outcome variables, the number of patents, the probablity of an equity growth outcome, and the amount of venture capital raised, the pre-trend is flat and precisely estimated around zero. For the fourth one, the number of trademarks, the estimates are more noisy but still hover roughly close to zero. Together, these values suggest the fixed-effects method is able to take care of selection into migration reasonably well.

Second, the change in performance after migration is economically meaningful and persistent up to six years after moving. By this time, migrants register about 1.7 more patent applications and 0.2 more trademarks than other migrants who have not yet moved, raise $4.6 million dollars more in venture capital financing, and are 7.1 percentage points more likely to achieve the equity growth outcome. Using the baseline values to get a sense of the relative effects leads to estimates that are close to those of the cross-sectional machine learning model. Five years after moving, we observe in migrants a 4.7X increase in patent applications, a 2.8X increase in trademarks, a 3.5X increase in venture capital ifnancing, and a 4.5X increase in the likelihood of equity growth.

Finally, the dynamics of the estimates also provide insight into the process through which firms are benefitting from migration. The slow increase in the number of patents, for example, is indicative of the potential difficulties firm may face on resource accumulation and knowledge procurement after moving. As well, the slow raise of VC financing suggests the process of moving is not overarchingly driven by VC financing events, but that it is instead the act of moving that allows a firm to access more capital. In contrast, the dynamics of the equity growth outcome do show a contemporaneous increase in the likelihood that a firm is IPO or acquired and migration. In this case, rather than differences accruing only some time after migration, firms that move are 2.4 percentage points more likely to be acquired than non-movers in the same semester of migration. This could suggest some movers move with the option of already collaborating closely with firms at the destination, and perhaps with the short term goal (and prospect) of vertically integrating with them. Understanding these dynamics better is an important question for future work.

4.5 Heterogeneity Analyses

4.5.1 Heterogeneity in Geographic Destination within Silicon Valley

Now, we move into the micro-location elements of entrepreneurial migration to consider the firm's individual destinations within Silicon Valley. Micro-location within Silicon Valley may impact performance because knowledge spillovers deteriorate quickly with distance, even at the level of a few blocks (W. Kerr & Kominers, 2014; Arzaghi & Henderson, 2008; Catalini, 2018), so that it is the specific neighborhood a firm moves to, rather than Silicon Valley more broadly, that may drive the regional benefits. Figure 9 illustrates the heterogeneity in destination by plotting the location of all Delaware startups born in Silicon Valley (left panel) and the destination location of the startups that moved to Silicon Valley (right panel). Table 5 is the main analysis. It uses the estimated entrepreneurial quality for the firms born in each ZIP Code in Silicon Valley to assess whether it predicts migrant performance, conditional on migrant characteristics. The preferred model is column (3), which also includes the LASSO controls, state of origin fixed effects, and year of migration fixed effects. The coefficient is positive and significant, consistent with the potential importance of knowledge spillovers partially accounting for the effect of location on performance.

4.5.2 Heterogeneity in Year of Migration

Finally, I consider heterogeneity in the business cycle when a firm moves to Silicon Valley. To do so, in Figure 8, I report the effect of migrating in specific years during two eras that were quite distinct in Silicon Valley: the dot-com boom and the dot-com bust.[16]

Figure 8 reports these coefficients (Panels B through F) for a series of outcomes. An important requirement to be able to draw comparisons is that the quality of migrants is consistent across years. Panel A shows this is roughly the case for the estimated quality used in this study. Panel B studies the likelihood of equity growth for migrants at different years. The patterns before and after the dot-com bust are striking. While there was a large benefit of moving to Silicon Valley during the boom years, this benefit becomes negligible in the bust years. Panel C studies VC financing. The pattern here is different. The benefit raises up to 2001 (the year the bubble burst) and then recedes gradually. Both patterns match well anecdotal accounts of the time period and general intuition: while there was a sharp drop in IPOs and acquisitions after the bubble bust (and the markets collapsed), some VC financing continued after 2001 as VCs more slowly unloaded the capital already fundraised.

Panels D, E, and F, look at outcomes less related to the boom and bust process of capital markets: patents, trademarks, and revenue. Interestingly, these outcomes show little movement across time, suggesting the effects of Silicon Valley on the 'real economy', such as knowledge spillovers or access to product markets are less cyclical. This is also intuitive: though the IPO market crashed in 2001, the scientists and engineers in the region continued to work and (presumably) produce after 2001.

Together, these results provide further support for a role of agglomeration on the performance of migrants, but also highlight how these benefits are not homogeneous, but depend on the specific outcome and the local condition of the destination ecosystem at the

[16] For all firms i born in region r, I run OLS regressions of the form $Y_{i,r} = \alpha + \boldsymbol{\beta' M_{i,r}} + \theta_i + \gamma_r + \epsilon_{i,r}$ where θ_i represents the startup's entrepreneurial quality, $Y_{i,r}$ is an outcome measure, λ_r are region fixed-effects, and $\epsilon_{i,r}$ is random noise. $M_{i,r}$ is a vector of 11 elements each of which takes a value of 1 if a firm moved to Silicon Valley in each of the 11 years between 1996 and 2006, and $\boldsymbol{\beta}$ are individual coefficients of interest—the effect of moving in each year.

time of migration.

4.6 Founder Wealth (or Utility) as a Constraint to Migration

So far, the benefits estimated from migration are large, yet the actual incidence of movers may appear relatively low given these estimates. As a final piece of analysis, I study how moving is limited by some personal founder characteristics. The resulting indirect evidence suggests that the presence of personal local wealth unrelated to the startup (e.g. owning a home, or the income of a spouse) often makes it personally unprofitable for founders to move, even when it would be beneficial for the firm. This result allows the rest of the paper to be economically concordant: rather than relying on a disequilibrium across startups and regions, where moving to Silicon Valley is rare in spite of being highly beneficial, it suggests the possibility of a spatial equilibrium in the wealth (or utility) maximizing choices of founders.

4.6.1 The Expected Value of Migration for Founder Wealth.

To begin understanding the founder level benefits and costs of migration, it is useful to first consider the expected value of migration on founder wealth.

Assume startups are founded by a wealth maximizing founder,[17] and that the wealth gained by successful venture-backed entrepreneurs after a company exit is a good guide for the returns to successful growth-oriented entrepreneurs in general. Hall and Woodward (2010) estimate the average wealth gains of founders who sell or IPO their company at $20 million dollars. If entrepreneurs are risk neutral, an increase of 5.8 percentage points on the probability of success (the estimated benefit of migration) translates into an expected wealth increase of $1.2 million dollars.[18] The key analytical question is whether this would be enough to entice all founders to move. A simple comparison may suggest this is not the case. For example, this amount is lower than the extra cost of a single family home

[17] This conceptualization focuses on a wealth simplicity, but all insights hold for a utility maximizing founder as well.

[18] Specifically Hall and Woodward (2010) estimate the average gain at $6 million, and only 30% of the founders have a positive gain (so that 6/0.3=20). I am thankful to Susan Woodward for her help in confirming this calculation.

for founders moving from low-cost housing regions, such as Austin, Texas, to Palo Alto, California.[19] Thus, in some cases, the founder may choose not to move even if it would have been beneficial for the startup, leading to founder wealth (or utility) to be a limit to the successful implementation of startup strategy.

One way to probe at this hypothesis indirectly is to look at the relationship of migration and founder age. Assuming localized wealth tends to increase with age, we should expect three relationships to be consistent with this pattern in a sample of matched migrants and non-migrants of same estimated quality. First, conditional on firm characteristics, migrant firms should have younger founders. Second, within migrants, older migrant founders would tend to be of higher quality, since those would have a higher expected value of migration to offset the higher cost. Finally, third, within non-migrants, there should be no relationship between quality and age.

4.6.2 Age and Migration.

To test these ideas I hand collect a sample tracking the age of a random sub-sample of 100 Silicon Valley migrants matched to 100 randomly selected non-migrants with the same quality, region of birth, and year of founding. Using detailed research of the firm's history using a mix of LinkedIn, Crunchbase, AngelList, WayBackMachine, and historical Whois records, I record for each firm to the original founder of the company and the year of college graduation, and define founder age at founding as the year of college graduation plus 22.[20]

T-tests in Table 6 show migrants are younger than non-migrants on average even if the firms are of same entrepreneurial quality. The age for non-migrants is 40 years old, an estimate close to Azoulay, Jones, Kim, and Miranda (2020).[21] The age for migrants is lower,

[19] In 2016, Zillow reports the average home value for a single-family home in Austin, Texas to be $323,900 and the average value in Menlo Park to be $2,019,900.

[20] In the case of multiple founders, I focus on the 'idea' founder (the original entrepreneur), rather than simply the highest position in the company. Who is the founder with the idea requires looking closely at the history of each company. In general, for companies created around a central innovation I take the inventor of this innovation (e.g. in Google this would be Larry Page or Sergey Brin), for companies created around a market concept, I take the original CEO who thought about such idea (e.g. in Salesforce this would be Marc Benioff). For firms where I could not find a founder, I simply re-match to a new one.

[21] Azoulay et al. (2020) report the age of founders at founding for all high growth startups in the US

36, and is statistically different from the non-migrant age in a two-sided t-test. The main difference is in how many migrants are particularly young and particularly old—migrants are twice as likely to be under 30 and half as likely to be over 50 than non-migrants. Table 7 reports a regression controlling for estimated founding quality and state-year pair fixed-effects. Column 3 is the preferred specification, where quality is controlled through a 4th order polynomial. The coefficient of age is -0.01 and significant. This coefficient is meaningful. For example, increasing age of the founder from 20 to 40 years old decreases the likelihood of migration by 20 percentage points, or 40%. Figure 10 shows the quality of migrants and non-migrants by age decade. While the non-migrant quality seems basically unrelated to age, the migrant quality is increasing with age. Table 8 reports OLS regressions with *Ln(Entrepreneurial Quality)* as the dependent variable and *Age of Founding* and *Is Migrant* as the independent variables. The coefficient of the interaction term positive and significant suggesting that, within migrants, older migrants tend to be higher quality.

The results in this section highlight a key tradeoff that conforms the basis a potential spatial equilibrium in migration choices startups: even if strategies are profitable and there are no principal-agent problems, under some conditions, the entrepreneur as a wealth (or utility) maximizing individual might make choices that are not consistent with his or her startup's profit maximizing strategies. The likelihood of migration is higher when the founders face lower personal costs (e.g. young founders), or the benefit of migration is higher (e.g. for higher quality startups).

5 Conclusion

The way in which location shapes the performance of startups has long been of interest in entrepreneurship research. Prior work emphasized important underlying differences across entrepreneurial ecosystems that may lead to differences in the quality and performance of startups, as well as the possibility that there is regional misallocation between the founding locations and those that are most productive (Stuart & Sorenson, 2003b; W. R. Kerr

using Census data, getting to a main value of 42.

& Robert-Nicoud, 2020; Saxenian, 1994; Duranton & Puga, 2001). This paper added to this literature by performing the first systematic evaluation of the way in which startups relocating across locations benefit at the destination, focused on entrepreneurial migration to Silicon Valley. Using a machine learning model and fixed effects methods, the results document a significant improvement of startups after moving, which cannot be explained by underlying selection into migration. Migration improves several outcomes for firms, including equity growth events, financing, patenting, product introductions, and startup revenues. The benefits are at least partially driven by knowledge spillovers, and sensitive to capital market conditions during migration. Despite the benefits to migration, most startups do not move. A simple analysis suggests this may be due to the personal costs of moving for founders themselves.

The results in this paper provide useful information for managers and entrepreneurs themselves, who often similarly struggle with location choice and understanding the benefits of moving to a high technology cluster. The trade-off between the home advantage and the benefits of moving is one of the key choices faced by entrepreneurs in deciding how to organize their early company. This paper suggests moving to high agglomeration locations can be beneficial. To take these results into managerial practice, future work needs to move beyond simply estimating the treatment on the treated of those who move, to instead also consider the boundaries of these benefits, the industries in which it may be higher or lower, and how growth orientation and other firm characteristics can change this calculation. That is, the results as currently presented still do not form a complete picture that can allow creating strategic advice to specific managers.

At a policy level, these results provide support to the idea of reallocating economic activity across the United States, and the potential benefits for firms themselves when doing so, particularly to innovative clusters such as Silicon Valley. They also hint at a possible lever for policy action: to the extent that geographic misallocation stems from a difference between utility-maximizing entrepreneurs and the profit maximization of the firms they own, then it is possible that subsidizing migration costs for entrepreneurs is socially beneficial. Using 'quality' markers of the form presented here could help reduce selection mistakes.

Finally, these results also shed light on the importance of uniquely characterizing entrepreneurs as a fundamental element of entrepreneurial strategy. Rather than considered firms as profit maximizing entities, the evidence here emphasizes the importance of embedding these profits on a utility maximizing entrepreneur, whose own satistfaction is not fully determined by startup performance. Even in the absence of any principal agent problems (since the entrepreneur is the manager and owner), these two competing goals place limits on entrepreneurial strategy.

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TABLE 1
SUMMARY STATISTICS

		All Firms		*Migrants (2 years)*	
		Mean	*Std. Dev.*	*Mean*	*Std. Dev.*
Outcomes					
Equity Growth	1 if a firm achieves IPO or acquisition in 6 years (Source: SDC Platinum)	0.008	(0.089)	0.049	(0.216)
Files Trademark	1 if a firm files a trademark in years 2-6 of life (Source: USPTO)	0.045	(0.206)	0.087	(0.283)
Files Patent	1 if a firm files a trademark in years 2-6 of life (Source: USPTO)	0.037	(0.188)	0.069	(0.254)
Gets VC	1 if a firm receives venture capital financing (Source: ThompsonReuters VentureXpert)	0.016	(0.126)	0.023	(0.148)
High Sales	1 if a firm files a trademark in years 2-6 of life (Source: USPTO)	0.039	(0.194)	0.062	(0.240)
Early Migration					
Migrant (Anywhere)	1 if a firm moved to a different state in the first two years	0.033	(0.179)	1.000	(0.000)
Migrant to Silicon Valley	1 if a firm moved to a different state in the first two years to Silicon Valley	0.002	(0.049)	0.988	(0.110)
Other Migration					
Migrant in 5 Years	1 if a firm moved to a different state in the first five years (censored)	0.052	(0.223)	1.000	(0.000)
Migrant Ever	1 if a firm moved to a different state ever (censored)	0.073	(0.260)	1.000	(0.000)
Business Registration Observables					
Corporation	1 if a firm is a corporation	0.426	(0.494)	0.625	(0.484)
Short Name	1 if a firm's name is 3 words or less	0.579	(0.786)	0.528	(0.705)
Delaware Jurisdiction		1.000	(0.000)	1.000	(0.000)
Intellectual Property					
Patent	1 if a firm files for a patent or has a patent assigned in the first year of business activity.	0.025	(0.156)	0.025	(0.156)
Trademark	1 if a firm files for a trademark or has a trademark assigned in the first year of business activity.	0.012	(0.108)	0.011	(0.103)
Observations		488960		16243	

91 observables from business registration records and IP filings used on a double LASSO procedure to control for observables not included. Outcomes must be are achieved by the firm within six years of founding. Migration is equal to 1 if the firm changes headquarters as evidenced in changes in its business registration across stats. For migrant companies, only success in the destination region is counted (e.g. filing a patent where the assignee is in the destination region). Equity Growth is a binary measure equal to 1 if a firm achieves IPO or acquisition. IP is a binary measure indicating whether the firm files a trademark or a patent. VC outcomes are measured from Thompson Reuters VentureXpert and High Sales is a binary measure equal to 1 if the firm is reported as having over $1 Million USD in sales by year 6 in the Infogroup USA database.

TABLE 2
QUALITY OF MIGRANTS AND NON-MIGRANTS
LINEAR PROBABILITY MODELS
DEPENDENT VARIABLE: MIGRANT (ANYWHERE)

	(1)	(2)	(3)	(4)
Ln(Firm Entrep. Quality)	0.0173**		0.0122**	0.0114**
	(0.00371)		(0.00253)	(0.00253)
Ln(State Entrep. Quality)		-0.0356**	-0.0172	
		(0.0127)	(0.0116)	
State F.E.	No	No	Yes	No
Year F.E.	No	No	Yes	No
State Year Pair F.E.	No	No	No	Yes
Observations	263083	227758	227758	263083
R-squared	0.006	0.014	0.069	0.084

Standard errors clustered at the state level. Dependent variable is a binary measure equal to 1 if the firm migrates in the first two years of life. Firm Entrepreneurial Quality is the predicted value of performance from a machine learning model (random forest) in a trained to predict Equity Growth from at-founding characteristics. The sample used for training is excluded from this analysis. State Entrepreneurial Quality is the average quality of *local* firms born in that state and year, including both Delaware and non-Delaware firms.* p < .1 ** p < .05

TABLE 3
OSTER TEST OF SIZE OF UNOBSERVABLES FOR EFFECT TO BE ZERO

	Size of Unobservables for effect to be zero	Size of Unobservables for effect to be not-significant at p =.05
All migrants (Comparing Panel A (3) with Panel A (5))	18:1	10:1
Migrants to Silicon Valley (Comparing Panel B (3) with Panel B (5))	36:1	25:1

'Oster Test' refers to the methodology in Oster (2017). Under the assumptions that (a) the unobservables are not more correlated than the observables with the bias and (b) differences in the R^2 comparing experimental vs observational studies in general provide a good guidance for the upper bound of variation accounted for (Oster suggests setting this value R_{max} at $1.3 \times R^2$) then it is possible to provide the expected size of unobservables to make the effect be of certain value. Estimates of size of unobservables to make the effect not significant also assume the same standard errors. The regressions and R^2 are available in the appendix.

TABLE 4
SILICON VALLEY MICRO-LOCATION CHOICES AMONG MIGRANTS AND PERFORMANCE
LINEAR PROBABILITY MODELS
DEPENDENT VARIABLE: EQUITY GROWTH

	(1)	(2)	(3)
Destination ZIP Code Local Entrepreneurship	0.0151	0.0416*	0.0310*
(Quality X Quantity)	(0.89)	(2.47)	(2.07)
Ln(Birth State Entrep. Quality)		0.00876	
		(0.67)	
LASSO Controls	No	Yes	Yes
State F.E.	No	No	Yes
Moved Year F.E	No	Yes	Yes
N	725	664	725

Dataset is only migrants to Silicon Valley. Robust standard errors in parenthesis. * p < .1
** p < .05

TABLE 5
AGE AT FOUNDING FOR MIGRANTS AND NON-MIGRANTS
HAND COLLECTED SAMPLE

	Non-Migrants		Migrants		Student's T-Test	
	Mean	Std. Error	Mean	Std. Error	t-statistic	P-Value
Ln(Firm Entrepreneurial Quality)	-4.38	(0.099)	-4.24	(0.109)	-0.98	0.33
Ln(State Entrepreneurial Quality)	-7.95	(0.092)	-7.94	(0.086)	-0.04	0.97
Age at Founding	39.81	(0.98)	36.32	(0.922)	2.59	0.01
Age Under 30	0.13	(0.034)	0.25	(0.044)	-2.18	0.03
Age 30 to 50	0.73	(0.045)	0.66	(0.048)	1.07	0.28
Age Over 50	0.14	(0.035)	0.09	(0.029)	1.11	0.27
	Obs	100	Obs	100		

Represents a sub-sample hand collected to estimate the age of founders at founding. The subsample initially consisted of migrants to Silicon Valley matched to non-migrants at the same quality, state and year of birth. I then search for the history of each company and find the original founder, then search for the employment history of that founder to estimate his or her age. The age is defined as 22 plus the number of years since college graduation.

TABLE 6
AGE AND MIGRATION
LINEAR PROBABILITY MODEL
DEPENDENT VARIABLE: IS MIGRANT

	(1)	(2)	(3)
Age at Founding	-0.00942**	-0.0100**	-0.00996**
	(0.00353)	(0.00480)	(0.00481)
Ln(Entrepreneurial Quality)		0.0547	
		(0.0618)	
State Year F.E.	No	Yes	Yes
Firm Quality 4th Order Polynomial	No	No	Yes
N	200	200	200
R^2	0.033	0.564	0.669

Sample is a hand-collected subsample re-creating the age of founders at the time their company is founded. The dataset is described in section X. Robust standard errors clustered at the state level in parenthesis. * p < .1 ** p < .05

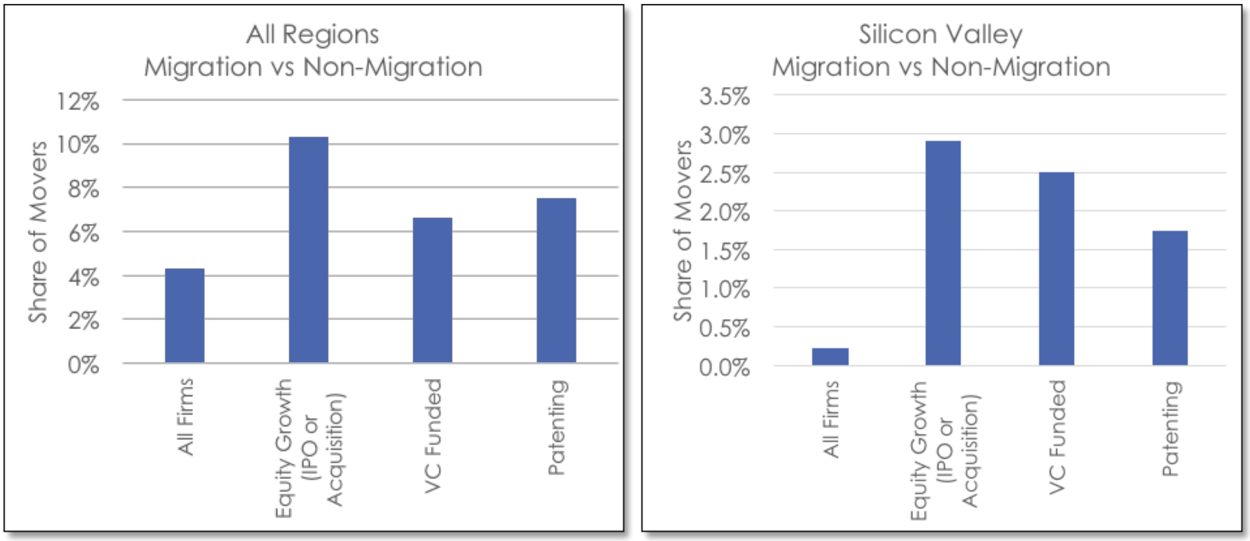
TABLE 7
AGE AND QUALITY FOR MIGRANTS VS NON-MIGRANTS
LEAST SQUARES REGRESSIONS
DEPENDENT VARIABLE: LN(FIRM ENTREPRENEURIAL QUALITY)

	Migrants	Non-Migrants	All
	(1)	(2)	(3)
Age at Founding	-0.0263**	0.0368*	-0.0234**
	(0.0106)	(0.0204)	(0.0106)
Is Migrant			-1.625**
			(0.671)
Age at Founding X Is Migrant			0.0491**
			(0.0179)
State Year F.E.	Yes	Yes	Yes
N	100	100	200
R^2	0.705	0.773	0.689

Sample is a hand-collected subsample re-creating the age of founders at the time their company is founded. The dataset is described in section X. Robust standard errors clustered at the state level in parentheses. * p < .1 ** p < .05

FIGURE 1

A. B.



Implied Odds of Migrant vs Non-Migrant

1	2.4X	1.5X	1.7X

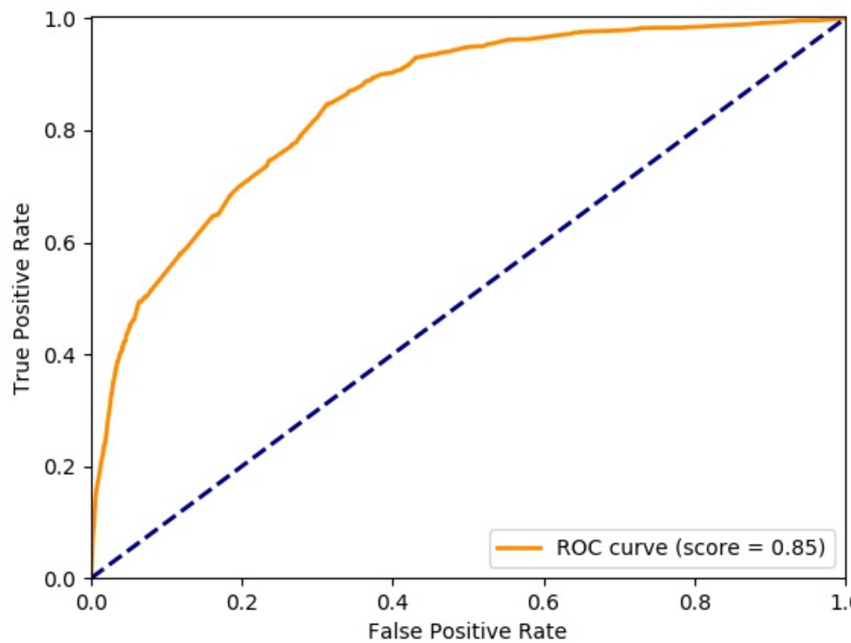
Implied Odds of Migrant vs Non-Migrant

1	13X	11X	8X

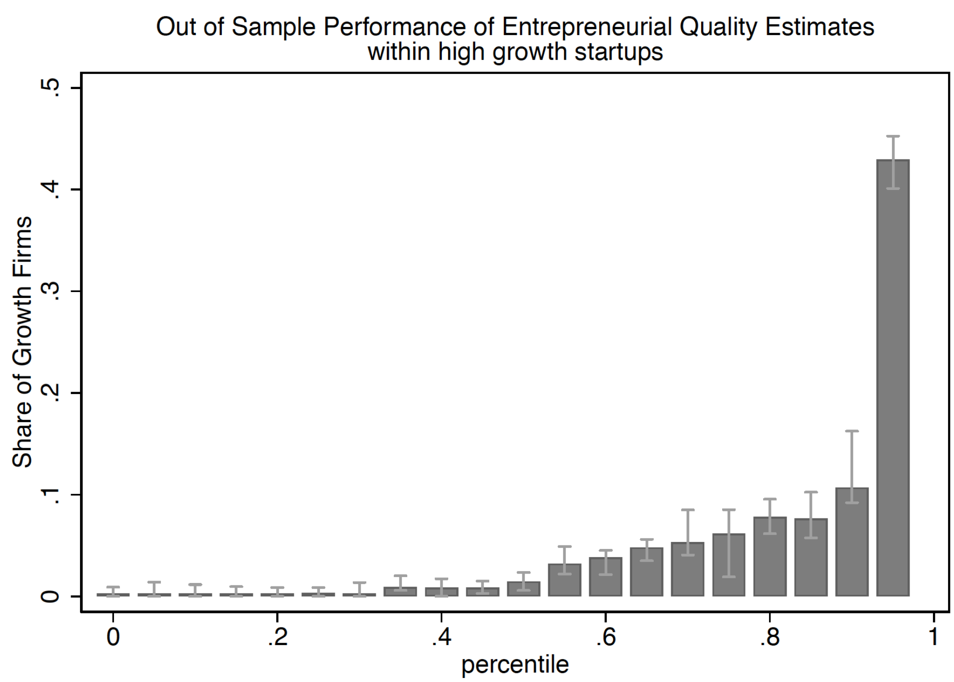
Notes: Reports the share of moves represented in each of the outcome measures as well as migrants in general. Implied odds is simply the column divided by the value of *All Firms* and represents the higher likelihood of a migrant having an outcome than expected at random

FIGURE 2

A. ROC Curve for predictive model in out of sample non-migrant firms.

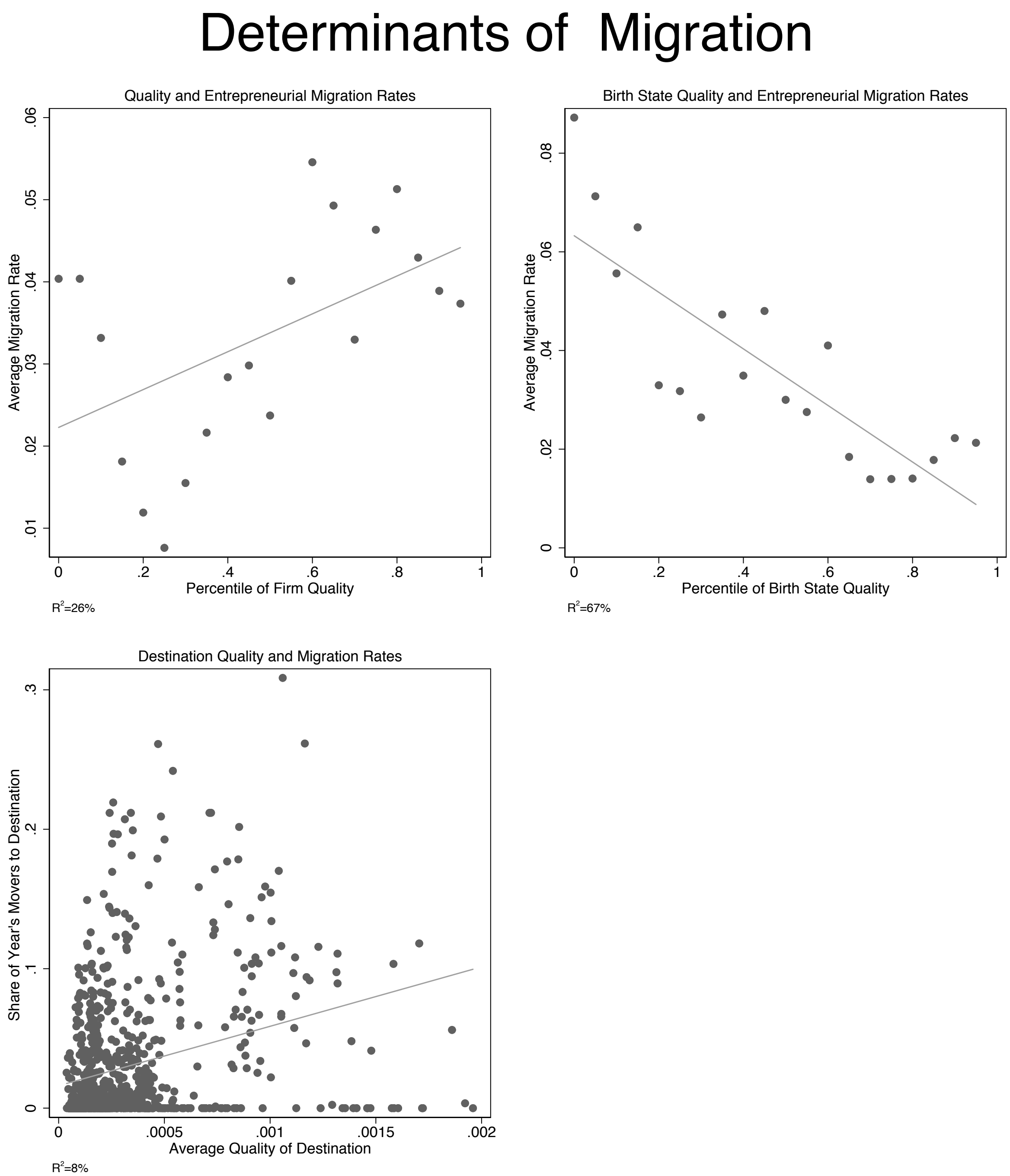


B. Ten Fold Cross Validation



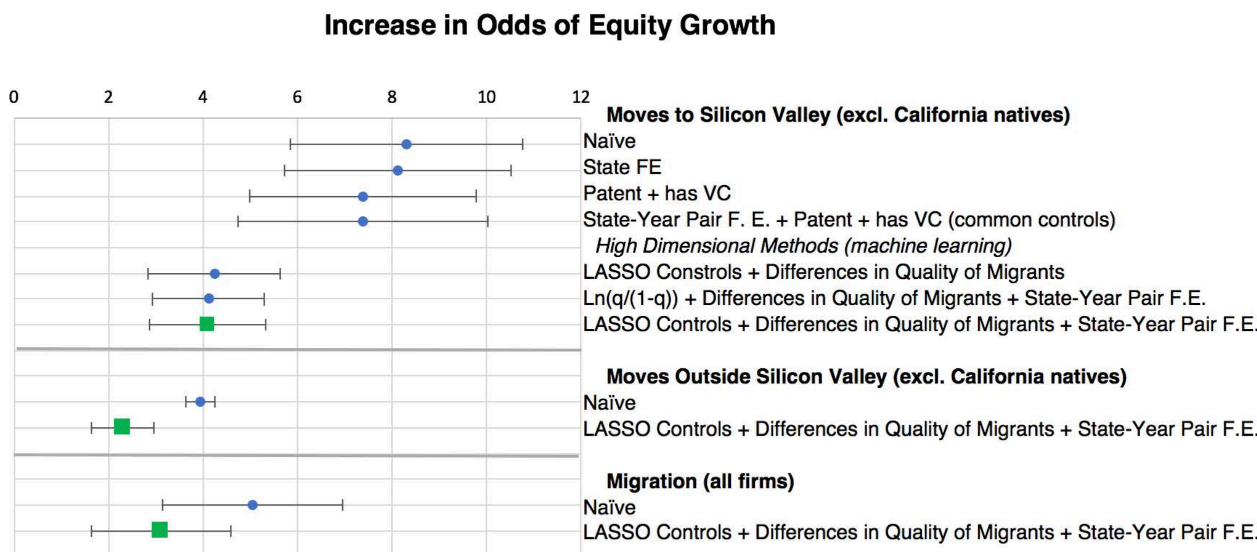
Notes: Figure A represents the receiver-operating-characteristic (ROC) score for the random forest predictive of entrepreneurial quality when estimated in a 50% hold-out sample of non-migrants. The dotted line represents the performance of an alternative algorithm that assigns quality at random. The area under the curve of the solid line compared to the dotted-line equals 70% of the total area above the dotted line. Figure B is an out of sample 10-fold algorithm that compares the ordering of firms by predicted quality to their actual realized outcomes, across bins that are 5-percent wide. The bars indicate the mean value, while the gray lines indicate the min and max.

FIGURE 3



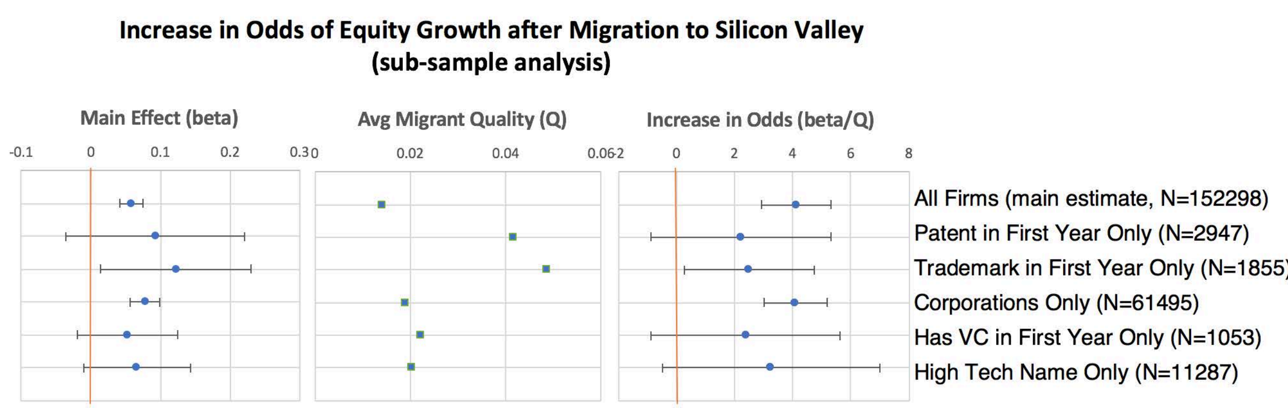
Notes: Figures A and B are the binned distribution of entrepreneurial quality and the percent of companies that move in each bin. Figure A is binned by quality of company, Figure B is binned bi quality of location. Figure C is a scatter of all movers binned by individual destination-year, and reports the average *local* quality of the destination and the share of all movers in that year that move to this destination.

FIGURE 4A



Each row represents an independent regression. Standard errors clustered at the state level (25 clusters). Sample excludes all California founded firms for first two groups. Moves to Silicon Valley estimates excludes all other migrants. Moves to other destinations excludes migrants to Silicon Valley. Increase in odds is the IRR of the effect minus 1. Standard errors are tighter for migrants outside S.V. due to a higher number of migrants in general. Green squares indicate preferred estimate. Appendix includes all regressions in tables and relevant statistics per regression.

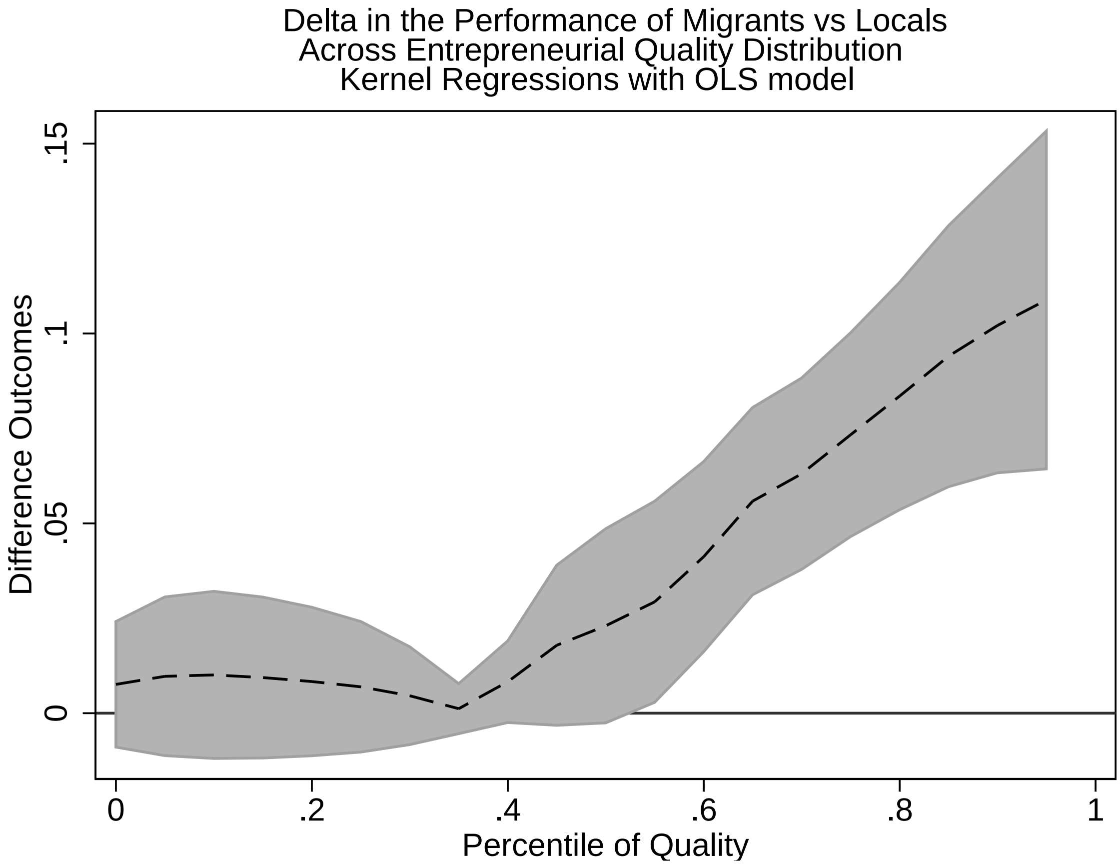
FIGURE 4B



Each row represents a different regression. Standard errors clustered at the state level (25 clusters). Sample excludes all California founded firms and migrants to other destinations outside Silicon Valley. Increase in odds is the IRR of the effect minus 1. Standard errors adjusted to reflects errors in odds in right panel. All regressions include state-year pair fixed-effects and controls for firm quality. It is not possible to include the same LASSO controls in each regression due to them being too many for the smaller samples, and the possibility that difference would make the estimator sparse and inconsistent.

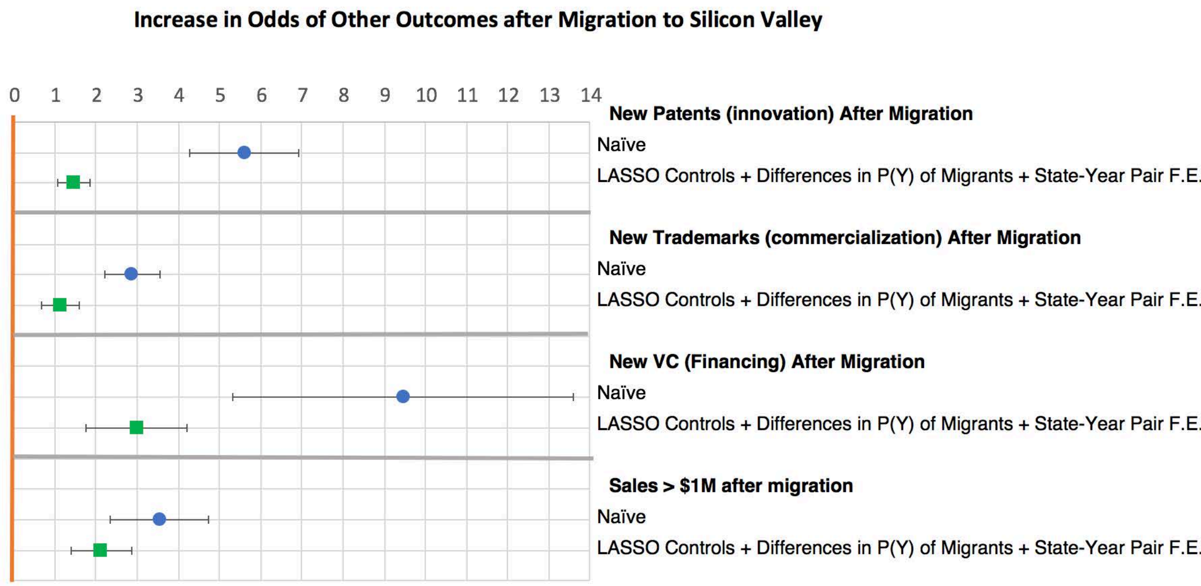
FIGURE 4C

Marginal Effects.
Heterogeneous Gains Across Quality and Sorting Distributions



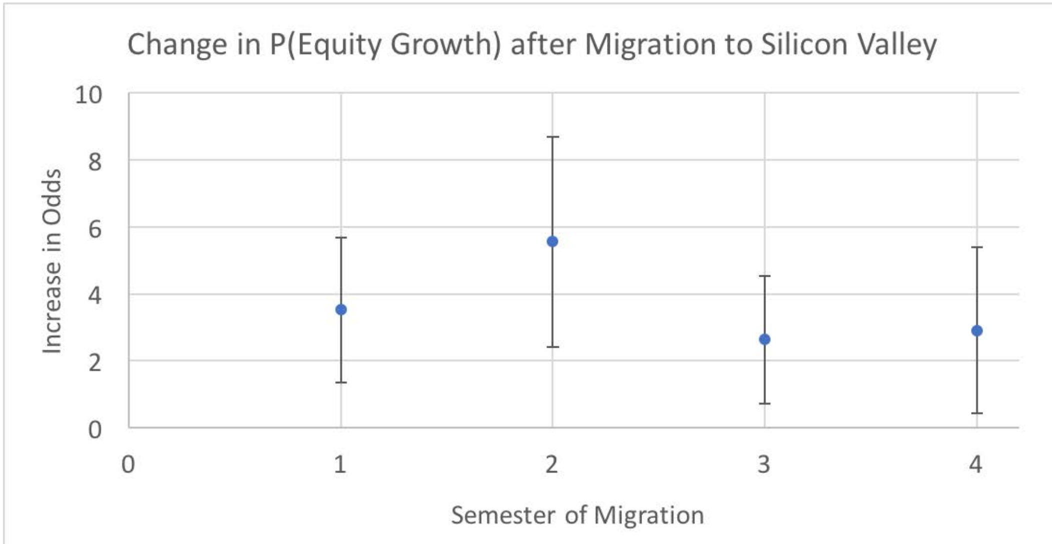
Notes: The figure reports a kernel regression of the coefficient of migration across different points in the quality distribution of firms, using an epanechnikov kernel and a bandiwdth of 0.5. All regressions include state-year fixed effects. Standard errors clustered at the state-year level.

FIGURE 5



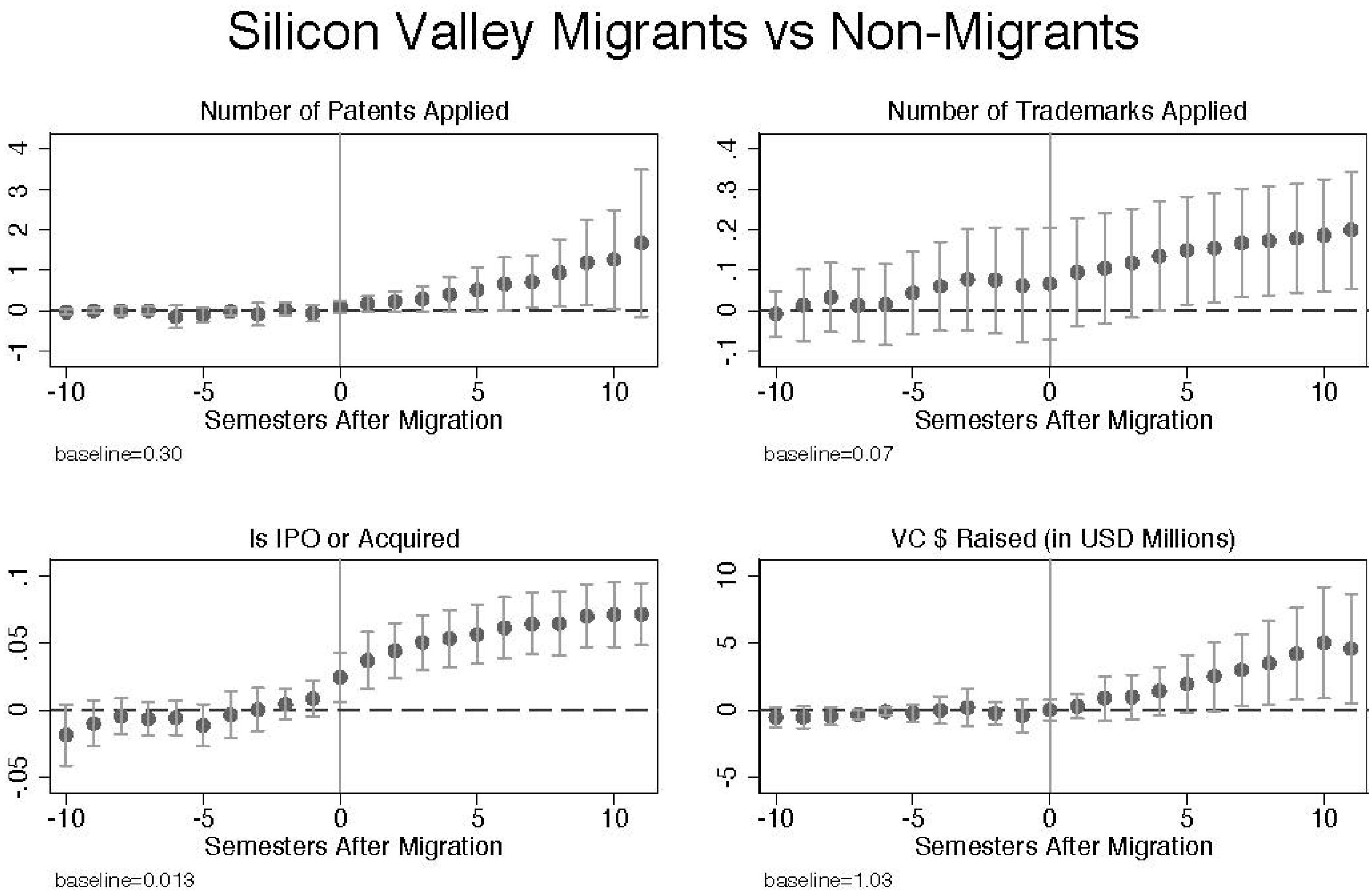
Each row represents a different regression. Standard errors clustered at the state level (25 clusters). Sample excludes all California founded firms and migrants to other destinations outside Silicon Valley. Increase in odds is the IRR of the effect minus 1. Standard errors adjusted to reflects errors in odds in right panel. All regressions include state-year pair fixed-effects and controls for firm quality. It is not possible to include the same LASSO controls in each regression due to them being too many for the smaller samples, and the possibility that difference would make the estimator sparse and inconsistent.

FIGURE 6



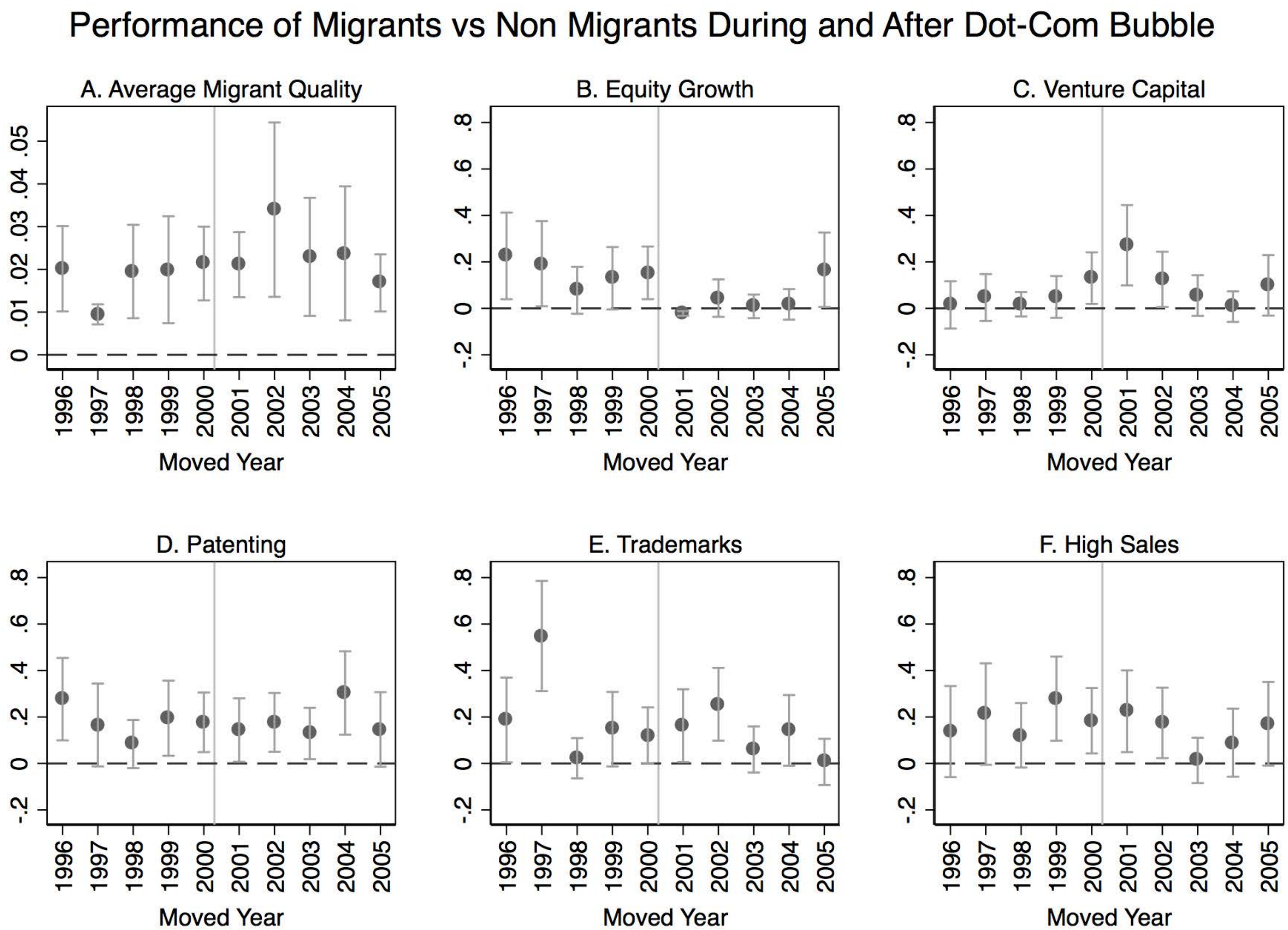
Notes: Represents the by-semester of migration coefficients of an equivalent regression of Table 8, Column 3—a linear probability model with equity growth as an outcome and LASSO controls and State-Year pair fixed effects. Standard errors are clustered at the state-year pair level.

FIGURE 7



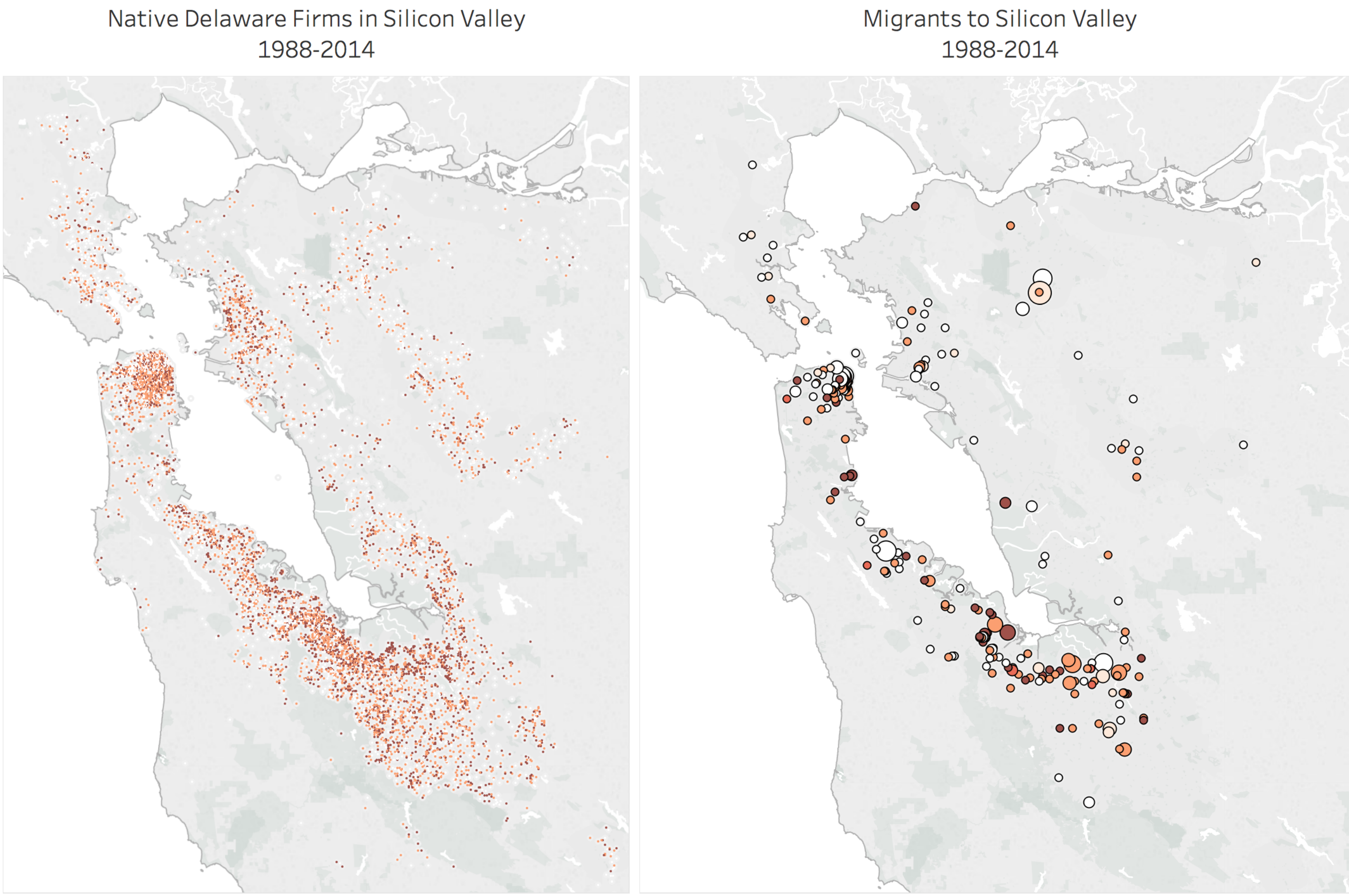
Notes: Model includes firm and age fixed effects, and reports the coefficient of time to migration by semester of age. Standard errors clustered by birth state (26 clusters). Dependent variables measured as cumulative values (stock) rather than per-period (flow).
Baseline is the mean value of Y_{it} at t=11 for a matched sample of non-migrants of same quality

FIGURE 8



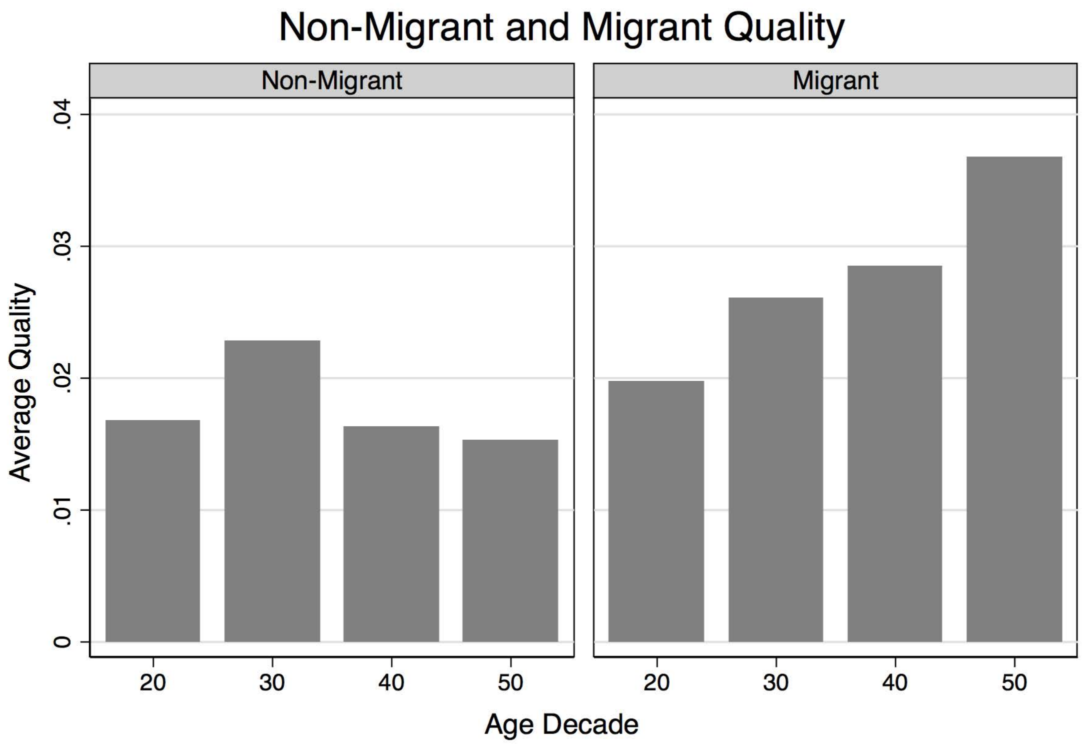
Notes: Figure A is the mean quality and 95% percent confidence interval of mean quality for migrants that moved to Silicon Valley in each year. Figures B through F are individual year coefficients for the impact of moving to Silicon Valley across different outcomes, in a regression that also includes LASSO Controls and state-year pair fixed effects. The vertical line in each graph is on March, 31, of 2001, the date in which the NBER Business Cycle Dating Committee considers the post dot-com recession to have started.

FIGURE 9



Notes: This figure represents every address for which there is a Delaware firm in Silicon Valley. The color of the point is the aveage quality of firms, the size of the point is the number of firms founded in that address. The panel on the left represents all firms Delaware firms that are originally founded in Silicon Valley , and the panel on the right represents all migrants and their destination location. The scale of the points on the right is much larger than on the left to allow an easier comparability.

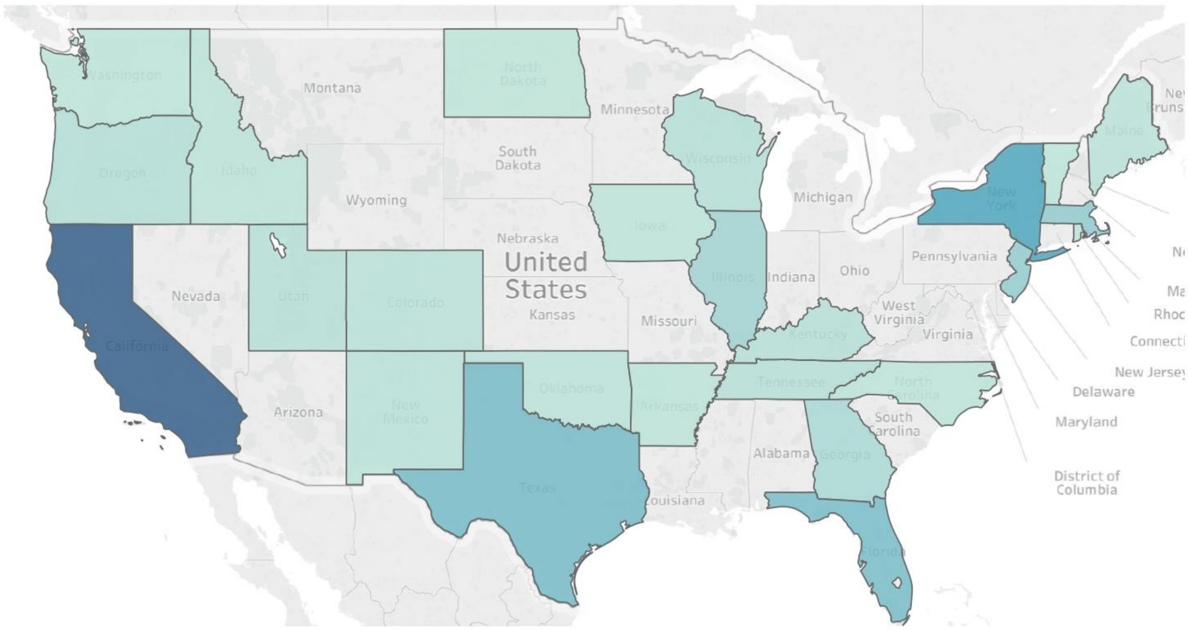
FIGURE 10



Notes: Represents the average entrepreneurial quality of migrants and non migrants by age in a sample of matched companies by quality. While there is no discernible relationship between quality and age in the non-migrant group, there is a positive relationship in the migrant group.

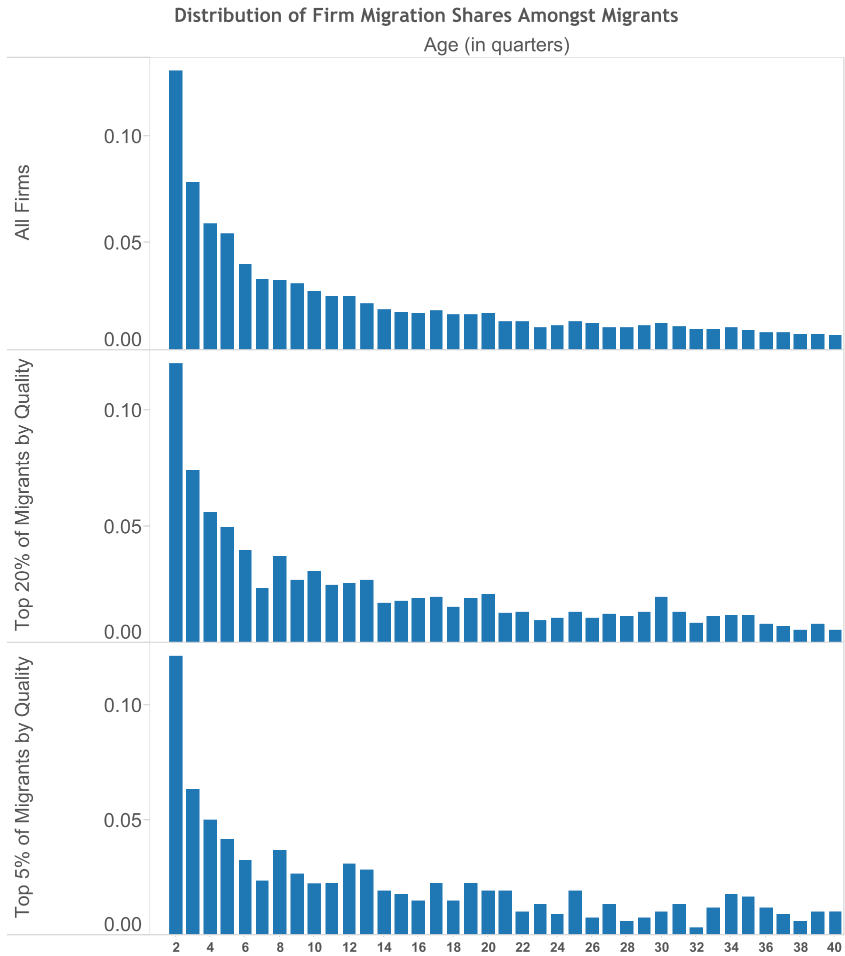
FIGURE A1

States in Sample



Notes: All states in the data represented. The color represents the number of firms registered in Delaware in each state.

FIGURE A2



Notes: this figure shows the share of migrant firms that migrate within each of the quarters of firm life at different levels of firm quality. Firms are required to live at least a quarter in their location of birth to be considered migrants. It is easy to see a monotonic decline in migration rates, suggesting migration is mostly entrepreneurial.

TABLE A1

MIGRATION RATES FOR ALL FIRMS BORN BEFORE 2001*

Does not migrate	89.9%
Entrepreneurial Migration	
Migrates before 2 years of age	4.2%
Migrates before 5 years of age	6.7%
All Migration	
Migrates from age 6 to 15	10.1%

*Migration rates estimated only for firms born before 2001 to allow at least 15 years for firms to migrate.

TABLE A2

ENTERPRENEURIAL QUALITY MODEL
LOGIT REGRESSION
DEPENDENT VARIABLE: EQUITY GROWTH

	(1)	(2)
Business Registration		
Short Name	1.517**	1.419**
	(0.0590)	(0.0517)
Corporation	10.44**	8.549**
	(0.902)	(0.672)
Intellectual Property		
Patent		5.849**
		(0.372)
Trademark		3.827**
		(0.319)
Name Based Industry		
Local	0.817**	0.909
	(0.0725)	(0.0797)
Traded	1.030	1.178**
	(0.0607)	(0.0664)
Biotechnology	3.191**	2.252**
	(0.293)	(0.220)
E-Commerce	1.418**	1.311**
	(0.0842)	(0.0818)
IT	1.831**	1.534**
	(0.153)	(0.118)
Semiconductors	2.385**	1.558*
	(0.528)	(0.358)
Medical Devices	0.942	0.808**
	(0.0691)	(0.0610)
State F.E.	Yes	Yes
Year F.E.	Yes	Yes
N	488960	488960
pseudo R-sq	0.097	0.141

Incidence rate ratios reported. Standard errors clustered at the state-year pair level. * p < .1 ** p < .05.

TABLE A3
PERFORMANCE OF MIGRANTS
LINEAR PROBABILITY MODELS
DEPENDENT VARIABLE: EQUITY GROWTH

PANEL A: MIGRATION ANYWHERE

	OLS					Logit (IRR)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Migrant (Anywhere)	0.0410**	0.0410**	0.0348**	0.0312**	0.0314**	6.340**	3.360**
	(0.00794)	(0.00794)	(0.00801)	(0.00771)	(0.00760)	(1.712)	(0.779)
Ln(Firm Entrep. Quality)			0.0112**	0.0106**			3.278**
			(0.00166)	(0.00146)			(0.226)
Ln(State Entrep. Quality)							0.524**
							(0.0794)
LASSO Controls					Yes		
State-Year F.E.				Yes	Yes		
State F.E.							Yes
Year F.E.							Yes
N	232315	232315	232315	232315	232315	232315	197537
R^2 / Pseudo R^2	0.002	0.002	0.020	0.031	0.049	0.012	0.207
Mean Quality (All Firms)	0.00813						
Mean Quality (Migrants)		0.0101	0.0101	0.0101	0.0101		
Implied Increase in Odds	***5.047***	***4.071***	***3.454***	***3.097***	***3.114***	***6.340***	***3.360***

PANEL B: MIGRATION TO SILICON VALLEY

	OLS						Logit (IRR)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migrant to Silicon Valley	0.0675**	0.0675**	0.0609**	0.0583**	0.0577**		11.38**	1.844**
	(0.0102)	(0.0102)	(0.00982)	(0.00852)	(0.00880)		(2.616)	(0.265)
Migrant Outside Silicon Valley						0.023**		
						(0.00341)		
Ln(Firm Entrep. Quality)			0.00915*	0.00878**				1.093**
			(0.00177)	(0.00169)				(0.0629)
Ln(State Entrep. Quality)								-0.537**
								(0.184)
LASSO Controls					Yes	Yes		
State-Year F.E.				Yes	Yes	Yes		
State F.E.								Yes
Year F.E.								Yes
N	152298	152298	152298	152298	152298	232315	152298	130895
R^2 / Pseudo R^2	0.003	0.003	0.016	0.029	0.041	0.048	0.012	0.176
Mean Quality (All Firms)	0.00813							
Mean Quality (Migrants)		0.0141	0.0141	0.0141	0.0141	0.00990		
Implied Increase in Odds	***8.301***	***4.802***	***4.333***	***4.146***	***4.107***	***2.282***	***11.38***	***6.322***

Robust standard errors clustered at the state level are reported. Firm Entrepreneurial Quality is the predicted value of performance from a machine learning model (random forest) in a trained to predict Equity Growth from at-founding characteristics. The sample used for training is excluded from this analysis. State Entrepreneurial Quality is the average quality of local firms born in that state and year, including both Delaware and non-Delaware firms. Mean quality is the average expected performance for all firms in the sample. Pseudo R2 is the McFadden (1974) R2 estimate. Estimates of size of unobservables to be non-significant assume the standard errors of the effect are the same. * p < .1 ** p < .05

TABLE A4
PERFORMANCE OF MIGRANTS VS NON MIGRANTS
OTHER OUTCOMES
LINEAR PROBABILITY MODELS

PANEL A: MIGRANT TO SILICON VALLEY

	(1)	(2)	(3)	(4)	(5)
DEPENDENT VARIABLE:	Patent	Trademark	Venture Capital	Sales	Latent Profits
Migrant to Silicon Valley	0.0944**	0.0739**	0.0728**	0.113**	0.854**
	(0.0118)	(0.0139)	(0.0155)	(0.0171)	(0.0929)
LASSO Controls	Yes	Yes	Yes	Yes	Yes
State, Year F. E.	Yes	Yes	Yes	Yes	Yes
Observations	152298	152298	152298	152298	152298
R-squared	0.483	0.095	0.100	0.079	0.300
Mean of Outcome	0.0260	0.0379	0.0105	0.0375	-0.0612

PANEL B: MIGRANT ANYWHERE

	(1)	(2)	(3)	(4)	(5)
DEPENDENT VARIABLE:	Patent	Trademark	Venture Capital	Sales	Latent Profits
Migrant Anywhere	0.0451**	0.0766**	0.0245**	0.0509**	0.476**
	(0.00644)	(0.0108)	(0.00601)	(0.00718)	(0.0473)
LASSO Controls	Yes	Yes	Yes	Yes	Yes
State, Year F. E.	Yes	Yes	Yes	Yes	Yes
Observations	232315	232315	232315	232315	232315
R-squared	0.520	0.107	0.121	0.079	0.343
Mean of Outcome	0.0347	0.0434	0.0170	0.0380	-0.0120

Robust standard errors clustered at the state level are reported. Outcomes of patent and trademark do not include the first year of observations for the firm (which are incorporated in the quality model). Sales is an indicator variable on whether the firm reaches 1 million dollars. Latent profits is the projection of the first principal component of the outcomes IPO, Acquisition, Patent, Trademark, Venture Capital, and Sales. * p < .1 ** p < .05