Entrepreneurial Teams:

Diversity of Experience and Firm Growth*

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Abstract

We use the employer-employee linked data to track employment history of employees prior to startup formation and construct measures of diversity of experience within founding teams for a large cohort of startup firms in the U.S. We find that founding teams with broader pre-startup industry exposure outperform their matched peers in the same cohorts, industries and local economies. They grow faster over the first four years and are more likely to achieve outlier growth (top 1%). Our results hold when we use county-level industry distribution to instrument for the observed team-level experience. We also find that the effect of team diversity is independent of the potential benefit of having a "jack of all trades" founder. Using information from a novel dataset, we construct an industry-level measure for innovativeness and show that the positive effect of team experience diversity on startup performance is stronger in more innovative industries. Overall, our results suggest that startups in which the founding team has a more diverse set of skills achieve greater initial success.

JEL codes: L25, L26, J24

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I. Introduction

Team-specific human capital can be an important source of value, and collaborations within teams increase innovation (Mailath and Postlewaite, 1990; Jaravel, Petkova, and Bell, 2016; Azoulay, Graff Zivin, and Wang, 2010). Team effects can be particularly relevant inside startup firms when human capital is the critical resource that differentiates one startup firm from another, as argued by Wenerfelt (1984) and Rajan (2012). Recent studies have shown that quality of the founding team is viewed as the most important factor for the success of startup firms by early investors (Bernstein, Korteweg and Laws, 2017) and venture capital firms (Gompers, Gornall, Kaplan and Strebulaev, 2016). Our goal is to identify specific characteristics that determine the effectiveness of teams in promoting startup growth. We find that the diversity of the founding team's pre-startup work experience is a strong predictor of the firm's initial success. Firms in which the founding team has a greater breadth of industry experience grow significantly faster than firms founded at the same time in the same industries and metro areas that have founding teams with more similar backgrounds. They are also more likely to be "unicorns" (i.e., firms with growth rates in the top 1% of the sample distribution). Consistent with the human capital channel, the effects are concentrated among startups in more innovative industries measured by a higher than expected flow of new graduates with research experience in science, technology, engineering and mathematics (STEM) fields into the industry.

Though team composition along many dimensions could matter for firm performance, we concentrate on breadth of industry experience. Theoretically, our approach builds on ideas from Lazear (2005). Starting a new business requires a diverse set of skills and expertise. Yet, the initial resources available to startups are often limited. Resource constraints could prevent the firm from addressing deficiencies in the skillsets of the founders by hiring new employees. Moreover, if and when the founders can hire employees to supplement the skills inside the firm, they must have sufficient expertise to choose high quality applicants. Thus, a broad set of skills among the founding team is likely to facilitate initial success of the venture. We use experience across industries as an observable proxy for the breadth of employees' skillsets. Workers who change industries (or work in diversified firms) are likely to invest in bundles of skills that weight specific skills from each of the industries (Lazear, 2009; Tate and Yang, 2015). Likewise, the team-level bundle of skills is likely to weight a larger number of distinct skills as the group's experience across industries increases. Though Lazear (2005) focuses on entrepreneurs, we find strong effects of team skillsets that are distinct from those of the initial leader of the firm.

To conduct our analysis, we combine data across several U.S. Census Bureau data products. First, we identify the full set of U.S. startup firms for the year 2010 using the Longitudinal Business Database (LBD). We then match startups to the Longitudinal Employer-Household Dynamics (LEHD) data to identify the initial paid employees in each startup firm, to whom we refer as the "founding team." The LEHD data are a quarterly worker-firm matched panel that allows us to track the paid employment histories of each founding team member across all 50 U.S. states. Our LEHD sample begins in 2002, so that our observations of employment history cover roughly a decade prior to the founding of the startup. To aggregate individual industry experiences into a founding team measure, we first identify the main industry in which each team member worked prior to joining the startup. We then compute a Herfindahl measure of the diversity of past industry experience within the team, using the number of quarters each worker spent in her main industry as weights. We also compute a second measure in which we use the empirically observed mobility of human capital across industries pairs to proxy for the economic distance between industries and adjust the index value downwards for cases in which industries in the bundle are closely related (Tate and Yang, 2017; Neffke and Henning, 2013). By down-weighting "adjacent" industries, we can better isolate the contributions of industry pairs that are likely to require distinct worker skills and, therefore, to truly diversify the skill bundle of the founding team. However, distinct skillsets employed in adjacent industries could have more productivity-enhancing complementarities than distinct skillsets from non-adjacent industries. By comparing the effects of our two indices on startup growth, we can assess the relative importance of each of these economic channels. Finally, we adapt both approaches to measure the diversity of the top member of the team by considering the set of industries in which she worked over the decade preceding the founding of the startup. These measures allow us to distinguish the effect of team skill diversity from the entrepreneurial "jack of all trades" effect modeled by Lazear (2005).

We consider three measures of initial startup performance: startup three-year employment growth and indicator variables that equal one for startups that (1) survive for at least three years and (2) are in the top percentile of the three-year employment growth distribution. We regress each of these dependent variables on our measures of founding team experience diversity and a host of controls, including team size and detailed controls for the team's demographic composition (age, race, ethnicity, etc.). We also include state-level industry fixed effects so that we only compare the performance of startups with other nearby startups that are contemporaneously founded in the same industry. We find that startups in which the founding team has broader cross-industry experience significantly outperform peer firms. A one standard deviation increase in founding team diversity using our mobility-adjusted measure predicts a six percent increase in three-year employment growth and a 15% increase in the probability that the startup is in the top percentile of the growth distribution, conditional on survival. While we do not find a positive association between founding team diversity and survival in our baseline specifications, we do find that startups with broader industry experience at the time of startup are significantly more likely to survive when we control for the diversity of the industry experience of the highest paid member of the founding team. The founder's experience, instead, has a significant negative effect on survival. Moreover, controlling for diversity of the individual founder's industry experience has essentially no influence on our estimates of the team diversity effect on either measure of firm growth, suggesting that the team diversity channel is largely distinct from the "jack of all trades" channel. Across measures, we generally find that the results from the mobility-adjusted diversity index are economically smaller than the results from the simple Herfindahl measure, suggesting not only that there are benefits from a broader set of team-level skills, but also that the complementary of those skills is greater when they have applications in adjacent industries.

A potential concern is that the diversity of the backgrounds of founding employees is not exogenous. Founding team members and employees are either actively selected or self-select into the venture; they are not randomly assigned. To address this concern, we consider two instruments for the diversity of the team's industry backgrounds. First, we use the industry distribution of firms located in the same county as the startup over the time period starting five years and ending two years before its founding to construct a Herfindahl measure of local industry diversity. Second we compute the fraction of workers in the county over the same period who work in diversified firms. Both instruments exploit constraints on the geographic mobility of workers. If labor markets are largely local, then founding teams that happen to reside in areas that had more diversified job opportunities will be more likely to have differing industry experiences. Moreover, workers in locations that had more diversified firms are more likely to have worked in such a firm and, as a result, to have more individual cross-industry work experience (Tate and Yang, 2015). Our identifying assumption is that industry diversity of local firms in the past does not affect startup survival or growth except through the work histories of the startups' founding employees. Using this approach, we confirm the results from our baseline analysis.

To provide further support for the human capital channel, we also measure the heterogeneity of the effect across startups with differing reliance on high-skill human capital as an input to the production process. Using data on research grants from the Census Bureau's Innovation Measurement Initiative (IMI), we identify "innovative" industries as those that experience an abnormal inflow of graduating students with research experience in STEM fields to the industry. We then estimate the interaction effect between an indicator for operating in an innovative industry and the background diversity of the startup's founding team on startup initial performance. We find a significantly stronger positive effect of background diversity on employment growth, survival, and the probability of achieving growth in the upper percentile of the distribution in the subsample of startups in innovative industries.

Overall, our results suggest that startups in which the founding team has a more diverse set of skills achieve greater initial success than closely matched startups from the same cohorts, industries, and local economies. The effects are not concentrated in a unique "founder;" instead, the team effects have distinct empirical properties from parallel measures of the diversity of the founder's skillset. Moreover, the effects are most pronounced among the industries that disproportionally attract the highest skilled labor market entrants, suggesting they are of particular economic importance among the class of startups that are likely to contribute to innovation and economic dynamism.

Our results contribute to the literature studying determinants of entrepreneurial success. Existing work suggests that both personal histories (Gompers et al, 2010) and the histories of peers (Lerner and Malmendier, 2013) help potential entrepreneurs make better decisions regarding if and when to start a new venture. This work builds on a larger set of papers that emphasize the relation between various traits of top executives and firm outcomes, typically among large publicly-traded firms for which data is most readily available (e.g., Bertrand and Schoar, 2003; Malmendier and Tate, 2005, 2008; Bennedsen, Perez-Gonzalez, and Wolfenzon, 2006; Malmendier, Tate, and Yan, 2011; Kaplan, Klebanov, and Sorensen, 2012; Graham, Harvey, and Puri, 2013; Custodio, Ferreira, and Matos, 2013; Benmelech and Frydman, 2015; Tate and Yang, 2015). We exploit the richness of the U.S. Census data to extend this line of inquiry by considering newly formed ventures and their entire founding teams. Our results demonstrate not only the significance of team effects (Berstein, Korteweg, and Laws, 2017; Gompers, Gornall, Kaplan, and Strebulaev, 2016), but also that they function distinctly and, in some cases, in different directions from the effects of the top manager. Given the decline over time in the average age of successful entrepreneurs (Levine and Rubenstein, 2017), scalability of skills across team members could become increasingly important going forward relative to the accumulation of individual skills by a single entrepreneur.

We also contribute to the literature studying the role of teams in production. Azoulay, Graff Zivin, and Wang (2010) and Jaravel, Petkova, and Bell (2016) use the deaths of prominent team members to demonstrate the importance of team-specific capital for the research productivity of scientists and inventors, respectively. These papers are part of a broader literature demonstrating the importance of peers to productivity (e.g., Borjas and Doran, 2014; Oettl, 2012; Waldinger, 2010, 2012). Consistent with these effects, Hayes, Oyer and Schaefer (2006) demonstrate that a CEO departure increases the likelihood of other departures from the management team, particularly when the management team has a longer tenure together in the firm. Campell, Saxton, and Banerjee (2014), Groysberg and Lee (2009), and Ouimet and Zarutskie (2016), show that team moves from one employer to another can preserve productivity relative to individual job changes. Instead of focusing on the existence of team effects, we instead study types of teams, identifying and measuring specific team characteristics that are associated with success.

Finally, our analysis relates to the literature that studies the consequences of employee diversity for performance. Most of this literature focuses on demographic diversity. For example, Hjort (2014), Lyons (2017) and Glover, Pallais, and Pariente (2017) document negative effects of ethnic discrimination on worker productivity, though other work (e.g., Adams and Ferreira, 2009) finds that director diversity can improve a board's performance of its monitoring function. Our analysis includes controls for demographic diversity, even though we do not focus on this dimension per se. Instead, our focus is on how the diversity of skill sets among firm leaders affects firm performance.

II. Data

We use several research databases available from the U.S. Census Bureau to conduct our analysis on entrepreneurial firms. We use the Longitudinal Business Database (LBD) to identify startup firms. The LBD includes all non-farm establishments in the U.S. and contains information on birth or closure (if any), ownership, location, industry, employment and total payroll, reported at the end of the first quarter of each calendar year (March 12). We identify startup firms as businesses in their first year of activity that report at most 10 employees. We impose the latter restriction to minimize measurement error, both in the classification of the firm as a startup and in the identification of the firms' founding employees. However, it is not crucial for our results.[4] We use the total employment and payroll data to calculate growth rates for each startup over time, and further supplement information on annual sales from the Business Register whenever it is available.

For each startup firm, we first identify all the employees who worked in the firm during the first year of operation from the full-coverage Longitudinal Employer Household Dynamics (LEHD) program. The LEHD data is constructed using administrative records from the state unemployment insurance (UI) system and the associated ES-202 program. The coverage of the state UI system is broad and generally comparable from state to state: it contains about 96% of

[4] Our results hold qualitatively if we restrict the sample to include startup firms that report at most 5 employees.

civilian jobs in the U.S.[5], and includes information on quarterly employment and wage.[6] We link the LBD data to the LEHD data using the federal employer identification number (EINs). When merging the two datasets, we require no more than a one year gap between the years in which we first observe the firm in the two research databases. Though it is not generally possible to link workers to specific LBD establishments within a state and industry, our focus on single-establishment startups allows us to infer the establishment-worker match with a higher degree of confidence than would otherwise be possible.

We define the founding employees as workers who appeared at the startup firm during its first year of operations and were present for at least four of the firm's first five quarters. For each founding employee, we use the full-coverage LEHD data to construct her employment history within the entire U.S. prior to joining the startup firm. We use the 2010 Decennial Census to obtain demographic information on founding employees including gender, age, race, ethnicity, and place of birth. We link the LEHD data and 2010 Decennial data using the anonymous Personal Identification Key provided by Census Bureau.[7] To maximize the matching rate with 2010 Decennial Census, our baseline tests only include startups that were founded in the year of 2010. Our final sample includes 181,000 startup firms. For robustness checks, in unreported regressions, we expand our sample to include startup firms from 2005 to 2010. Results are qualitatively the same.

II.1. Summary Statistics: Startup Firms

In Table 1, we report summary statistics of startup firms in our sample. We first describe the industry distribution at the two-digit NAICS level. Our sample covers a wide variety of

[5]Workers not covered by the state unemployment insurance system include many agricultural workers, independent contractors, some religious and charitable organizations, the self-employed, some state government workers, and employees of the federal government (who are covered under a separate insurance system). For detailed information on UI covered employment, see *The BLS Handbook of Methods:* http://www.bls.gov/opub/hom/homch5_b.htm.

[6] Wages reported to the state UI system include bonuses, stock options, profit distributions, the cash value of meals and lodging, tips and other gratuities in most of the states, and, in some states, employer contributions to certain deferred compensation plans such as 401(k) plans. See http://www.bls.gov/cew/cewfaq.htm#Q01 for additional details.

[7] For more information on PIK: https://www.census.gov/about/adrm/linkage/technical-documentation/processing-de-identification.html

industries. The most represented industry is Professional, Scientific, and Technical Services (NAICS 54), accounting for 16.7% of our sample. Other prominent industries include Healthcare and Social Assistance (NAICS 62), Construction (NAICS 23), Retail Trade (NAICS 44-45), and Accommodation and Food Services (NAICS 72), each covering roughly 10% of our sample. On the other hand, we observe a lower incidence of startup firms in Manufacturing, Agriculture, and Utilities. Overall, our sample includes startup firms in both low- and high-tech industries. We exploit this important heterogeneity later in the paper to capture differences in the effect of the team background diversity on startup performance based on the intensity of human capital at the industry level.

On the dimension of geography, our sample includes startup firms in all 50 U.S. states. To comply with the disclosure requirements at the Census Bureau, we report statistics by Census Divisions. The most represented Census Divisions are the South Atlantic – which includes Delaware, Maryland, Virginia, West Virginia, the District of Columbia, North Carolina, South Carolina, Georgia, and Florida – and the Pacific – which includes California, Oregon, and Washington. Roughly 20% of startups are founded in the Northeast, which is comprised of the Middle Atlantic (New York, New Jersey, and Pennsylvania) and New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont). About one third of startups in our sample have only one employee, and about 70% have three or fewer employees in their first year of activity.

In Panel B of Table 1, we report summary statistics for the main firm-level variables used in our analysis. The average startup firm in our sample has 3.03 founding employees, with an average annual salary of $33,150. About 86% of our startups survive by the end of the first year, and about 58% do so by the end of their fourth year.[8] Among surviving firms, the average cumulative growth rate ranges from 9% at the end of the first year to 29% at the end of the fourth year of activity, but the variation in growth across startups is substantial, with a standard deviation of 73% in the fourth year. In Panel C of Table 1, we consider the demographic characteristics of workers in our sample. The average founding employee is about 40 years old.

[8] Since our data ends in 2014, this is the last year we observe for startup firms formed in 2010.

The majority of team members are white (77%). Asian and Hispanic employees each account for 13% of the average team and African-American employees make up about 5% of the average team. About one quarter of all entrepreneurial team members were born outside of the United States, which suggests that foreign ethnicity is an important dimension to consider in our analysis.

II.2. Measuring Team Diversity in Experience

To measure team diversity in experience, we track workers' industry exposure from their employment history before joining the startup firm. Our data are uniquely suited for this purpose because the employer-employee linkage provided in the LEHD data allows us to track employment history at the worker level. Specifically, for each founding employee in our sample, we record all industries in which she has worked and the corresponding number of quarters for the employment from 2002, the first year of our LEHD sample, to 2009, the last year before joining the startup firm. So, our observations of employment history cover roughly a decade prior to the founding of the startup. We define industries based on three-digit NAICS codes, and aggregate over multiple firms within each individual's history if they belong to the same industry. For each founding employee, we first identify the main industry of the employment based on the length of time spent on the job. To focus on experiences that are substantial, we only include main industries when total length of employment in the industry lasts at least four quarters for the employee. Then, we aggregate over all founding employees to compute the distribution of time spent over all main industries. For example, suppose we have three founding employees and their main industries are identified as 1 (10 quarters), 2 (8 quarters), and 1 (6 quarters), respectively. We would identify the firm with two main industries – 1 and 2 with time equal to 16 (i.e., 10+6) quarters and 8 quarters, respectively.

Our Simple Diversity Index (SDI) is a Herfindahl index that is defined over the distribution of main industries among all founding employees:

$$SDI = 1 - \sum_{i=1}^{n} p_i^2$$

where $p_i = \frac{m_i}{\sum_{i=1}^{n} m_i}$ and is the percentage of time for industry i.

SDI takes into account both the number of main industries and the length of time spent in each industry. A higher SDI suggests more diverse experience in the entrepreneurial team. By construction, SDI is in the range of $\left[0, \frac{N-1}{N}\right]$ where N is the number of founding employees. If all founding employees share the same main industry, SDI equals zero – the team is not diverse at all. On the other hand, when founding employees came from different industries with equal tenure, SDC equals to $\frac{N-1}{N}$, and the team has a very diverse, implying a more balanced skillset. By construction, the SDI tends to be higher for bigger teams, so we control for team size in all of our regressions. Our results are robust when we exclude startup firms of only one employee.

SDI is based on the notion that experience in different industries, irrespective of the similarities and differences across these industries, represents a source of diversity in the skills the individual developed throughout her employment. It is reasonable to expect that industries that employ similar workers might require more similar skills than industries that employ different workers. Thus, it is plausible that an employee that worked for two firms belonging to industries that hire from a similar pool of workers has developed less diverse skills than an employee that worked for two firms belonging to industries that hire from very different pools of workers. To account for the similarity of the skills required by each pair of industries, which we label "relatedness" of industries, we construct a second version of diversity index weighted by industry relatedness.

We measure industry relatedness using the Human Capital Transferability Index developed by Tate and Yang (2017). The intuition is that two industries between which we observe higher labor flows (i.e., between which human capital more easily transfers) are more likely to require related skills than two industries for which we rarely observe labor flows. We use a 10% sample of the LEHD data to compute the relatedness of each pair of industries based on observed worker movement between industries in the external labor market. We provide additional details on the construction of the human capital transferability index in the appendix. The Mobility-adjusted Diversity Index (MDI) is then defined as follows:

$$MDI = 1 - \sum_{i=1}^{n} w_i p_i$$

where $w_i = \sum_{j=1}^{n} h_{ij} p_j$ and w_i is the multiplier for industry i which is adjusted to account for differences in human capital transferability between industry i and each other industry j (h_{ij}). Following the approach in Neffke, Otto, and Weyh (2017), we transform the index h_{ij} so that it is bounded between -1 and 1.[9] Conditional on the number of industries and length of time employed, teams with employees who worked in industries with higher relatedness (i.e. utilizing transferable skills) have lower MDI compared to teams with employees who worked in industries with lower relatedness (i.e. utilizing non-transferable skills).

Table 2 reports a set of summary statistics for our two diversity indices, SDI and MDI, computed for startup firms in our sample. For both indices, there is a large cross-sectional variation. As expected, larger firms have higher diversity index than smaller firms.

III. Team Diversity and Startup Performance

We first explore the association between diversity and employment growth in the raw data. Figure 1 reports the cumulative employment growth rate one, two, three and four years after startups' formation. Since our data ends in 2014, the longest horizon for which we can evaluate firm performance is four years. Panel A of Figure 1 plots the results when we use the Simple Diversity Index, whereas Panel B reports the results using the Mobility-adjusted Diversity Index. In both panels, the solid line refers to the average growth rate for startups whose diversity index lies above the median of the distribution, and the dashed line refers to the average growth rates for startups with diversity index values below the median. Across all years, startups with high team background diversity grow substantially more than startups with low background diversity. On average, the difference in growth at each point in time is about 10 percentage points higher for startups with high diversity, compared to startups with low diversity. Notably, the wedge between these two groups of firms materializes already in the very early years of startup activity and does not reduce over time. The results in Figure 1 suggest that in the raw data, startups with higher entrepreneurial team diversity grow more than other startups as soon

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[9] See Appendix for details.

as in the first year of activity, and startups with lower levels of diversity do not appear to catch up over time.

III.1. Baseline Results on Team Background Diversity

Although suggestive, the raw data results described above do not control for systematic, observable differences across startups with different level of team diversity. Team diversity is likely not random and could correlate with startup size, industry and location. In this section, we examine the association between entrepreneurial teams' background diversity and startup-level performance in a multivariate setting.

Specifically, we estimate a set of ordinary-least-squares specifications of the following form:

$$Startup\ Performance_{f,k,s} = \alpha + \beta Team\ Diversity_f + \boldsymbol{X}'_{f,k,s}\boldsymbol{\gamma} + \eta_{ks} + \epsilon_{f,k,s} \quad (1)$$

where startup firm *f* operates in industry *k* and location *s*.

We measure performance of startup firms ($Startup\ Performance_{f,k,s}$) in three dimensions. First, we define an indicator variable that equals 1 if the startup survived up to year 3 (*Survival*). The average survival rate by year 3 is 66% in our sample. Second, conditional on survival, we consider the cumulative growth rate of employment in year 3 (*Growth*). Lastly, we define an indicator variable that equals 1 if the startup is an "outlier" with respect to employment growth compared to the other firms in our sample in year 3 (*Outlier*). We define outliers as startups whose employment growth is in the top one percent of the distribution in the sample.[10] Identifying outlier startups is important, because it allows us to verify whether the results we detect for the average startup in our sample are also true for those startups that are likely to be exceptionally successful throughout their life cycle.

[10] Outlier firms have cumulative growth rates above 182% in year 3.

$Team\ Diversity_f$ is either the Simple Diversity Index (SDI) or the Mobility-adjusted Diversity Index (MDI) for startup *f* measured based on the entrepreneurial teams. $\boldsymbol{X}'_{f,k,s}$ is a set of control variables measured in the first year for the startup firm. It includes firm size (the logarithm of number of employees), a proxy for the level of human capital in the team (the logarithm of the average wage), employee age (the average age of the founding employees), gender composition (the percentage of female employees) and race composition (percentages of White, Black, Asian, and Hispanic employees, respectively). In addition, we follow Parrotta, Pozzoli and Pytlikova (2014) to measure demographic diversity and ethnicity diversity using a Herfindahl index. For both measures, we compute the index as one minus the sum of the square of the proportion of founding employees in each group (i.e., $1 - \sum_{i=1}^{n} p_i^2$). The indices can be interpreted as the probability that two randomly drawn founding employees belong to different groups. The demographic diversity index is constructed from the intersection of gender and four age quartiles (8 categories in total). For the ethnicity diversity index, founding employees are grouped into the following 8 categories based on their place of birth: North America and Oceania, Central and South America, Africa, West and South Europe, formerly Communist countries, Asia, East Asia, and Muslim countries. Finally, η_{ks} denotes a full set of fixed effects for the industry-state in which the startup operates.

Table 3 reports the results of estimating equation (1) using ordinary least squares.[11] In the left panel of Table 3, the measure of team diversity is the Simple Diversity Index. Higher team diversity is associated with a slightly lower probability of survival by year three. At the same time, higher team diversity is also associated with substantially higher average employment growth and with a higher probability of achieving outlier employment growth. Calculated at the mean, a one-standard-deviation increase in SDI is associated with a 32% higher growth rate in three years and a 26% higher chance of outlier growth.

[11] We report the marginal effects for estimating a linear probability model when considering dummy outcome variables to guarantee symmetry with our instrumental-variable results, but marginal effects are qualitatively and quantitatively similar if we estimate the specification with a non-linear probability model.

In the right panel of Table 3, we consider the Mobility-adjusted Diversity Index. We no longer observe a negative association between team diversity and startup survival. Note that both the size of the estimated coefficient and its statistical significance drop substantially compared to the estimate using the simple diversity index even though the sample size is unchanged. At the same time, the positive associations between team diversity and employment growth and the likelihood of outlier growth are both confirmed when we use the Mobility-adjusted diversity index. Again calculating at the mean, a one-standard-deviation increase in MDI is associated with a 26% higher employment growth and 15% higher probability of achieving outlier growth.

Among the control variables, we find that startups with younger founding employees, higher percentages of women, and greater demographic and ethnic diversity grow faster. Interestingly, demographic diversity has opposite partial correlations with average employment growth and outlier growth – greater demographic diversity is associated with higher average growth, but a lower probability of extreme growth. These results confirm an empirical distinction between demographic diversity and our measure of skill diversity. Economically, demographic diversity could capture growth-relevant factors such as differences in beliefs or perspectives that arise from differences in life experiences. Our interest, instead, is in diversity of skills and expertise, which are more directly related to the diversity of work backgrounds.

To check the robustness of our results, we consider an alternative proxy for team background diversity that simply counts the number of main industries in which the entrepreneurial team members were employed prior to founding the startup. We report summary statistics of this measure side-by-side with our two main diversity indices in Table 2. Though a crude proxy for background diversity compared to our main indices, it shares similar associations with startup growth rate (see Table A.1 of the appendix). Thus, we confirm that the results do not depend on the specific complexities of our index construction.

We also consider the robustness of our results to the inclusion of finer controls for local economic conditions. Our baseline specification in equation (1) exploits cross-sectional variation in startups' team background diversity within industry and states. To assess whether unobserved local geographic effects might be driving our results, we repeat the estimation with more restrictive industry×county fixed effects. We find that the estimates reported in Table 3 are robust, suggesting that local geographic effects are unlikely to be responsible for our results.

As Table 1 shows, about one third of the startups in our sample have only one employee at the founding date. By construction, the measures of diversity for these startups are zero. To be sure that the mechanical differences in team diversity between these startups and startups with more than one employee do not drive our results, we re-estimate equation (1) excluding all of the startups with only one initial employee. We find estimates that are similar to those we report in Table 3.

Finally, we assess the concern that in our baseline results, we only look at the cohort of startups founded in one year (2010).[12] As economic conditions vary over the business cycle, the effect of team diversity on startup success could also vary over the business cycle. To ensure that our estimates of the effect of team diversity are not unique to the economic conditions that prevailed in 2010, we estimate a panel version of equation (1) in which we include cohorts of startups from 2005 to 2010 and add a full set of year fixed effects. We again find estimates that are very similar to those reported in Table 3.

III.2. Instrumental-Variable Strategy

A potential concern with our OLS estimates is that the background diversity of founding employees is not exogenous. It is possible that unobservable startup characteristics lead founding team members to select into the venture and at the same time are responsible for its subsequent performance. To tackle this challenge, we propose an instrumental-variable strategy to isolate the variation in team background diversity that is unlikely to be driven by other unobservable startup-level characteristics determined at the founding date. We exploit constraints on the geographic mobility of workers and use the heterogeneity in industry distribution in local labor markets to capture worker exposure. Tate and Yang (2015) show that the less than 5% of U.S. workers migrate across states, even in case of forced employment

[12] Our baseline research focuses on startups founded in 2010 to maximize number of matches from the 2010 Decennial Census.

discontinuity following plant closure. If labor markets are largely local and founding employees are more likely to come from the location where the startup is founded, then the more industries that are available in the area, the more likely it is that founding employees will have diverse employment backgrounds.

Specifically, we propose two instruments for team background diversity. First, we measure industry diversity in the county in which the startup was founded between 2002 and 2005. We exclude the years 2006-2009 so that our measure captures the diversity of local job opportunities on the supply side of the labor market when founding employees are accumulating work experience, but is less likely to correlate with current market conditions that could affect startup performance between 2010 and 2014. We measure industry employment at the 2-digit NAICS level using the LBD. We then define the variable *Diversity_Ind* as one minus the average annual Herfindahl index of industry employment in the county. We expect the diversity of opportunities in the local job market to positively predict the diversity of work experience that the startup founding team acquired during that time period. Applying the same economic reasoning to internal rather than external labor markets, our second instrument is the percentage of employment in diversified firms in the county in which the startup operates (*Pct_Div*). Tate and Yang (2015) show that workers in diversified firms gain greater cross-industry work experience than focused firm peers in part by taking advantage of job opportunities within internal labor markets. To exploit this source of industry variation in job supply, we define diversified firms as firms that employ at least 10% of their workers in at least two distinct 2-digit NAICS industries and compute the average percentage within the county again over the period from 2002-2005, at least five years prior to the founding of the startups in the regression sample. We predict that a higher percentage of employment in diversified firms increases the diversity of team industry experience.

To provide valid identification, our instruments must also satisfy an exclusion restriction. That is, each instrument should only affect startup performance through its effect on team background diversity. Though we cannot test directly whether the restriction is satisfied, our setting does address some important potential sources of violation. First, all of our resgressions include industry×state fixed effects, which ensure that we only exploit variation in the diversity of industry composition at the county level within U.S. states. Because most business legislation and regulation occurs at the state (or federal) level, these unobserved dimensions that could in principle affect both the distribution of industries and startup performance cannot be captured by our instrumental-variable estimates. Moreover, as described in Section III.2, our baseline results are similar if we add a more restrictive set of geographic fixed effects to the specification, such as industry×county fixed effects. Thus, more generally, local business cycles or unobserved local regulations are unlikely to drive our results. In addition, most unobserved dimensions that could affect both background diversity of the local workforce and startup performance are likely to affect the diversity of the work experience of *both* founders and other members of the founding team. Then, one way to correct for such factors would be to control directly for diversity of founder work experience. When we add the diversity of founder experience to our specifications (see Section V), the baseline association between workers' diversity and startup performance does not change. This result suggests that a violation of the exclusion restriction in our setting would require the instrument to capture unobserved variation that determines both worker background diversity and startup performance, but not founders' own background diversity.

To implement our instrumental-variable strategy, we estimate the following system of linear equations using a two-stage least squares procedure:

$$Team\ Diversity_{f,k,s} = \alpha_1 + v_1\ Diversity\_Ind_f + v_2\ Pct\_Div_f + \boldsymbol{X}'_{f,k,t}\boldsymbol{\gamma_1} + \eta_{ks,1} + \epsilon_{f,k,s,1} \quad (2)$$

$$Startup\ Performance_{f,k,s} = \alpha_2 + \beta\ Team\ \widehat{Diversity}_{f,k,s} + \boldsymbol{X}'_{f,k,s}\boldsymbol{\gamma_2} + \eta_{ks,2} + \epsilon_{f,k,s,2} \quad (3)$$

Equation (2) is the first stage. We predict that both industry diversity and the percentage of diversified firms are positive related to team diversity ($v_1 > 0$ and $v_2 > 0$). All control variables are the same as those used in Equation (1). Equation (3) is the second stage. It corresponds to Equation (1) except that we use only the variation in the Mobility-adjusted Diversity Index that is predicted by the instrument in the first stage to identify β.

Table 4 Panel B reports the results for estimating the first stage. The relevance criterion for the validity of our instruments is satisfied, because both instrumental variables are positively associated with the Mobility-adjusted Diversity Index even after controlling the full set of controls in equation (1). Table 4 Panel A reports the results for estimating the second stage. In this case, Mobility-adjusted Diversity Index is the instrumented analog of the actual index in Equation (1). The positive association between team background diversity and employment growth is confirmed in the two-stage least squares specification. Also consistent with the estimation of Equation (1), the instrumented Mobility-adjusted Diversity Index is not significantly related to the likelihood the startup survived up to the third year after the founding date. It is important to note that the size of the second-stage estimates is substantially larger than corresponding OLS estimates in Table 3, especially when we consider cumulative employment growth up to year 3 as an outcome. It is of course possible that endogeneity of team experience causes the OLS estimates to understate the true effect of diversity on startup growth. For example, startups in more challenging environments could devote more attention to the composition of their initial teams. If so, then this negative selection effect could dampen the positive relation between team diversity and performance. Nevertheless, given the magnitude of the estimate inflation (and the relatively modest statistical strength of the first stage estimates), we view the instrumental-variable strategy mainly as a robustness test. Though the estimates confirm qualitatively the baseline results we documented in Section III, we rely on the OLS framework in the remainder of the analysis.

IV. Innovative Industries

Our results so far suggests that startup firms with more diverse experience on average grow faster and are more likely to achieve extreme growth. In addition to assessing effects on the average startup, the entrepreneurship literature often focuses on startups in highly innovative industries. The rationale is that startups in those industries are likely to create more specialized employment opportunities, produce research-oriented innovations, and ultimately become the engine of economic growth. In this section, we analyze whether the baseline associations between team background diversity and startup-level outcomes are more prominent in more innovative industries.

IV.1. Innovation Index

To measure innovativeness by industry, we exploit data from the Innovation Measurement Initiative (IMI) project, a novel project recently undertaken at the Census Bureau that collects information on all the individuals who receive money from Federal grants to conduct research at U.S. universities.[13] We track the industries in which all graduate and undergraduate students on research grants accept jobs following graduation and use the relative flow of students compared to job opportunities available in those industries. The resulting Innovation Index captures the demand for highly skilled, research-trained employees in each industry. Following the methodology of D'Acunto, Tate, and Yang (2017), we compute the Innovation Index for each three-digit NAICS industry as the share of students placed in the industry reported by the IMI data scaled by the share of all U.S. employees in the industry:

$$Innovation\ Index_k = \frac{Students_k / \sum_k Students_k}{Jobs_k / \sum_k Jobs_k}$$

where $Students_k$ is the number of students who started their first job after graduation in industry k; and $Jobs_k$ is the total number of jobs in industry k (measured using aggregate employment from the LBD).

To ensure that we observe sufficient numbers of job entries to compute meaningful differences across industries, we pool job entries across multiple years (2002 to 2010) in the IMI data, scaled by corresponding total employment. Higher values of the index indicate that the industry attracts a higher share of research-trained first-time employees than its share of all employees in the economy. Industries that rely heavily on innovation and that are close to the technological frontier are likely to have higher values of the Innovation Index. A novel feature of this index is that it provides large variation in innovation intensity not only across manufacturing industries, like indices based on patents or R&D, but also across services industries, in which innovation is often not patented and hence not captured by standard

[13] The pilot version of the project we can access includes information from 13 US universities for the period 2002-2014.

measures of innovation used in the literature (Lerner and Seru, 2015). In addition, compared to patents, which are output from innovation, our Innovation Index constructed using job flows captures the inputs to innovation activities as they are occurring.

IV.2. Team Diversity and Performance by Industry Innovativeness

To assess whether the baseline effects differ across startups by industry innovativeness, we split all 3-digit NAICS industries in two groups based on the value of their Innovation Index. We classify all industries with an Innovation Index larger than 2 as innovative industries (i.e. D_Innovation =1). [14] About 20% of all startups in our sample are in innovative industries. We estimate the following:

$$Startup\ Performance_{f,k,s} = \alpha + \beta\ Team\ Diversity_f + \delta\left(Team\ Diversity_f \times D_{Innovation_k}\right) + \boldsymbol{X}'_{f,k,s}\boldsymbol{\gamma} + \eta_{ks} + \epsilon_{f,k,s} \quad (4)$$

where $D\_Innovation$ is a dummy variable that equals 1 for startups in industries whose Innovation Index is larger than 2, and all the other variables are defined as in Equation (1). Note that, because the innovation dummy is defined at the industry level (k), the fixed effects we add to the specification fully absorb any variation in the level of $D\_Innovation$ across industries.

We report the results of estimating Equation (4) in Table 5. Similar to Table 3, the left panel refers to the Simple Diversity Index, whereas the right panel shows results using the Mobility-adjusted Diversity Index to measure team background diversity. The first row of Table 5 shows that all the baseline results discussed in Section III are confirmed for the subsample of startups in industries that are not highly innovative. More interestingly, the second row shows that startups in innovative industries receive additional effects from team background diversity. Two features of the results are notable. First, the positive association between team background diversity and employment growth is substantially higher for startups in innovative industries than for other startups. The coefficient of team diversity on 3-year cumulative growth is approximately 40% higher in innovative industries than that from the benchmark. When

[14] Our results are robust when an alternative threshold of 3 is used.

considering the likelihood of outlier growth (i.e. growth within the top one percent of the distribution), the effect of team diversity is about twice as large for startups in innovative industries as for other startups. Second, the baseline negative association between team background diversity and the likelihood the startup survives at least three years disappears for the sample of innovative startups. When we use the Mobility-adjusted Diversity Index, the sign of the association becomes positive, which suggests that for the most innovative industries startups with higher team background diversity are more likely to survive than other startups.

To assess the robustness of the results, we use an alternative measure for skills based on the average wage in the industry and find qualitatively similar estimates. That is, the effect of team background diversity has a stronger association with startup performance in industries that employ high-skill workers.

V. Team Diversity or Founder Diversity?

Our results so far focus on diversity of the work experience of the entrepreneurial team and document a positive relationship between team diversity and startup employment growth. At the same time, Lazear (2005) suggests that founders' skill diversity is crucial to entrepreneurial success and proposes the view of successful entrepreneurs as "jacks of all trades." A potential interpretation of our results might be that entrepreneurs who acquired varied skills throughout their employment career and have more diverse background might also hire teams that are more diverse. If this was the case, then the variation in team experience diversity might be a mere proxy for founders' experience diversity, which in turn is associated with startup performance based on earlier results.

The LEHD does not provide information on founders. To gauge the effect, we identify the "founder" of each startup as the highest paid member of the founding team and control for her experience. This approach is common in the literature. However, the approximation is not perfect. Hyatt, Murray and Sandusky (2018) show that business owners do not always show up in the LEHD data as employees. On the other hand, Kerr and Kerr (2017) and Babina and Howell (2018) find that business owners are usually among a firm's top initial earners, Moreover, Azoulay et al. (2017) point out that the W-2 data that is the basis for the LEHD data must be filed for all employees, including owners who actively manage the business. Our results are robust if we instead identify the "founder" as the firm member who appeared in the first quarter of the startup and had the longest tenure in the first two years, relying less on the signal provided by relative pay levels.

An advantage of our unique data is that we can construct measures of experience diversity for any individual directly. We construct a diversity index for the founder's industry experience similar to what is done for the entrepreneurial team, but based on founder's employment history over time. That is, we record all the industries in which the founder has worked for at least four quarters prior to founding the start-up firm. We then compute a Simple Diversity Index based on the set of industries and corresponding number of quarters and a Mobility-adjusted Diversity Index adjusting for the relatedness between any pair of industries. A higher diversity index suggests that the founder has experience in a broader set of industries prior to founding the startup (i.e., "jack of all trades"). Table A.2 in the Appendix provides summary statistics for the diversity indices computed at the founder level.

Table 6 reports the estimation of the equivalent of Equation (1) but with founder diversity as the main covariate. In all specifications, for brevity, we only report results using the Mobility-adjusted Diversity Index for founders and/or the entrepreneurial team. Our results are qualitatively similar when we use the Simple Mobility Index. As in earlier tables, we use three measures for firm performance – survival, cumulative growth and outlier growth, all measured in year 3. In columns (1) - (3), we include founder diversity by itself, and in columns (4) - (6), we include the diversity of the work experience of both the founder and the entrepreneurial team.

The two measures of diversity appear to capture different sources of variation in the cross section of startup performance. Our baseline results for team experience diversity do not change after we control directly for founder experience diversity. If anything, the association between team diversity and the likelihood of survival becomes significantly positive, both statistically and economically, instead of being insignificant. The associations between team diversity and outlier growth are largely unchanged. The estimated coefficients on founder experience diversity itself are quite robust with or without including team diversity. We detect qualitatively similar positive associations of diversity with startup employment growth. However, the association between the founder's experience diversity and the likelihood of survival is negative. Moreover, these patterns are robust to instrumenting for founder experience diversity using *Diversity_Ind*.[15] Here, the logic behind the instruments is the same, but we find first stage estimates that are far stronger statistically (and second stage estimates that are more in line with the OLS results).

Table 7 reports the results for estimating the analog of equation (2) when adding both founder experience diversity and its interaction with the dummy of industry innovativeness. For brevity, we only report results based on Mobility-adjusted Diversity Index for both the team and the founder. Results are robust when we use the Simple Diversity Index. Again, we find similar results on team diversity as in the baseline models. Specifically, team experience diversity increases employment growth and likelihood of becoming an outlier for startups in less innovative industries, but the positive association is about twice as large for startups in more innovative industries. For founder experience diversity, we do not detect these systematic patterns across startups in different industries, which adds to the conjecture that founder experience diversity and team experience diversity capture alternative sources of variation across startups in our sample.

Overall, the results suggest that our measures of team diversity capture a source of variation which is orthogonal to the variation in founder diversity.

VI. Conclusion

We use comprehensive data on a cohort of startups matched with detailed individual-level data on employment histories and demographics to estimate the effect of team experience on the startups' initial success. We hypothesize that for a given team size, a firm with founding employees whose collective skillset encompasses a greater number of distinct skills will experience greater initial success. Our hypothesis extends the logic of Lazear (2005) to the team

[15] Only the effect on outlier growth is statistically insignificant in the second stage (with a point estimate of 0.0053 and a t-statistic of 1.26).

level, a distinction that is important given the recent trend towards younger and, presumably, less individually experienced founders in U.S. new ventures. To proxy for this breadth of team skills, we construct two index measures of the diversity of the founding teams' pre-startup industry experience. In our main measure, we adjust for the observed mobility of human capital across industries since "nonadjacent" industries between which workers infrequently move may be more likely to utilize truly distinct worker skillsets.

We find that founding teams with broader pre-startup industry experience indeed experience faster initial growth over the first four years of operation. Both employment growth and the probability of extreme growth (i.e., growth in the top 1% of the distribution) significantly increase with our measures of team experiential diversity. We find that the results continue to hold when we use information on the past county-level distribution of jobs across industries to instrument for the team's observed experience. We also apply our approach to measuring industry experience to the top employee on the team to distinguish team effects from the potential benefits of having a "jack of all trades" founder, in the spirit of Lazear (2005). We find that the effects are distinct; moreover, only team experience positively predicts startup four-year survival. Finally, we find that the relative benefit of diverse industry experience is larger for startups in industries that are magnets for more innovative human capital. This result confirms the human capital channel driving the results. It also suggests that our economic mechanism could be particularly important among the most innovative and dynamic subset of startups.

Overall, our analysis suggests a fruitful endeavor in moving beyond the question of whether team effects matter to address the question of which types of teams produce the greatest success.

Appendix: Computation of the Human Capital Transferability Index

We define the expected labor flow from industry i to j as $\widehat{F_{ij}} = \frac{F_{i.} \times F_{.j}}{F_{..}}$ where $F_{i.}$ is the number of workers moving from industry i, $F_{.j}$ is the number of jobs in industry j, and $F_{..}$ is the total number of jobs in the sample. Thus, the expected movement from industry i to j is computed under the assumption that the fraction of job changers who originate in industry i who end up accepting jobs in industry j should equal the overall frequency of jobs in industry j in the economy. We then compute the ratio between the actual and expected flows as $r_{ij} = \frac{F_{ij}}{\widehat{F_{ij}}} = \frac{F_{ij} \times F_{..}}{F_{i.} \times F_{.j}}$, or the ratio of the actual number of job moves between industry i and industry j to the expected number. r_{ij} greater than 1 indicates more flows than predicted. Since r_{ij} is strongly right-skewed, we transform r_{ij} according to the formula $\overline{r_{ij}} = \frac{r_{ij}-1}{r_{ij}+1}$, following Neffke, Otto, and Weyh (2017). $\overline{r_{ij}}$ is centered around zero and ranges from -1 to 1. We then compute a two-way transferability index between industries i and j by taking the average $h_{ij} = \frac{\overline{r_{ij}}+\overline{r_{ji}}}{2}$. By construction, $h_{ij} = h_{ji}$.

The final Human Capital Transferability Index is a three-year average of the index described above.[16] Intuitively, a higher index suggests greater transferability of human capital and skills between industries, and therefore higher industry relatedness.

[16] When we construct the Mobility-adjusted Diversity Index for different years (e.g., in our robustness tests that look at startups between 2005 and 2010 instead of the single 2010 cross-section), we use the average of the index over the three prior years to compute the Human Capital Transferability Index for each year.

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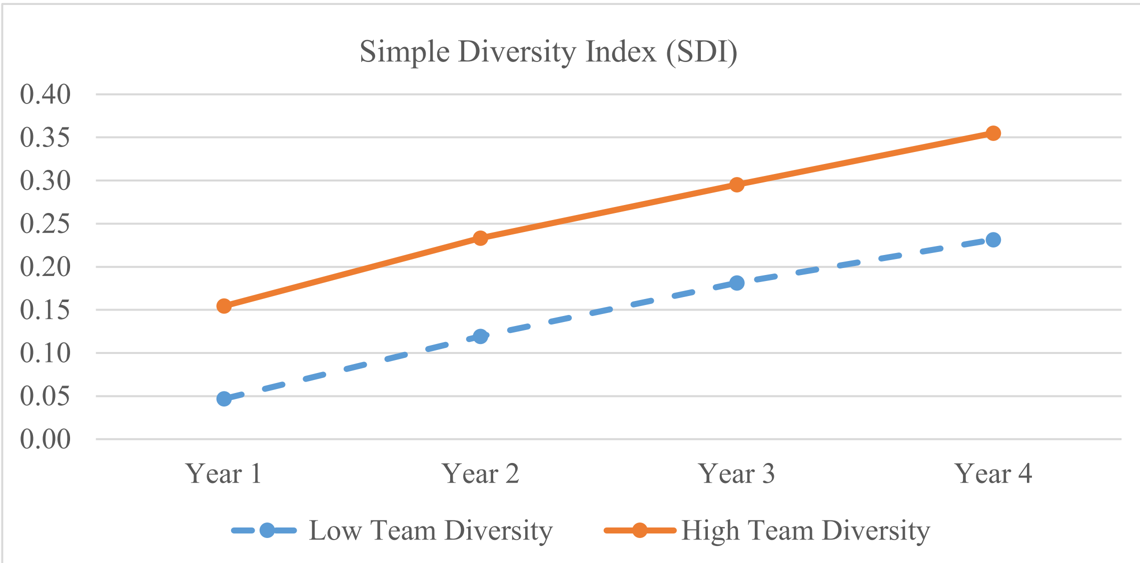
Figure 1: Team Diversity and Cumulative Growth Over Time

This figure presents the average cumulative growth rate by team diveristy index for startup firms in year 1,2,3, and 4 following the firm foundation. For each index, High Diversity refers to startups above the median in the distribution of the Diversity Index, whereas Low Diversity refers to startups below the median in the distribution of the Diversity Index.



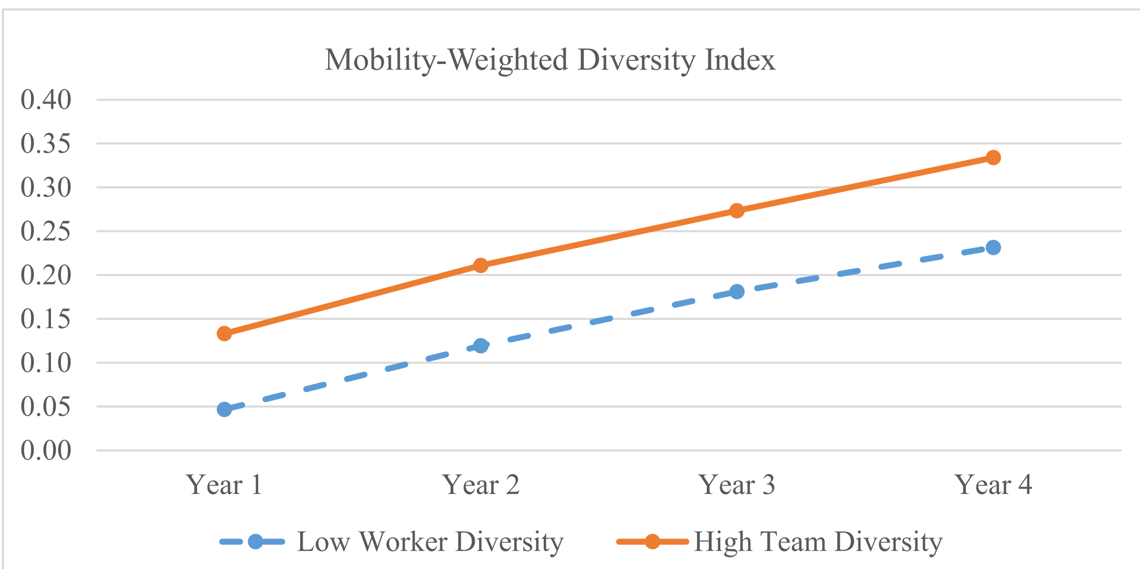


Table 1. Summary Statistics

This table reports summary statistics for the samples we use in the analysis. Panel A reports the distribution across NAICS-2 industries, Census Divisions, and by the number of employees at foundation. Panel B reports statistics at the firm level. Surv_1, Surv_2, Surv_3, and Surv_4 are indicator variables that equal 1 if the startup survived up to year 1,2,3,4 after foundation, and zero otherwise. Growth_1, Growth_2, Growth_3 and Growth_4 measure the cumulative employment growth rates in year 1,2,3,4 following foundation, respectively. Panel C and Panel D report statistics for startup employee- and founder-level demographic variables. Age is the age of the worker. Female is an indicator variable that equals to 1 for female worker and zero otherwise. African-American is an indicator variable that equals to 1 for African workers and zero otherwise. Asian is an indicator variable that equals to 1 for Asian workers and zero otherwise. Hispanic is an indicator variable that equals to 1 for Hispanic workers and zero otherwise. Foreign is an indicator variables indicator that equals to 1 for non-US workers and zero otherwise.

Panel A: Distribution of Firms

Industry	Percentage
Accommodation	8.9
Administrative	5.4
Agriculture	0.3
Arts and Entertainment	1.6
Construction	10.5
Education	1.3
Finance	4.7
Healthcare	10.8
Information	1.4
Management	0.1
Manufacturing-1	0.7
Manufacturing-2	0.7
Manufacturing-3	1.5
Mining	0.3
Other svc	8.1
Professional service	16.7
Real Estate	4.9
Retail-1	10.0
Retail-2	3.2
Transportation-1	3.1
Transportation-2	0.3
Utilities	0.1
Wholesale	5.4
Total	100
Observations	181000

Geographic Division	Percentage
East North Central	12.2
East South Central	4.6
Middle Atlantic	16.5
Mountain	7.9
New England	2.0
Pacific	17.6
South Atlantic	22.3
West North Central	4.9
West South Central	11.9
Total	100
Observations	181000

# of Workers	Percentage
1	32.5
2	22.8
3	13.8
4	9.7
5	6.3
6	4.7
7	3.4
8	2.8
9	2.2
10	1.9
Total	100
Observations	181000

PANEL B - SUMMARY STATISTICS: FIRMS

	# of Employees	Wage (in $000's)	Surv_1	Surv_2	Surv_3	Surv_4	Growth_1	Growth_2	Growth_3	Growth_4
Mean	3.03	33.15	0.858	0.751	0.664	0.576	0.092	0.168	0.230	0.286
Std.	2.29	54.48	0.349	0.432	0.472	0.494	0.506	0.617	0.686	0.732
Observations	181,000	181,000	181,000	181,000	181,000	181,000	155,000	136,000	120,000	104,000

PANEL C - SUMMARY STATISTICS: WORKERS

	Age	Female	White	Black	Asian	Hispanic	Foreign
Mean	40.14	0.42	0.77	0.05	0.13	0.13	0.26
Std.	10.02	0.41	0.37	0.19	0.30	0.29	0.39
Observations	181,000	181,000	181,000	181,000	181,000	181,000	181,000

Table 2: Summary Statistics: Diversity Indices

This table reports summary statistics for the team background diversity indices used in the analysis. The definition for Simple Diversity Index (SDI) and Mobility-weighed Diversity Index (MDI) is provided in Section II.A and Section VI of the paper. We define industries at the 3-digit NAICS level.

	Simple Diversity Index (SDI)	Mobility-Weighted Diversity Index (MDI)	# of Industries
Mean (All Firms)	0.22	0.47	1.72
Std. (All Firms)	0.28	0.34	1.16
Firms w/ ≤5 Employees (85%)	0.19	0.43	1.55
Firms w/ >5 Employees (15%)	0.39	0.67	2.70
T-Stat for difference	-106.40	-114.90	-110.67
# of Firms	181,000	181,000	181,000

Table 3: Team Diversity and Firm Performance

This table reports the results for regressing firm performance variables on team diversity measures. The dependent variable is survival (an indicator variable that equals 1 if the startup survived up to the third year after foundation) in column (1) and (4), cumulative growth rate measured in year 3 in column (2) and (5), and outlier (an indicator variable that equals 1 if the startup belongs to the top 1% of the distribution of employment growth 3 years after foundation) in column (3) and (6). Coefficients are computed by estimating a linear specification by ordinary least squares. Team Diversity is based on simple diversity index in column (1) to (3) and mobility-weighted diversity index in column (4) to (6) defined in section II.A.Log(Initial Wage) is the logarithm of the wage bill the startups paid in the foundation year. Log(Initial Employees) is the logarithm of the number of initial employees in the startup at foundation. Avg. Worker Age is the average age of the firm's employees. Share Female Workers is the fraction of female founding employees. Share White Workers, Share Black Workers, Share Asian Workers, and Share Hispanic Workers refer to the fraction of the founding employees that are White, African American, Asican or Hispanic, respectively. Demographic Diversity and Ethnic Diversity are defined based on Parrotta, Pozzoli and Pytlikova (2014) described in Section III.1. All specifications include a full set of fixed effects at the State*Industry level (2-digit NAICS codes). Standard errors are double-clustered at the industry and the State level. t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Simple Diversity Index			Mobility-Weighted Diversity Index		
	Survival	Growth	Outlier	Survival	Growth	Outlier
Team Diversity	-0.0308 ***	0.262 ***	0.0094 ***	-0.0085	0.175 ***	0.0045 ***
	(-3.89)	(12.52)	(4.89)	(-1.54)	(15.05)	(4.12)
Log(Initial Wage)	0.131 ***	0.181 ***	0.0081 ***	0.131 ***	0.184 ***	0.0082 ***
	(12.6)	(7.47)	(7.27)	(12.65)	(7.56)	(7.29)
Log(Initial Employees)	0.0506 ***	-0.373 ***	0.0092 ***	0.0499 ***	-0.370 ***	0.0093 ***
	(10.50)	(-22.24)	(8.69)	(10.18)	(-22.36)	(8.66)
Avg. Worker Age	0.0096	-0.296 ***	-0.0034 ***	0.0123	-0.302 ***	-0.0039 ***
	(0.92)	(-12.50)	(-3.27)	(1.21)	(-12.15)	(-3.62)
Share Female Workers	0.0356 **	0.0687 ***	-0.0002	0.0359 **	0.0664 ***	-0.0003
	(2.47)	(3.19)	(-0.36)	(2.47)	(3.07)	(-0.49)
Share White Workers	0.0136 *	0.0097	0.0013	0.0132 *	0.012	0.0014
	(1.73)	(0.87)	(1.38)	(1.68)	(1.08)	(1.50)
Share Black Workers	-0.0388 ***	0.0229	0.0052 *	-0.0394 ***	0.0248	0.0053 *
	(-2.94)	(1.47)	(1.75)	(-2.95)	(1.56)	(1.78)
Share Asian Workers	0.0263	-0.0234	0.0007	0.027	-0.0265	0.0006
	(-1.31)	(-1.06)	(0.60)	(1.33)	(-1.19)	(0.48)
Share Hispanic Workers	0.0186 ***	0.0097	-0.0002	0.0191 ***	0.0073	-0.0003
	(2.80)	(1.31)	(-0.28)	(2.85)	(0.96)	(-0.41)
Demographic Diversity	0.0742 ***	0.323 ***	-0.0079 ***	0.0641 ***	0.349 ***	-0.0059 ***
	(4.90)	(6.05)	(-5.04)	(4.98)	(6.11)	(-4.45)
Ethnic Diversity	-0.0255 ***	0.120 ***	0.0032 **	-0.0279 ***	0.128 ***	0.0037 **
	(-3.20)	(6.39)	(2.15)	(-3.38)	(6.42)	(2.45)
Observations	181000	120000	120000	181000	120000	120000
State×Industry FE	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.077	0.173	0.016	0.076	0.171	0.015

Table 4. Team Diversity and Firm Performance: Instrumental-Variable Strategy

This table reports the results for instrumenting the mobility-weighted diversity index of a startup's employees. Panel A reports the second-stage results. The dependent variable is survival (an indicator variable that equals 1 if the startup survived up to the third year after foundation) in column (1), cumulative growth rate measured in year 3 in column (2), and outlier (an indicator variable that equals 1 if the startup belongs to the top 1% of the distribution of employment growth 3 years after foundation) in column (3). Panel B reports the first-stage results for the samples of startups for which we observe each of the main outcome variables listed on top of the column. Diversity_Ind is defined as 1 minus the Herfindahl Index computed based on industry (2-digit NAICS) employment in the County. Pct_Div measures the percentage of employment in diversified firms in the county. Diversified firms are defined as firms that operate in multiple 2-digit NAICS industries. Herf_Ind and Pct_Div are measured from 2002 to 2005. We use the same control variables as those listed in Table 3. All specifications include a full set of fixed effects at the State*Industry level (2-digit NAICS codes). Standard errors are double-clustered at the level of the industry and the State. t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

Panel A: Second-Stage	(1) Survival	(2) Growth	(3) Outlier
Team Diversity - IV	0.607	3.672 ***	0.275 **
(Mobility Wtd.)	(1.19)	(3.40)	(2.54)
Log(Initial Wage)	0.0330 **	-0.449 ***	0.0031
	(2.34)	(-16.69)	(1.18)
Log(Initial Employees)	0.128 ***	0.177 ***	0.0076 ***
	(37.83)	(23.44)	(10.93)
Avg. Worker Age	0.124	0.412	0.0514 **
	(1.33)	(1.87)	(2.32)
Share Female Workers	0.0351 ***	0.0620 ***	-0.0006
	(7.51)	(5.59)	(-0.77)
Share White Workers	0.0052	-0.0390	-0.0025
	(0.49)	(-1.54)	(-1.09)
Share Black Workers	-0.0627 ***	-0.108 **	-0.0050
	(-2.77)	(-2.19)	(-1.07)
Share Asian Workers	0.0408 ***	0.0543	0.0069 *
	(2.62)	(1.44)	(1.92)
Share Hispanic Workers	0.0253 ***	0.0413 **	0.0023
	(3.73)	(2.07)	(1.32)
Demographic Diversity	-0.285	-1.602 ***	-0.157 ***
	(-0.98)	(-2.67)	(-2.60)
Ethnic Diversity	-0.0975 *	-0.268 **	-0.0270 **
	(-1.68)	(-2.21)	(-2.21)
Observations	181000	120000	120000
State×Industry FE	Y	Y	Y

Panel B: First Stage	(1) Survival	(2) Growth	(3) Outlier
Diversity_Ind	0.0953 ***	0.0974 **	0.0974 **
	(2.94)	(2.40)	(2.40)
Pct_Div	0.616 **	1.005 ***	1.005 ***
	(2.39)	(3.18)	(3.18)
Log(Initial Wage)	0.0037 ***	0.0019	0.0019
	(3.04)	(1.19)	(1.19)
Log(Initial Employees)	0.0274 ***	0.0227 ***	0.0227 ***
	(14.98)	(10.02)	(10.02)
Avg. Worker Age	-0.182 ***	-0.204 ***	-0.204 ***
	(-46.16)	(-45.10)	(-45.10)
Share Female Workers	0.0012	0.0013	0.0013
	(0.71)	(0.58)	(0.58)
Share White Workers	0.0136 ***	0.0152 ***	0.0152 ***
	(3.49)	(2.86)	(2.86)
Share Black Workers	0.0380 ***	0.0380 ***	0.0380 ***
	(7.04)	(5.24)	(5.24)
Share Asian Workers	-0.0221 ***	-0.0226 ***	-0.0226 ***
	(-4.38)	(-3.54)	(-3.54)
Share Hispanic Workers	-0.0096 ***	-0.0088 ***	-0.0088 ***
	(-3.54)	(-2.54)	(-2.54)
Demographic Diversity	0.568 ***	0.558 ***	0.558 ***
	(100.28)	(90.80)	(90.80)
Ethnic Diversity	0.113 ***	0.113 ***	0.113 ***
	(22.78)	(18.44)	(18.44)
Observations	181000	120000	120000
State×Industry FE	Y	Y	Y
Adjusted R-squared	0.393	0.377	0.377

Table 5: Team Diversity, High Human-Capital Industries and Firm Performance

This table reports the results for regressing firm performance variables on team diversity measures and industry human-capital intensity. The dependent variable is survival (an indicator variable that equals 1 if the startup survived up to the third year after foundation) in column (1) and (4), cumulative growth rate measured in year 3 in column (2) and (5), and outlier (an indicator variable that equals 1 if the startup belongs to the top 1% of the distribution of employment growth 3 years after foundation) in column (3) and (6). Coefficients are computed by estimating a linear specification by ordinary least squares. Team Diversity is based on simple diversity index in column (1) to (3) and mobility-weighted diversity index in column (4) to (6) defined in section II.A.High HCI is an indicator that equals to 1 if HCI Index is above 2 .Log(Initial Wage) is the logarithm of the wage bill the startups paid in the foundation year. Log(Initial Employees) is the logarithm of the number of initial employees in the startup at foundation. Avg. Worker Age is the average age of the firm's employees. Share Female Workers is the fraction of female founding employees. Share White Workers, Share Black Workers, Share Asian Workers, and Share Hispanic Workers refer to the fraction of the founding employees that are White, African American, Asican or Hispanic, respectively. Demographic Diversity and Ethnic Diversity are defined based on Parrotta, Pozzoli and Pytlikova (2014) described in Section III.1. All specifications include a full set of fixed effects at the State*Industry level (2-digit NAICS codes). Standard errors are double-clustered at the industry and the State level. t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Simple Diversity Index			Mobility-Weighted Diversity Index		
	Survival	Growth	Outlier	Survival	Growth	Outlier
Team Diversity	-0.0358 ***	0.234 ***	0.0080 ***	-0.0151 **	0.155 ***	0.0038 ***
	(-3.45)	(7.99)	(4.50)	(2.14)	(7.90)	(3.41)
Team Diversity * High HCI	0.0291 ***	0.160 ***	0.0081 ***	0.0391 ***	0.119 ***	0.0043 ***
	(3.40)	(3.81)	(3.98)	(3.85)	(3.82)	(3.37)
Log(Initial Wage)	0.131 ***	0.181 ***	0.0080 ***	0.131 ***	0.183 ***	0.0081 ***
	(12.51)	(7.42)	(7.19)	(12.59)	(7.51)	(7.26)
Log(Initial Employees)	0.0506 ***	-0.373 ***	0.0092 ***	0.0498 ***	-0.370 ***	0.0093 ***
	(10.48)	(-22.33)	(8.60)	(10.17)	(-22.38)	(8.61)
Avg. Worker Age	0.0100	-0.294 ***	-0.0032 ***	0.0128	-0.300 ***	-0.0039 ***
	(0.96)	(-12.85)	(-3.11)	(1.27)	(-12.40)	(-3.46)
Share Female Workers	0.0355 **	0.0684 ***	-0.0002	0.0356 **	0.0656 ***	-0.0003
	(2.46)	(3.14)	(-0.38)	(2.47)	(2.97)	(-0.53)
Share White Workers	0.0137 *	0.0102	0.0013	0.0134 *	0.0121	0.0014
	(1.72)	(0.91)	(1.45)	(1.69)	(1.09)	(1.53)
Share Black Workers	-0.0387 ***	0.0235	0.0052 *	-0.0392 ***	0.0250	0.0053 *
	(-2.93)	(1.52)	(1.76)	(-2.95)	(1.59)	(1.79)
Share Asian Workers	0.0262	-0.0242	0.0007	0.0269	-0.0271	0.0006
	(1.30)	(-1.10)	(0.57)	(1.32)	(-1.22)	(0.47)
Share Hispanic Workers	0.0186 ***	0.0093	-0.0002	0.0190 ***	0.0070	-0.0003
	(2.79)	(1.22)	(-0.24)	(2.82)	(0.91)	(-0.35)
Demographic Diversity	0.0737 ***	0.320 ***	-0.0080 ***	0.0633 ***	0.346 ***	-0.0060 ***
	(4.96)	(6.00)	(-4.97)	(5.09)	(6.07)	(-4.42)
Ethnic Diversity	-0.0252 ***	0.122 ***	0.0033 **	-0.0274 ***	0.129 ***	0.0037 **
	(-3.17)	(6.34)	(2.24)	(-3.37)	(6.40)	(2.51)
Observations	181000	120000	120000	181000	120000	120000
State×Industry FE	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.077	0.174	0.016	0.077	0.172	0.015

Table 6: Founder Diversity and Team Diversity

This table reports the results for regressing firm performance variables on founder diveristy and team diversity measures. The dependent variable is survival (an indicator variable that equals 1 if the startup survived up to the third year after foundation) in column (1) and (4), cumulative growth rate measured in year 3 in column (2) and (5), and outlier (an indicator variable that equals 1 if the startup belongs to the top 1% of the distribution of employment growth 3 years after foundation) in column (3) and (6). Coefficients are computed by estimating a linear specification by ordinary least squares. Team Diversity is based on the mobility-weighted diversity index defined in section II.A and Founder Diversity is based on mobility-weighted diversity index defined in Section VI. Log(Initial Wage) is the logarithm of the wage bill the startups paid in the foundation year. Log(Initial Employees) is the logarithm of the number of initial employees in the startup at foundation. Avg. Founder Age is the age of the firm's founder. Female Founder is an indicator that equals to 1 if the founder is female. White Founder, Black Founder, Asian Founder and Hispanic Founder are indicator variables that equal to one if founder is White, African American, Asican or Hispanic, respectively. Founder Exp is an indicator variable that equals 1 if founder has worked in the same industry of the startup firm for at least four quarters previously. Workforce Control variables include Share Female Workers, Share White Workers, Share Black Workers, Share Asian Workers Share Hispanic Workers, Demographic Diversity, and Ethnic Diversity. All specifications include a full set of fixed effects at the State*Industry level (2-digit NAICS codes). Standard errors are double-clustered at the level of the industry and the State. and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Survival	Growth	Outlier	Survival	Growth	Outlier
Team Diversity				0.0333 ***	0.174 ***	0.0033 ***
(Mobility Wtd.)				(4.71)	(16.14)	(2.94)
Founder Diversity	-0.0152 **	0.0559 ***	0.0052 ***	-0.0182 ***	0.0374 ***	0.0046 ***
(Mobility Wtd.)	(-2.20)	(3.91)	(4.46)	(-2.83)	(2.90)	(3.69)
Log(Initial Wage)	0.109 ***	0.241 ***	0.0083 ***	0.103 ***	0.184 ***	0.0084 ***
	(10.04)	(10.61)	(7.86)	(9.19)	(7.69)	(7.56)
Log(Initial Employees)	0.0484 ***	-0.21 ***	0.0092 ***	0.0297 ***	-0.369 ***	0.0096 ***
	(8.85)	(-16.81)	(9.52)	(6.78)	(-23.08)	(8.45)
Founder Age	-0.0304 ***	-0.223 ***	-0.0026 **	-0.0391 ***	-0.0550 ***	-0.0004
	(-4.71)	(-9.57)	(-2.30)	(-5.21)	(-4.66)	(-0.24)
Female Founder	0.0272 ***	0.0635 ***	-0.0003	0.0069	0.0361	-0.0001
	(3.49)	(3.71)	(-0.65)	(1.64)	(3.53)	(-0.08)
White Founder	0.014 ***	-0.0059	0.0000	0.0075	-0.0014	-0.0010
	(2.90)	(-0.66)	(0.01)	(0.76)	(-0.10)	(-0.61)
Black Founder	-0.0137	0.0143	0.0023	0.0034	-0.0355 **	-0.0029
	(-1.38)	(1.45)	(1.62)	(0.23)	(-2.03)	(-1.24)
Asian Founder	0.0137	-0.0254	-0.0003	0.0080	-0.0080	-0.0010
	(1.06)	(-1.45)	(-0.32)	(0.99)	(-0.43)	(-0.49)
Hispanic Founder	0.0139***	0.0257***	-0.0002	0.0038	-0.0161	-0.0005
	2.84	3.48	(-0.17)	(0.61)	(-1.48)	(-0.29)
Founder Exp	0.268 ***	0.0261 ***	-0.0024 ***	0.269 ***	0.0423 ***	-0.0023 ***
	(19.12)	(3.43)	(-3.81)	(19.24)	(6.65)	(-4.07)
Workforce Control	N	N	N	Y	Y	Y
State×Industry FE	Y	Y	Y	Y	Y	Y
Observations	181000	120000	12000	181000	120000	120000
Adjusted R-squared	0.146	0.137	0.01	0.148	0.173	0.016

Table 7: Founder Diversity, Team Diversity, and High Human-Capital Industries

This table reports the results for regressing firm performance variables on founder diveristy and team diversity measures controlling for industry human-capital intensity. The dependent variable is survival (an indicator variable that equals 1 if the startup survived up to the third year after foundation) in column (1), cumulative growth rate measured in year 3 in column (2), and outlier growth (an indicator variable that equals 1 if the startup belongs to the top 1% of the distribution of employment growth 3 years after foundation) in column (3). Coefficients are computed by estimating a linear specification by ordinary least squares. Team Diversity is based on the mobility-weighted diversity index defined in section II.A and Founder Diversity is based on mobility-weighted diversity index defined in Section VI. Log(Initial Wage) is the logarithm of the wage bill the startups paid in the foundation year. Log(Initial Employees) is the logarithm of the number of initial employees in the startup at foundation. Founder Exp is an indicator variable that equals 1 if founder has worked in the same industry of the startup firm for at least four quarters previously. Founder Control variables include Founder Age, Female Founder, and Founder Race (White, Black, Asian or Hispanic). Workforce Control variables include Share Female Workers, Share White Workers, Share Black Workers, Share Asian Workers Share Hispanic Workers, Demographic Diversity, and Ethnic Diversity. High HCI is an indicator variable that equals to 1 if the industry (2-digit NAICS) has HCI index above 2 and zero otherwise. All specifications include a full set of fixed effects at the State*Industry level (2-digit NAICS codes). Standard errors are double-clustered at the level of the industry and the State. and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Survival	Growth	Outlier
Team Diversity	0.0282 ***	0.153 ***	0.0026 **
	(3.25)	(8.13)	(2.18)
Team Diversity*High HCI	0.0271 ***	0.122 ***	0.0045 ***
	(4.06)	(4.07)	(3.14)
Founder's Diversity	-0.0103	0.0401 **	0.0043 ***
	(-1.50)	(2.60)	(3.04)
Founder's Diversity*High HCI	-0.0444 ***	-0.0087	0.0022
	(-6.22)	(-0.36)	(1.08)
Log(Initial Wage)	0.103 ***	0.183 ***	0.0084 ***
	(9.08)	(7.62)	(7.46)
Log(Initial Employees)	0.0295 ***	-0.370 ***	0.0096 ***
	(6.66)	(-23.21)	(8.22)
Founder Exp	0.269 ***	0.0424 ***	-0.0023 ***
	(19.22)	(6.47)	(-4.00)
Founder Controls	Y	Y	Y
Workforce Controls	Y	Y	Y
State×Industry FE	Y	Y	Y
Observations	181000	120000	120000
Adjusted R-squared	0.148	0.173	0.016

Table A.1: Team Diversity and Firm Performance -- Alternative Proxy for Diversity

This table reports the results for regressing an indicator variable that equals 1 if the startup survived up to the third year after foundation (columns (1) and (4)), the startup's cumulative employment growth over the first 3 years of activity (columns (2) and (5)), and the an indicator variable that equals 1 if the startup belongs to the top 10% of the distribution of employment growth 3 years after foundation (columns (3) and (6)) on a set of firm-level characteristics. Coefficients are computed by estimating a linear specification by ordinary least squares. Workers' Diversity is the average number of industries in which the startup founding employees worked before joining the startup's workforce. Log(Initial Wage) is the logarithm of the wage bill the startups paid in the foundation year. Log(Initial Employees) is the logarithm of the number of initial employees in the startup at foundation. Avg. Worker Age is the average age of the firm's employees. Share Female Workers is the fraction of the firm's employees that are women. Share White Workers is the fraction of the firm's employees that are white. Share Black Workers is the fraction of the firm's employees that are African-American. Share Asian Workers is the fraction of the firm's employees that are Asian. Share Hispanic Workers is the fraction of the firm's employees that are Hispanic. Demographic Diversity is an index of demographic diversity of the employees at foundation. Ethnic Diversity is an index of ethnic diversity of the employees at foundation. All specifications include a full set of fixed effects at the sate*industry level (2-digit NAICS codes). Standard errors are double-clustered at the level of the industry and the state and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		# of Industries Worked			# of Industries Worked	
	Survival	Growth	Outlier	Survival	Growth	Outlier
Team Diversity	-0.0129***	0.0880***	0.0049***	-0.0134***	0.0804***	0.0046***
	(-6.62)	(14.79)	(6.84)	(-5.74)	(12.15)	(6.40)
Team Diversity* High HCI				0.0027	0.0461***	0.0024**
				(1.17)	(4.40)	(2.35)
Log(Initial Wage)	0.1320***	0.1720***	0.0075***	0.132***	0.171***	0.0074***
	(12.60)	(7.12)	(6.95)	(12.58)	(7.08)	(6.90)
Log(Initial Employees)	0.0542***	-0.3970***	0.0076***	0.0542***	-0.398***	0.0076***
	(11.74)	(-21.32)	(8.35)	(11.72)	(-21.46)	(8.34)
Avg. Worker Age	0.0072	-0.2850***	-0.0019**	0.0073	-0.283***	-0.0018**
	(0.70)	(-12.34)	(-2.15)	(0.72)	(-12.91)	(-1.98)
Share Female Workers	0.0354**	0.0701***	-0.0001	0.0353**	0.0700***	-0.0001
	(2.45)	(3.28)	(-0.15)	(2.45)	(3.25)	(-0.16)
Share White Workers	0.0140*	0.0080	0.0011	0.0140*	0.0085	0.0011
	(1.79)	(0.72)	(1.14)	(1.79)	(0.76)	(1.20)
Share Black Workers	-0.0379***	0.0182	0.0047	-0.0379***	0.0189	0.0048*
	(-2.90)	(1.18)	(1.65)	(-2.89)	(1.23)	(1.67)
Share Asian Workers	0.0258	-0.0221	0.0010	0.0258	-0.0229	0.0010
	(1.28)	(-1.01)	(0.75)	(1.28)	(-1.05)	(0.72)
Share Hispanic Workers	0.0183***	0.0107	-0.0001	0.0183***	0.0102	-0.0001
	(2.75)	(1.42)	(-0.11)	(2.75)	(1.34)	(-0.13)
Demographic Diversity	0.0782***	0.322***	-0.0104***	0.0780***	0.320***	-0.0106***
	(5.19)	(5.78)	(-6.63)	(5.22)	(5.79)	(-6.49)
Ethnic Diversity	-0.0225***	0.1040***	0.0017	-0.0224***	0.106***	0.0018
	(-2.97)	(6.46)	(1.22)	(-2.96)	(6.45)	(1.30)
Observations	181000	120000	120000	181000	120000	120000
State×Industry FE	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.077	0.18	0.019	0.077	0.181	0.019

Table A.2: Summary Statistics: Diversity Index Founders

This table reports summary statistics for the diversity indices used in the analysis for sturtup founders. The definition for Simple Diversity Index (SDI) and Mobility-weighed Diversity Index (MDI) is provided in Section II.A and Section VI of the paper. We define industries at the 3-digit NAICS level.

	Simple Diversity Index (SDI)	Mobility-Weighted Diversity Index (MDI)	# of Industries
Mean (All Firms)	0.60	0.65	2.45
Std. (All Firms)	0.36	0.30	1.30
Firms w/ ≤5 Employees (85%)	0.60	0.65	2.46
Firms w/ >5 Employees (15%)	0.57	0.64	2.42
T-Stat for difference	12.80	3.80	4.90
# of Firms	181,000	181,000	181,000