Entrepreneurial Teams:
Diversity of Skills and Early-Stage Growth

by

Francesco D'Acunto
Boston College

Geoffrey Tate
University of Maryland and NBER

Liu Yang
University of Maryland

CES 20-45 December, 2020

The research program of the Center for Economic Studies (CES) produces a wide range of economic analyses to improve the statistical programs of the U.S. Census Bureau. Many of these analyses take the form of CES research papers. The papers have not undergone the review accorded Census Bureau publications and no endorsement should be inferred. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Republication in whole or part must be cleared with the authors.

To obtain information about the series, see www.census.gov/ces or contact Christopher Goetz, Editor, Discussion Papers, U.S. Census Bureau, Center for Economic Studies 5K038E, 4600 Silver Hill Road, Washington, DC 20233, CES.Working.Papers@census.gov. To subscribe to the series, please click here.

Abstract

We use employer-employee linked data to track the employment histories of team members prior to startup formation for a full cohort of new firms in the U.S. Using pre-startup industry experience to measure skillsets, we find that startups that have founding teams with more diverse collective skillsets grow faster than peer firms in the same industries and local economies. A one standard deviation increase in teams' skill diversity is associated with an increase in five-year employment (sales) growth of 16% (10%) from the mean. The effects are stronger among startups in innovative industries and among startups facing greater ex-ante uncertainty. Moreover, the results are robust to a variety of approaches to address the endogeneity of team composition. Overall, our results suggest that teams with more diverse collective skillsets adapt their strategies more successfully in the uncertain environments faced by (innovative) startup firms.

Keyword*:* Economic Growth, Startups, Teams, Diversity, Innovation, Personnel Economics

JEL Classification: L25, L26, J24, M51

* We thank Benjamin Friedrich, Camille Hebert, Arthur Korteweg, Yaxuan Xi, Luana Zaccaria and seminar participants at the Census RDC Annual Research Conference, CES/BLS Workshop, Midwest Finance Association Annual Meetings, 2019 City University of Hong Kong International Finance Conference, 2019 Finance, Organization and Markets (FOM) Conference, 2019 European Finance Association Annual Meeting, Southern Economic Association Annual Meetings, University of British Columbia, University of Illinois, and University of Toronto for helpful suggestions. We thank Michael Freiman and Joseph Staudt at Census Bureau for their help during the disclosure process. Research in this paper was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau. This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191 and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

D'Acunto: Carroll School of Management, Boston College; email: dacuntof@bc.edu.
Tate: Robert H. Smith School of Business, University of Maryland and NBER; email: gtate@umd.edu.
Yang: Robert H. Smith School of Business, University of Maryland; email: lyang1@ umd.edu.

I. Introduction

New firm starts and, more generally, high-growth young businesses are an important driver of job growth in the U.S. economy, with the latter set of firms accounting for up to half of gross job creation (Decker et al, 2014). They can also be a source of disruptive innovation, creating substantial social returns (Jones and Summers, 2020). Yet, new businesses are highly risky ventures. For example, only 55.5% of the new establishments that started between April of 2014 and March of 2015 survived for five years.[4] Detecting the drivers of the early-stage growth of new firms is thus important to understand the ultimate roots of local and aggregate economic growth (Glaeser, Kerr, and Kerr, 2015).

Early stage investors believe that founding teams are crucial to entrepreneurial success (Gompers, Gornall, Kaplan, and Strebulaev, 2016; Bernstein, Korteweg, and Laws, 2017). However, the characteristics that make some founding teams more successful than others as well as the size of the effects are difficult to determine because representative data on new firms is limited. In this paper, we test directly for relations between founding team characteristics and firm growth, using data from the U.S. Census Bureau's Longitudinal Business Database (LBD), Longitudinal Employer-Household Dynamics (LEHD) program, and Innovation Measurement Initiative (IMI). This unique combination of data allows us not only to observe a complete set of U.S. startups across all geographic regions, but also to observe the characteristics and work histories of all startup employees and to identify startups in innovative industries using a novel measure of the flow of research-trained graduates into the workforce.

Motivated by an extension of the entrepreneurship model from Lazear (2005), we measure variation across startups in the diversity of founding employees' collective skillsets. We find that new firms in which the founding team members have broader skills experience higher employment and sales growth. The left panel of Figure 1 documents our baseline result in the raw data, comparing employment growth rates over five years between subsamples of startups with teams that have high and low skill diversity.

---

[4] Source: The U.S. Bureau of Labor Statistics (bls.gov/bdm/us_age_naics_00_table7.txt)

Figure 1. Diversity of Entrepreneurial Teams' Skills and Growth: Raw Data

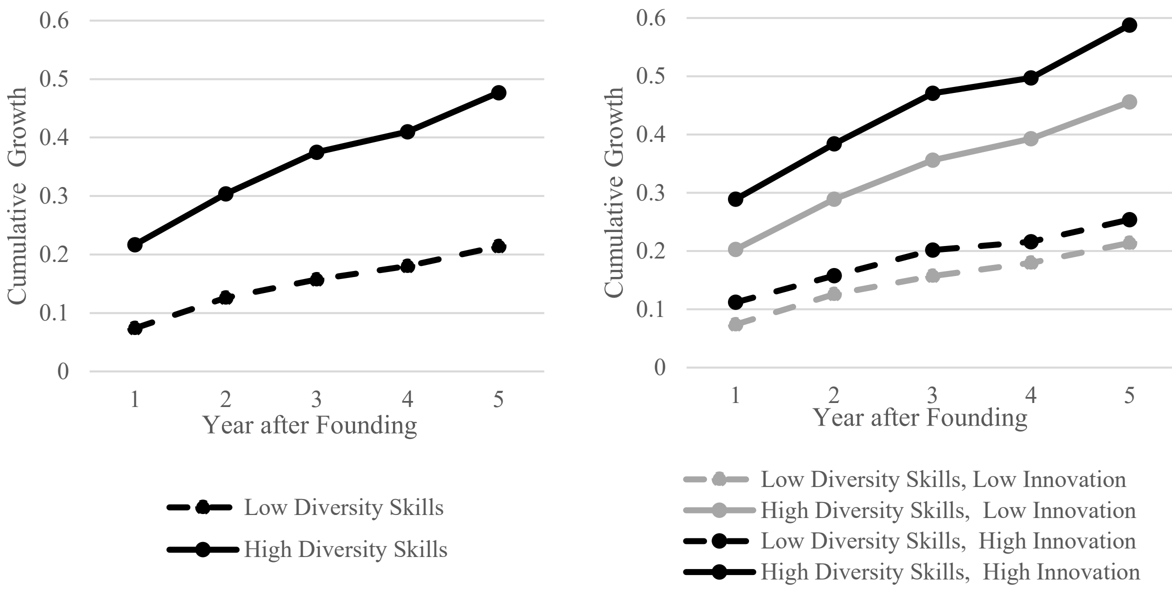

Figure 1 plots the average yearly cumulative employment growth rate for all low- and high-diversity-skill startup firms (left panel) and separately for firms in low- and high-innovation industries (right panel). We measure diversity of founding teams' skills using the diversity index (DIV-All) defined in section III.1. Low (high) diversity-skill firms have diversity index values in the bottom (top) quartile. We measure the innovativeness of industries using the HCI index defined in section IV.1. Low- (high-)innovation industries have HCI index values lower (greater) than 2.

Decomposing the diversity measure, we find that it is diversity across team members rather than the diversity of individual team members' own skills (or, the presence of generalists) that correlates the most strongly with firm performance. A one standard deviation increase in diversity across team members is associated with a 3.8 (4.1) percentage point increase in five-year cumulative employment (sales) growth, an increase of 16% (10%) from the sample mean. The pattern is stronger among startups in industries in which sales are less predictable, suggesting that skill diversity could facilitate adaptation to changing business conditions. We also find that the pattern is significantly stronger among startups in innovative industries. The right panel of Figure 1 illustrates the result, using the inflow of research-trained labor market entrants to measure industry innovation. Thus, skill diversity is especially important among the types of startups that are the most likely to become engines of job creation.

Our focus on the diversity of the teams' collective skillsets builds on the theoretical framework from Lazear (2005). In his model, successful entrepreneurship requires a wider range of skills than paid employment. In equilibrium, entrepreneurs invest in more balanced skillsets, becoming competent in a variety of tasks but specializing in none. We broaden his approach, focusing on the collective skillset of the founding team rather than the individual skillset of the entrepreneur. Changing the unit of analysis creates several important distinctions between our approach and the baseline model. First, a team with a broad collective skillset can still include one or more members with highly specialized skills. By contrast, the costs of investing in specialized skills for an individual entrepreneur can preclude investments in the general bundle of unrelated skills necessary to become an entrepreneurial "jack of all trades." While a truly generalist skillset could be sufficient to run a small business, specialized technical skills could be necessary to found the types of innovative ventures that become engines of job creation. Moreover, in our extension of the model, a lack of prior investment in a general skillset does not preclude a specialist with a good idea from successfully switching to entrepreneurship if she can complement her skills by building a diverse team.[5] In our context, the constraint on the breadth of team skills comes from resource constraints or the potential for contracting frictions and collective action problems rather than from the cost of individual human capital investments. Because startups face a combination of resource constraints and uncertainty, we predict that teams with diverse skillsets will be able to adapt their strategies more quickly and effectively, leading to higher entrepreneurial success.

To conduct our empirical analysis, we first identify the full set of U.S. startups from the year 2010 using the Longitudinal Business Database (LBD).[6] We then match startups to the 50-state quarterly worker-firm matched data available from the Longitudinal Employer-Household Dynamics (LEHD) program to identify the initial paid-employees in each firm.[7] We refer to this set of workers as the "founding team." The skillsets of workers are difficult to define and to measure. To construct a homogeneous and comprehensive measure of skillsets, we exploit variation in the industries in which team members have prior work experience. Thus, our measurement strategy relies on the assumption that workers invest in industry-specific human

[5] This scalability of skills across team members can be important also because of the secular decline in the average age of successful entrepreneurs (Levine and Rubenstein, 2017; Liang, Wang, and Lazear, 2018).
[6] In our baseline analysis, we use the 2010 cohort because we observe detailed individual-level demographic characteristics measured in 2010 through the Decennial Census. As a robustness check, we confirm that our analysis extends to a broader sample of startups founded between 2006 and 2010.
[7] The LEHD data also include the District of Columbia and other U.S. territories.

capital (Neal, 1995). These investments could be in the form of investments in specialized skills or in different industry-specific weights on general skills, in the spirit of Lazear (2009). In either case, we assume that a broader set of industry experience among team members translates to a broader set of specialized skills or a more balanced weighting on general skills. We track each team member's employment history back to 2002 to identify industry spells. We then aggregate the quarters of experience in each industry across team members and calculate a Herfindahl index of the diversity of the team's experience. Thus, the index accounts for the number of industries in which team members have experience as well as the total amount of time spent in each one. We also distinguish between the effects of the breadth of experience across workers and the general skills of individual team members. To do so, we construct two additional measures. First, we construct a Herfindahl index of team experience diversity using only the immediate prior industry spell for each founding team member. Second, we construct a Herfindahl index of the time series of industry experience for each individual team member and then take an average across all team members. Our inferences are robust to a number of variations of these indices, such as considering only the industry in which each team member worked for the most quarters or adjusting the Herfindahl measures for differences in observed worker mobility between industry pairs.

We estimate the association between the diversity of team industry experience and firm performance measures at the intensive and extensive margin – employment growth, sales growth, and survival – year-by-year over a five-year horizon. Our main regression specifications include fixed effects for industry-state pairs and the number of initial employees so that we identify the coefficients using only comparisons across firms of the same size that are founded simultaneously in the same local markets. We also control directly for a variety of team demographic characteristics. We find that diversity of prior industry experience is positively associated with cumulative employment and sales growth at all horizons. The latter correlation is important because it dismisses the concern that employment growth is driven by new hires to correct for deficiencies of the initial team. Decomposing the association between diversity and growth, we find that it comes mainly from the cross-sectional diversity of team members' experience rather than the heightened presence of team members with generalist skillsets. On the other hand, more general skills among the average team member are associated with significantly higher failure rates. We also find that teams with a broader cross-section of industry experience fail at higher rates over longer horizons (the short-run effect is positive); however, the effect is driven by cases in which team members also tend to be generalists.

We also consider cross-sectional differences in the relation between skill diversity and growth, estimating the relation between the diversity of team experience and performance separately among startups in innovative and non-innovative industries. We consider four measures of innovation. We construct three measures based on the industry-level employment of high-skilled workers who are likely to be a necessary input to the production of innovation . First, we use the classification from Goldschlag and Miranda (2020), who identify "high-tech" industries to be those industries that employ high concentrations of workers in STEM occupations. Second, we construct a novel measure of the unexpected industry-level inflow of research-trained undergraduate and graduate students using data from the IMI program. The IMI program identifies all individuals who received compensation as part of federal research grants. We classify industries that attract disproportionately high numbers of these research-trained workers to be innovative industries. Our measure has the advantage of being an ex ante flow-based measure of innovative investment. Third, we partition industries based on the rates at which they employ workers from the top quartile of the overall wage distribution. We also use industry-level R&D spending as an alternative measure of innovativeness. Using all four measures, we find that the diversity of team members' prior industry experience has a significantly higher positive association with growth among innovative industries, which push the technological frontier and are among the main drivers of aggregate growth (Jones, 2016).

We also test the prediction that diverse skillsets allow founding teams to better adapt to the uncertainty that characterizes startup firms, particularly in innovative industries. To do so, we consider two sources of variation in uncertainty. First, we measure the industry-level persistence of sales and then the relation between diversity of experience and firm growth separately among firms in industries with high and low sales predictability. Consistent with the hypothesis, the relation between diversity and growth is significantly stronger among the latter set of firms. Second, we extend our sample to cover the period between 2006 and 2010. The resulting sample allows us to test for differences in the relation between diversity and growth among startups that start in expansion and recession environments. We observe that recession-year startups exhibit a stronger positive association between diversity and growth, again, consistent with the theory.

In our baseline analysis, we document a novel set of stylized facts on the relations between team characteristics and growth on the full universe of startup firms in the U.S. without directly addressing the potential endogeneity of our measures of team diversity. Some aspects of the identification problem are likely to be of second-order importance relative to establishing these baseline facts. For example, from the perspective of a financier, knowing that diversity predicts entrepreneurial success is likely to be more important than distinguishing whether the result comes from founders with high-quality ideas assembling diverse teams or from more diverse teams being better at executing ideas. Nevertheless, in the second part of our analysis, we take several steps to address the fact that team members are not randomly assigned. Of particular concern is the possibility that individuals with diverse industry experience are more likely to recognize and join startups with better prospects.

First, to limit the influence of location selection on our analysis, we estimate the relation between diversity of team industry experience and growth among the set of startups in which the highest-paid employee (or "manager") already resided in the county ten years prior to founding the startup. Among these startups, it is unlikely that the founder chose a location to start the firm based on contingent economic characteristics.[8] We confirm that our main results continue to hold. Second, to limit the influence of team member selection, we estimate the relation among family firms, among which family ties rather than industry experiences are likely to be the primary selection criterion.[9] We again confirm our main results.

Next, to address omitted variable concerns, we propose an instrumental variables strategy. We use two instruments for the diversity of the founding team's industry experience, both of which build on the assumption that labor markets are at least partially segmented. First, we use variation in the intensity of mining activity in the startup's county up to 2002 among the sample of startups located in counties with at least one mine.[10] Glaeser, Kerr, and Kerr (2015)

[8] We use the 2000 Decennial Census to identify the residential locations of founding team members.

[9] We use information from the 2000 and 2010 Decennial Census to identify family firms as cases in which multiple workers from the firm are part of the same household.

[10] We exclude variation on the extensive margin because it is more likely to be confounded by other county-level differences.

argue that the mining industry, which was often in place as early as the Second Industrial Revolution, tended to dominate the local economy where it developed. We argue that the resulting lack of diversity in the local distribution of industries provides a source of plausibly exogenous variation in the backgrounds of team members in local startups, after correcting for industry fixed effects. Second, we use the fraction of firms in the county as of 2005 that were diversified across industries. Tate and Yang (2005) show that workers within diversified firms develop skills across the set of industries in which diversified firms operate. Thus, we use the historical presence of such firms as a source of plausibly exogenous variation in team members' prior industry experience, conditional on controls for county-level opportunities. Using the instruments, we again confirm a positive relation between diversity of the industry experience of the founding team and firm growth.

We also perform an event study analysis around cases in which founding team members exit the startup within its first year of operation without reappearing at another firm during the remainder of the sample. We compare changes in survival rates and employment growth between cases in which the exiting team members' industry experience is replicated by the experience of another team member and cases in which it is not. We find a significantly larger increase in the likelihood of failure in the latter case. We also observe significantly lower growth rates over the subsequent three years. Overall, taking a variety of approaches to deal with specific concerns arising from the endogeneity of team characteristics, we confirm the value of diverse teams' skillsets during the initial years of a startup firm.

As a final step, we explore potential economic mechanisms for the results. First, to tighten the link between industry experience and worker skills, we measure variation in the relevance of external industry skillsets to new startups using economy-wide measures of cross-industry labor mobility. We find that experience in industries from which workers more frequently transition to the start-up's industry is more valuable. Moreover, our findings are robust when we measure team diversity across industries that experience infrequent transitions, consistent with the presence of truly distinct skillsets. Second, we document differences in the evolution of leadership over time for startups with more diverse founding teams. We find that firms with diverse teams graduate more quickly to professional management by external, generalist managers from outside the firm's industry.

Our results contribute to the literature studying team effects in production (Mailath and Postlewaite, 1990). 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. 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. Building on the existence of team effects, we study how specific team characteristics relate to firms' productivity.

Our focus on entrepreneurship builds on recent work suggesting the importance of team effects in that context (Berstein, Korteweg, and Laws, 2017; Gompers, Gornall, Kaplan, and Strebulaev, 2016). Existing work suggests that both personal histories (Gompers et al, 2010; Kerr, Kerr, and Xu, 2017) and the histories of peers (Lerner and Malmendier, 2013; Hacamo and Kleiner (2020)) help potential entrepreneurs to make better decisions regarding if and when to start a new venture. This work builds on a literature that emphasizes the relation between traits of top executives and firm outcomes, typically among large, mature publicly-traded firms for which data is most readily available (e.g., Bertrand and Schoar, 2003; Malmendier and Tate, 2005, 2008; Malmendier, Tate, and Yan, 2011; Kaplan, Klebanov, and Sorensen, 2012; Graham, Harvey, and Puri, 2013; Custodio, Ferreira, and Matos, 2013; Tate and Yang, 2015). We exploit the richness of the Census data to extend this line of inquiry to new firms and their founding teams in a fully representative sample. We demonstrate not only that team effects are significant but also that they function distinctly from the effects of the top manager.

Finally, our analysis relates to the literature that studies the consequences of employee diversity for performance. Most of this literature focuses on demographic diversity (e.g., Adams and Ferreira, 2009; Hjort, 2014; Lyons, 2017; and Glover, Pallais, and Pariente, 2017). Our analysis includes controls for demographic diversity; however, we focus on how the diversity of skillsets affects firm performance above and beyond demographic diversity.

II. Data

We construct our sample of workers in startup firms in several steps, using data from the U.S. Census Bureau. We start from the Longitudinal Business Database (LBD), which we use to identify startup firms. The LBD includes all non-farm establishments in the U.S. and contains information on birth and death, ownership, location, industry, employment, and total payroll, reported at the end of the first quarter of each calendar year (March 12). We consider the set of single-establishment LBD firms with birth years between 2006 and 2010. We then use federal employer identification numbers (EINs) to link LBD startups to the worker-firm matched data available from the 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 data is broad and generally comparable from state to state: it contains about 96% of civilian jobs in the U.S.[11], and includes information on quarterly employment and wages.[12] To minimize the effect of reporting errors, we allow at most a one-year difference between the years in which we first observe the firm in the two databases. We also require that there is at least one quarter among the first four quarters that the firm appears in the LEHD data at the end of which it reports 10 or fewer employees and during which we observe 20 or fewer total employees drawing wages from the firm. Though it is not generally possible to link worker-level information from the LEHD data to specific LBD establishments within a state and industry, our focus on single-establishment firms allows us to infer the establishment-worker match with a high degree of confidence. For the resulting set of matched firms and workers, we supplement the worker-level demographic information in the LEHD data with information from the 2000 or 2010 Decennial Censuses, including information on residential locations and family links to

[11]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.

[12] 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.

other workers in the firm. We also supplement the firm-level information from the LBD with annual sales information from the Standard Statistical Establishment List (SSL), when it is available. In order to limit the attrition of workers from the sample who do not appear in the 2010 Decennial Census, we focus much of our analysis on the 2010 cohort of 191,000 startups.[13]

In Panel A of Table 1, we report the distributions of the sample by geography, industry, and employment. Our sample includes startup firms in all 50 U.S. states. 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).

We also observe a wide distribution of startups across industry groups, measured at the 2-digit North American Industry Classification System (NAICS) level. The most represented industry is Professional, Scientific, and Technical Services (NAICS 54), accounting for 16.2% of the 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 accounting for roughly 10% of sample firms. Startups in the manufacturing sector, on the other hand, make up a relatively small portion of the sample (roughly 3%). These patterns suggest the importance of distinguishing between entrepreneurial ventures that are founded with an objective to grow and more general small business creation. In particular, the latter pattern highlights the potential pitfalls of using a patent-based approach to identify innovative entrepreneurship, given that patents are heavily tilted towards the manufacturing sector.

Turning to the distribution of startups by employment, we observe (not surprisingly) that many of the new firms in the sample start small. Roughly 31% of the sample consists of

[13] We demonstrate the robustness of our results on the full multi-year panel in Section VI. We also use the time-series data to explore business cycle interactions with our effects of interest.

firms that report only a single employee at startup. Given that our objective is to measure the effect of team characteristics on startup growth, we exclude these firms from our regression analysis. We also drop the 5.5% of firms that report employment greater than 10 to impose consistency with the employment information from the LEHD data. However, our results do not generally depend on imposing either of these restrictions.[14] In Table 1, we also report the distribution of startups by industry and geography in our main regression sample, after imposing these constraints.[15] We observe very few differences from the overall sample distributions.

In Panel B of Table 1, we present summary statistics of firm and worker characteristics among the 118,000 startups in the main regression sample.[16] Roughly 19% of startups have at least two initial employees that were part of the same household in the 2000 or 2010 Decennial Census ("family firms"). In 39% of firms, the highest-paid initial employee was a resident of the county in which the firm operates as of the 2000 Decennial Census. Consistent with prior literature, we find high failure rates. The failure rate is highest in the initial year of operations (12.3%) and monotonically declines year-by-year over the first five years of operations. After five years, nearly half of the firms have failed. However, conditional on survival, the average firm experiences 23.4% growth in employment and 40.7% growth in sales. Both growth rates have high standard deviations, reflecting very high growth rates among "unicorn" startups in the right tail of the growth distribution. The average firm has roughly 56% male workers, 25% workers of foreign origin, an average worker age of 39.7, and a mean wage of $29,900.

III. Team Diversity and Startup Performance

Our objective is to understand the link between the characteristics of founding teams and the performance of startup firms. In particular, we focus on the diversity of the skillsets that the initial group of employees bring to the firm. In this section, we first construct an empirical

---

[14] Our results are similar when we impose various size constraints including, e.g., expanding the sample to include startups with up to 15 workers.

[15] In addition to imposing the size constraints, we lose some additional observations due to missing values of independent variables in our baseline regression specifications.

[16] Due to disclosure requirements by the U.S. Census Bureau, all reported sample sizes are rounded at the nearest hundred.

measure of the diversity of founding teams' employment experience and then measure the association of the measure and other team characteristics with startup growth and survival rates.

III.1. Measuring Diversity of Founding Teams' Skillsets

To measure the diversity of founding teams' skillsets, we track each team member's employment history before joining the startup firm. We record all industries in which the worker was employed and the corresponding number of quarters beginning in 2002 and ending in the last year prior to joining the startup firm.[17] We define industries using three-digit NAICS codes, and aggregate over multiple firms within each worker's history if the firms belong to the same industry.[18] Because we are interested in experiences during which workers accumulate industry-specific skills, we consider industry spells only if they last for at least four quarters. For each startup, we then aggregate industry experience over the set of all initial employees. We measure experience using industry quarters so that our diversity measure accounts both for the number of industries in which workers have experience and the relative amounts of time that they spent in each. For example, suppose that a firm has three employees. Suppose that employee 1 has 4 quarters of experience in industry 1 and 8 quarters of experience in industry 2. And, suppose that employees 2 and 3 have 12 quarters of experience in industries 1 and 3, respectively. Then, for the founding team, we calculate the distribution of industry experience as 16 quarters in industry 1, 8 in industry 2, and 12 in industry 3.

To measure the diversity of founding employees' collective work experiences, we construct a simple Herfindahl index over the team-level distribution of industry quarters.

[17] We cannot track worker histories beyond 2002 because that is the initial year of our sample of LEHD data. However, we find in Section III.2 that it is workers' most recent experience that matters the most for startup growth. Thus, the data censoring appears unlikely to alter our main conclusions.
[18] Our measure of industry is at the firm-unit level. This is important because startup workers could have prior experience in large, multi-unit firms that operate in many different industries. We can distinguish the units (and therefore industries) in which such workers have direct experience.

$$DIV\_All = 1 - \sum_{i=1}^{N} p_i^2 \qquad (1)$$

where $p_i = \frac{q_i}{\sum_{i=1}^{N} q_i}$, or the percentage of the team's prior employment quarters that were spent industry i. *DIV_All* ranges between 0 and $\frac{N-1}{N}$, where N is the number of unique industries in which team members have prior work experience. If all team members' prior work experience is in the same industry, then *DIV_All* will equal 0. If workers have prior experience in N distinct industries with spells of exactly equal length, then *DIV_All* will equal $\frac{N-1}{N}$. Thus, *DIV_All* increases with the number of industries in which team members have experience. By construction, *DIV_All* also accounts for differences in the length of time that workers have collectively spent in each industry. If the spell lengths differ across N distinct industries (where $N > 1$), then *DIV_All* will be less than $\frac{N-1}{N}$, reflecting the skew in experience towards one or more dominant industries. To correct for differences in the granularity of *DIV_All* across teams of different sizes, we include fixed effects for team size in all of our regressions.

We also construct several sub-measures to allow us to isolate specific sources of variation in *DIV_All*. First, to allow for differences in the relevance of industry-specific skills depending on when they were acquired, we consider separately each worker's most recent job prior to joining the startup and the rest of her employment history. For each type of employment, we aggregate across workers to create a team-level distribution of industry experience. We then compute Herfindahl measures for each distribution, using Equation 1. The resulting indices *DIV_Last* and *DIV_AllButLast* measure the industry diversity of founding team members' immediate pre-startup employment and the remainder of their employment histories, respectively. Second, we construct an additional measure that enables us to distinguish between variation in *DIV_All* that comes from diversity of specific workers' employment histories and diversity that comes from the cross-section of their most recent employment spells. To do so, we consider separately the industry distributions of each member of the startup's founding team. We use Equation 1 to compute a worker-specific measure of the diversity of past industry experience, or the degree to which each worker is a "generalist" or "specialist." We then compute *DIV_Worker* as the average across founding workers in each startup of these individual Herfindahl indices.

In Table 2, we report summary statistics of our main measures of the diversity of founding workers' prior industry experience. *DIV_All*, which aggregates all of the past industry experience among the founding team, has a mean of 0.47 and a standard deviation of 0.29. Thus, the typical startup does not consist of a team of specialists from the same industry, but instead has workers with work experience from several industries. The summary statistics also suggest that the variation in the overall measure comes both from the presence of "generalist" workers among the founding team and from diversity in the last industries in which team members were employed. The means of *DIV_Worker* and *DIV_Last* are 0.27 and 0.22, respectively.

We consider a number of alternative approaches to measure diversity of team members' work experience. Instead of using Herfindahl indices to capture diversity, we construct simple diversity measures that count the number of industries in which team members have prior experience, either collectively or individually. Using the latter measure, we also create an indicator variable that classifies a worker as a generalist if she has prior experience in at least two distinct industries prior to joining the startup. This approach does not result in substantively different conclusions in our regression analyses. We also construct a measure of team diversity in which we first exclude all but the modal industry from each worker's employment history and then compute a Herfindahl of team industry experience using Equation 1. This measure generally behaves similarly to *DIV_All* and *DIV_Last* in our analyses. Finally, we construct alternative versions of our main measures in which we make an additional adjustment for the general mobility of workers between pairs of industries in the external labor market. These measures "down-weight" diversity that comes from related industry pairs. We provide more details in Section VI.

III.2. Baseline Results

The association between the diversity of the industry skillsets that founding workers bring to startups and employment growth is positive in the raw data (Figure 1; Introduction). Although suggestive, simple differences in means are challenging to interpret. The locations in which entrepreneurs choose to start new firms are unlikely to be random. Differences in opportunities and resources across locations are likely to correlate with the likelihood that we observe new firms, their subsequent growth rates, and the characteristics and skillsets of local workers. Moreover, the diversity of founding employees' past work experience could be correlated with other worker characteristics (age, education, etc.) or startup characteristics (industry, size, etc.), that predict startup performance. To begin to address these concerns, we estimate the association between the diversity of founding employees' prior industry experience and startup growth within a multivariate regression framework. We provide additional evidence to address the selection concern as well as the possibility of unobservable omitted variables in Section V.

We estimate ordinary-least-squares specifications of the following form:

$$Startup\ Performance_{fks} = \boldsymbol{Team\ Diversity}'_f \boldsymbol{\beta} + \boldsymbol{X}'_{fks}\boldsymbol{\gamma} + \eta_{ks} + \epsilon_{fks} \qquad (2)$$

where startup firm f operates in industry k and location s. The matrix $\boldsymbol{Team\ Diversity_f}$ includes one or more of the measures of the diversity of the founding team's industry experience defined in Section III.1. $\boldsymbol{X}_{f,k,s}$ is a set of control variables measured in the startup's first year. Among these controls, we include the average age of the startup's founding employees as well as the fraction of women, the fraction of workers born outside the United States, and the fractions of workers in four racial categories (White, Black, Asian, and Hispanic). We also include controls for founding workers' general ability: the average wage of the startup's workers in their last pre-startup jobs and their average years of education. These controls allow us to distinguish between the breadth of the team's pre-startup experience, as captured by the team diversity measures, and the team's skill level. To distinguish between team experience in outside industries and experience in the industry in which the startup operates, we control for the fraction of team members whose last job prior to joining the startup was in the startup's industry. We also control for the diversity of the team along dimensions other than prior industry experience. We measure racial diversity among a startup's founding team as one minus the Herfindahl index of employment shares across the four racial categories.[19] Similarly, we measure diversity in the place of birth of founding team members by computing one minus the Herfindahl index of employment shares across eight Census-defined categories: North America and Oceania, Central and South America, Africa, West and South Europe, formerly Communist countries, Asia, East Asia, and Muslim countries. For continuous measures (age, years of education, and last wage prior to joining the startup), we first assign founding team members to

[19] The exact computation is $1 - \sum_{i=1}^{n} p_i^2$, where p_i is the fraction of the founding team in racial category i.

quartiles of the full-sample distribution of the characteristic and then construct similar Herfindahl-based measures. Our approach to measuring demographic diversity is similar to the one followed by Parrotta, Pozzoli, and Pytlikova (2014), though we apply it separately characteristic by characteristic. The indices can be interpreted as the probability that two randomly drawn employees belong to different categories of the characteristic.

We control non-parametrically for startup size by including a fixed effect for each observed aggregate employment level.[20] Thus, we identify our estimates of $\boldsymbol{\beta}$ using only variation in team diversity among startups with the same number of employees. We also include fixed effects, denoted by $\boldsymbol{\eta_{ks}}$, for the industry-state pairs in which startups operate, where we measure industries at the 3-digit NAICS level. Because our main sample is a single cohort of startups founded in 2010, these fixed effects ensure that we compare only firms that are subject to the same local industry conditions (i.e., we do not need to account for local or industry-level business cycle effects). Our results are robust to considering finer industry or geographic partitions – the results do not materially change if we instead saturate the regressions with industry-county pair fixed effects or 4-digit industry-state fixed effects. In all regressions, we cluster standard errors at the industry-state pair level.

In Table 3, we report estimates of Equation 2 using cumulative employment growth over various horizons (one year, three years, and five years) as the measure of startup performance. In Columns 1-3, we use *DIV_All* as the measure of team diversity of experience. At all three horizons, we confirm that more diversity of the industry experience of founding team members is associated with faster firm growth. The estimates of $\boldsymbol{\beta}$ are positive and significant in each case. Economically, we find that a one standard deviation increase in the diversity of team experience is associated with a three percentage point higher five-year cumulative growth rate, compared to a mean growth rate of 23%.

Among the controls, we observe several other team characteristics that have significant relations with employment growth. General ability of the team, as measured by average wages

[20] Because aggregate employment is measured as a snapshot at the end of the first quarter of each calendar year, but the LEHD data contains the full set of employees who drew wages from a firm each quarter (some could exit before the quarter ends), we include fixed effects for both the end-of-quarter aggregate employment and the total number of employees that we observe in the LEHD data.

and education, is positively associated with startup growth. The effects appear to take longer to materialize than the effect of diversity in industry experience: after year 1, both estimates are small and only the coefficient on average wages is (marginally) significant. We also find a significant negative association between the percentage of foreign-born workers on the team and firm growth as well as between the average age of founding team members and growth. Finally, we observe positive associations between employment growth and each of our measures of demographic diversity. We estimate positive and significant coefficients on all five of the Herfindahl-based indices of demographic diversity. Moreover, we find that startups with a higher fraction of women on the founding team grow more quickly over the 1- and 3-year horizons, though the effect disappears after five years. Economically, demographic diversity could capture growth-relevant factors such as differences in beliefs or perspectives that arise from differences in life experiences. Diversity of skills and expertise, instead, are more directly related to the diversity of work backgrounds. The ability to differentiate between these two forms of diversity in a representative sample of startups is a unique feature of our data.

In the remainder of Table 3, we decompose the variation in *DIV_All* to determine what drives the relation with employment growth. First, we explore the importance of the timing of industry experience, replacing *DIV_All* in Equation 2 with *DIV_Last* and *DIV_AllButLast*. We report the results in Columns 4-6. We find that workers' most recent industry experience has a stronger association with startup growth than experience in their more distant work histories. The coefficient estimates on *DIV_Last* are positive and significant at all three horizons. However, the coefficients of *DIV_AllButLast* are less than half the size and are significant only at the 3- and 5-year horizons. The economic magnitudes for *DIV_Last* are also larger than the corresponding magnitudes for *DIV_All* in Columns 1-3. For example, a one standard deviation increase in *DIV_Last* is associated with a 3.8 percentage point higher five-year growth rate. The results are consistent with a decline in the relevance of prior industry experience over time as technology shocks change the optimal mix of skills within the industry.

Second, we consider separately the diversity of industry experience in the cross-section of founding team members and the diversity of individual workers' industry experience in the time series. For this comparison, we include *DIV_Last* together with *DIV_Worker* as the measures of the diversity of industry experience. We report the results in Columns 7-9. We again find a strong positive association between *DIV_Last* and employment growth at all horizons; the estimates are very similar to the corresponding estimates in Columns 4-6. However, we find a weaker association between the degree to which the typical team member is a "generalist" and firm growth. The estimated coefficient is not significant at the one-year horizon, and we find smaller, though statistically significant coefficients at the 3- and 5-year horizons. Economically, a one standard deviation increase in the general skills of a typical worker is associated with a 1.4 percentage point higher five-year growth rate. Notably, the construction of the *DIV_Worker* measure also includes each worker's most recent industry experience. So, the result does not come from focusing only on stale industry experience (as it does for *DIV_AllButLast*).

Overall, we find strong evidence of associations between startup employment growth and the composition of the founding team. Focusing on prior work experience, we find that employment growth is most strongly associated with diversity in the skillsets of founding team members that comes from working in different industries in their most recent jobs.

III.3. Other Outcome Variables

III.3.1. Outlier Employment Growth

In the context of new business starts, it is important to distinguish between entrepreneurial ventures with high growth potential and small businesses. As a first step towards this goal, we focus on the subset of startups that achieve outlier growth relative to other startups in their industries. We estimate the association between team characteristics – most notably the industry experience of the founding team – and the likelihood that a startup is a member of this group. For our main analysis, we define outlier growth to be a cumulative growth rate in the top 10% of the distribution among startups in the 3-digit NAICS industry. However, our results are similar if we instead consider more extreme "unicorn" outcomes in the top 1% or top 5%.

In Table 4, we report the results of estimating Equation 2 using a dependent variable that indicates outlier growth over the 1-, 3-, or 5-year horizon. Because of the rich fixed-effect structure, we implement the regressions as linear probability models. Though we suppress the estimates for brevity, we include the full set of controls from Table 3. We measure founding team industry experience using the *DIV_Last* and *DIV_Worker* measures. We find a strong, positive association between industry diversity in the cross-section of team members' past work histories and the likelihood of outlier growth rates. A one standard deviation increase in team diversity is associated with a 2.2 percentage point higher likelihood that the startup's 5-year cumulative growth rate is in the top 10% in its industry. Thus, the association between the diversity of the team's industry experience and employment growth appears to be even stronger at the upper end of the growth distribution than it is at the average. Interestingly, we do not observe a positive association between the presence of more generalist workers with broader individual industry experiences in their prior work histories and the likelihood of extreme startup growth. Thus, it is diversity of skillsets among team members that again has the strongest relation with growth.

III.3.2. Sales Growth

The associations between the diversity of team members' industry experiences and employment growth allow (at least) two interpretations. One possibility is that employment growth reflects startup success. Another is that employment growth reflects the failure of the initial team of workers to operate the startup successfully without external help. To distinguish between these possibilities, we measure startup performance using cumulative growth in sales, rather than employment. Though sales is a more direct performance measure, we generally focus on employment growth in our analysis because sales information is only available for roughly 70% of our sample firms.

In Table 5, we report the results of estimating Equation 2 using cumulative sales growth over the 1-, 3-, or 5-year horizon as the dependent variable. We again focus on *DIV_Last* and *DIV_Worker* as the measures of the diversity of team industry experience. Because we use only a subset of the data from Tables 3 and 4, we again report coefficient estimates for the full set of controls. As in Tables 3 and 4, we find an association between general ability and performance, captured by the coefficients on average wages and education. We also find some evidence, though it is economically and statistically weaker, that diversity in demographic characteristics is associated with stronger sales growth (*Div (Race)*; *Div (Wage)*). Notably, we no longer observe a negative association between the presence of foreign workers and performance, but we do observe underperformance of startups with more female workers that grows over time.

Turning to the effects of industry experience, we again observe a positive and significant association between the breadth of industry experience among team members (*DIV_Last*) and cumulative sales growth over all horizons. At the 5-year horizon, a one standard deviation increase in diversity is associated with a 4.1 percentage point higher growth rate. Here, we also find some evidence of a positive association between the diversity of the average team member's personal industry experience and growth (*DIV_Worker*). However, the estimates do not turn positive and significant until year 3 (the estimate is negative and marginally significant in year 1). Overall, our results are consistent with interpreting the faster employment growth among startups with more diverse teams to be a measure of success.

III.3.3. Survival

Another outcome that is particularly salient in the context of startup firms is survival. In our sample, roughly 47% of startups exit the market within their first five years of operation. To understand how exit rates interact with team characteristics, we estimate Equation 2 as a linear probability model using dependent variables that indicate survival to the end of the first, third, and fifth year after the firm began operations. Because the survival or failure outcome is observable for all startups, we can estimate the regression on the full sample of 118,000 startups at all three horizons. We again focus on *DIV_Last* and *DIV_Worker* as the team diversity measures of interest and include the full set of controls from Table 3.

We report the results in Panel A of Table 6. We find again that general team ability, as measured by average wages just prior to joining the startup and average education, predicts heightened survival rates, though the effects are economically small and statistically weaker than the effect on conditional growth rates. We also observe some evidence of lower survival rates among startups with higher percentages of minorities on the founding team. We find generally weaker effects of the diversity of demographic characteristics on the likelihood of survival than on employment growth rates. However, we still observe that both diversity of pre-startup wages and education levels has a positive association with survival. This pattern suggests that while higher average ability is associated with a higher probability of survival, firms with a mix of "blue-" and "white-collar" workers have higher survival rates.

Turning to the diversity of team members' pre-startup industry experience, we find different patterns from those observed in the growth rate regressions. Beginning with the average industry diversity of the team members' individual work histories, we observe a significant negative association with startup survival rates. A one standard deviation increase in *DIV_Worker* is associated with a 1.6 percentage point increase in the likelihood of startup failure by year 5. Thus, having a team composed of generalists does not appear to be associated with startup survival, on average. The direction of the association between the breadth of team members' industry experience in the cross-section and startup survival rates depends on the horizon. In the first year of operations, more diverse teams are associated with a higher likelihood of survival. However, by year 3, the relation turns negative and remains so after five years. Economically, the effect is modest relative to the average failure rates in the sample. A one standard deviation increase in *DIV_Last* is associated with an increase in the likelihood of failure of 1.4 percentage points after 5 years, compared to an overall failure rate of 47%.

To probe deeper into these relations, we estimate alternative specifications of the regressions that allow for an interaction between *DIV_Last* and *DIV_Worker*. We report the results in Panel B of Table 6. We find that the interaction between the two diversity measures has a significant negative association with survival rates at all three horizons. Interestingly, including the interaction attenuates the level effect of *DIV_Last* compared to the regressions in Panel A. Here, we observe a significant positive association between the breadth of team members' industry experience and first-year survival and insignificant relations at all other horizons. The results help to establish boundaries on the positive relation between diversity of industry experience and startup performance. The breadth of industry skills among founding team members is associated with higher growth rates and with higher or equal survival rates. However, when the breadth of industry experience in the cross-section is accompanied by a higher presence of generalist workers, the association with survival turns negative. This pattern suggests that the presence of some specialized skills is important for startup success. We explore more directly the economic mechanisms behind the associations in Section VII.

IV. Innovative Entrepreneurship vs. Small Business Creation

Our analysis demonstrates a positive association between the diversity of the industry experiences of team members prior to founding a startup and its growth, particularly at the top end of the employment growth distribution. The latter finding suggests that the relation exists among high-growth entrepreneurial ventures as well as small business starts. Entrepreneurial ventures are of particular interest because they are likely to create more employment opportunities, produce research-oriented innovations, and ultimately become engines of economic growth. In this section, we exploit cross-sectional variation to distinguish more directly between the two types of startups. Among small businesses, founding teams largely face known risks and challenges. However, entrepreneurial teams that found ventures around innovative products or services face greater uncertainty about the nature of the markets in which they will operate, the challenges they will face, and the skillsets that will be required to succeed. In such an environment, diversity of experience among the founding team could prove particularly important to the firm's initial growth trajectory.

IV.1. Innovation Measures

To identify startups that are likely to be innovative ventures, we construct measures of innovativeness at the industry level. We then compare the associations between the diversity of team members' industry experiences and growth across startups in more and less innovative industries. We consider four measures of industry innovativeness. Because our goal is to capture entrepreneurial ventures at the forefront of innovation, we focus on "forward-looking" input-based measures, rather than "backward-looking" output-based measures such as patents. First, we consider differences across industries in the use of human capital inputs that are likely to be necessary to produce innovation, specifically the employment of workers in STEM occupations. We use the measure developed by Goldschlag and Miranda (2020) as part of the Census Bureau's Business Dynamics Statistics (BDS) program. To construct the measure, they use data from the Bureau of Labor Statistics' Occupational Employment Survey to measure the concentration of STEM employment among four-digit NAICS industries in 2005, 2012, and 2014. Following Hecker (2005), they identify the set of industries in each year in which the proportion of STEM workers is at least five times the average (Level I industries). They classify the union of the sets of Level I industries across the three years to be "High Tech." We use the resulting partition to distinguish between innovative and "non-innovative" industries.

A potential drawback of the BDS measure for our purpose is that it is a stock- rather than a flow-based measure and, therefore, is likely to be mostly determined by accumulated hires that occurred many years in the past. However, our goal is to understand new firm starts, which are likely to be more related to current industry dynamics. Moreover, it is not the case that all STEM employees are actively engaged in research or innovation, so that there is the possibility of measurement error in the classification. To address these shortcomings, we also construct a second human-capital-based measure of innovativeness. We exploit data from the Census Bureau's Innovation Measurement Initiative (IMI) project, which collects information on all individuals who receive money from Federal grants to conduct research at U.S. universities.[21] We track the industries in which graduate and undergraduate students on research grants accept jobs following graduation. We use the flows of research-trained students into industries to compute an index of innovativeness according to the following formula:

$$HCI_k = \frac{Students_k \big/ \sum_k Students_k}{Jobs_k \big/ \sum_k Jobs_k} \quad (3)$$

where $Students_k$ is the number of students who took 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). The denominator is a scaling factor that corrects for differences in the sizes of industries. Thus, the index can be interpreted as the unexpected flow of highly skilled, research-trained workers into the industry relative to the flow that we would observe in a hypothetical random assignment of new labor market entrants to industries. A value of the index equal to one indicates a flow exactly equal to what we would expect under random assignment. To ensure that we observe enough students to compute meaningful differences across industries, we calculate the index at the 3-digit NAICS level and pool together all the labor market entries in the IMI data between 2002 and 2010. In most of our analysis, we classify industries in which

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

the index is greater than two to be "innovative industries." We set the threshold above one to ensure that measurement error among industries with small absolute unexpected flows do not drive our results. However, our results are essentially unchanged if we use a threshold of one.

In addition to the two human capital input measures, we use Compustat data on R&D expenditures to construct a third measure. For each 3-digit NAICS industry, we calculate the average ratio of R&D expenditures to sales among firms in the industry. We then classify industries in the top quartile to be "innovative industries." R&D spending arguably provides the most direct measure of spending on innovation. However, it tends to be the highest among manufacturing industries. Innovation in services industries is often not patented and, as a result, is missed by standard measures of innovation, such as patents or R&D (Lerner and Seru, 2015). Thus, the R&D measure provides a good complement to our other measures, but not a substitute for them.

As a final approach to identify industries in which new firms are likely to innovate, we measure differences in average wages. Highly skilled workers are more likely to produce innovation, and higher skill levels should be reflected in higher wages. We construct an indicator that takes the value of one for industries in which more than 75% of the workers in the industry have salaries that are in the top quartile of the distribution of wages among all firms in the LEHD data. Industries for which the indicator is one disproportionately employ high-skill workers and, therefore, are more likely to be innovative. This measure generalizes the BDS classification, but allows for innovation to occur among highly skilled workers who do not necessarily work in STEM occupations. More generally, the measure allows us to distinguish between industries in which production is more and less skill-intensive.

IV.2. Team Diversity and Performance by Industry Innovativeness

To measure the association between the diversity of founding team members' prior industry experience and startup growth among the set of firms that are most likely to be entrepreneurial ventures, we estimate the following ordinary least squares regression specification:

$$Startup\ Performance_{fks} = \boldsymbol{Team\ Diversity}'_f\,\boldsymbol{\beta} + \left(\boldsymbol{Team\ Diversity_f} \times D\_Innovation_k\right)'\boldsymbol{\delta} + \boldsymbol{X}'_{fks}\boldsymbol{\gamma} + \eta_{ks} + \epsilon_{fks}\,. \tag{4}$$

$D\_Innovation$ is one of the four measures of innovation that we described in Section IV.1. Equation 4 is identical to Equation 2 except for the addition of the interaction of $D\_Innovation$ with $\boldsymbol{Team\ Diversity}$. Thus, we include the same set of control variables in matrix $\boldsymbol{X}$ that we used in our estimation of Equation 2 in Section III.2. Note also that we continue to include industry by state fixed effects in the specification, which absorb the level effect of the $D\_Innovation$ measure.[22] The coefficient vector $\boldsymbol{\beta}$ estimates the baseline associations between team diversity measures and growth; $\boldsymbol{\delta}$ estimates the differences in the associations from the baseline among new firms in innovative industries.

We report the results of estimating Equation 4 in Table 7. For brevity, we report results that measure startup performance over a three-year horizon. Three years provides a reasonable tradeoff between allowing time for the economic mechanisms that link team characteristics with performance to operate and limiting the effects of sample attrition. Nevertheless, we note any instances in which our conclusions are materially different if we instead consider shorter or longer horizons. In Columns 1 and 2 of Panel A, we define $D\_Innovation$ to be an indicator variable equal to one for industries classified as "High Tech" by the BDS measure. In Column 1, we measure startup performance using three-year cumulative employment growth and, in Column 2, we consider three-year cumulative sales growth. Using both performance measures, we observe a positive and significant association between the diversity of team members' final industry experience prior to joining the firm (*DIV_Last*) and startup growth. We also observe a positive relation between growth and the average diversity of team members' individual industry experience (*DIV_Worker*), though the estimate is only statistically significant in Column 2. We again find that diversity in the cross-section (*DIV_Last*) has a stronger association economically with growth than having an average worker who is more of an industry generalist. Turning to the interaction terms, we find that the association between growth and the diversity of team industry experience is significantly more positive among startups in innovative industries. Economically, a one standard deviation increase in diversity is associated with a 7.4 (7.4) percentage point higher cumulative three-year employment (sales)

[22] An exception is when we use the BDS measure of innovative industries, which is defined at the 4-digit NAICS level (our industry fixed effects are at the 3-digit level). In this case, we include the level effect in the regressions, though we suppress the estimated coefficient in the regression tables.

growth rate among firms innovative industries, relative to 2.1 (2.4) percentage point higher employment (sales) growth among startups in other industries. Increases in the general nature of the average worker's industry experience, on the other hand, generally have a negative association with startup growth among firms in innovative industries (though the association is statistically significant only in Column 1). Overall, the estimates suggest that cross-sectional skill diversity among founding team members is particularly important among the innovative entrepreneurial ventures that are the most important for economic growth. Moreover, the implications of diversity along different dimensions of experience are not the same: a low level of specialized industry experience for the average worker in a startup in an innovative industry is associated with, if anything, lower growth.

We also replicate the analysis using the HCI index in place of the BDS measure of industry innovation. Specifically, we define $D\_Innovation$ to be an indicator variable equal to one for industries in which the flow of research-trained students into the industry is at least twice as large as we would expect under random assignment of labor market entrants to industries. Figure 1 (Introduction) illustrates the unconditional difference between the correlations of employment growth and team diversity among firms in high- and low-HCI industries at various time horizons. In Column 3 of Table 7, Panel A, we confirm the significance of this pattern at the three-year horizon. In Column 4, we estimate the same regression using three-year cumulative sales growth as the dependent variable. Here, we do not observe a significant difference in the relations between diversity of team experience and sales growth among firms in innovative and non-innovative industries. However, at the five-year horizon, a significant gap appears: the relation between diversity and growth is 73% larger in innovative industries, a difference that is significant at the 5% level. Using the HCI measure, we do not observe that the relations between DIV_Worker and employment or sales growth turn negative among innovative firms; however, we do estimate insignificant negative coefficients on the interaction terms with the innovation indicator.

In Columns 5 and 6, we define $D\_Innovation$ to be an indicator variable equal to one for industries in which the ratio of R&D spending to sales among the average firm is in the top quartile of the sample distribution. Again, the results are very similar. Qualitatively, the patterns are nearly identical to those we observe using the BDS measure of innovative industries. The only difference is the sign of the coefficient estimates on the interaction term between DIV_Worker and $D\_Innovation$ in the sales growth regressions (both estimates are statistically insignificant). Thus, both the HCI and R&D measures of innovation confirm our basic conclusions: (1) the relation between the diversity of industry experience among team members and growth is more positive among firms in innovative industries and (2) there is no corresponding pattern for diversity of the average worker's individual industry experience.

Finally, in Panel B, we report estimates of the differences in the relation between the diversity of industry experience and startup growth by industry wage profiles. Specifically, $D\_Innovation$ is an indicator variable equal to one for industries in which more than 75% of workers earn wages that are in the top quartile of the full sample wage distribution. Here, we find even starker differences across the industry groups. For example, we do not observe a significant association between three-year employment growth and the diversity of team members' industry experience in the low-wage set of industries. However, among high-wage industries, a one standard deviation increase in diversity of industry experience is associated with a 9.1 percentage point higher three-year employment growth rate. The pattern is similar when we consider sales growth, though there is a small, significant positive association between team diversity and growth among low-wage industries. We do not observe any significant difference in how the diversity of the average worker's industry experience relates to growth across high- and low-wage industries. Viewing wage differences as a way to capture the likelihood of innovation (high wage workers are more likely to produce innovation than low wage workers), the results provide further confirmation of the evidence in Panel A. The analysis also serves a second purpose. Namely, it draws a tighter link between the patterns in growth that we associate with the diversity of industry experience and worker skills. The attainment of productive skills should map directly to worker wages. We observe that diversity of industry experience is positively related to growth only among industries that disproportionately employ highly skilled workers. This pattern suggests that it is indeed the diverse skills workers attain in their diverse industry spells that associate with higher startup growth rates.

V. Response to Economic Shocks

We find a positive relation between our measures of the diversity of founding team skillsets and startup growth, particularly among new firms in innovative industries. The latter result suggests that skill diversity matters not just among small businesses, but also among the new firms that become engines of economic growth. It also provides initial evidence consistent with the prediction of our motivating model that diverse skillsets allow firms to better adapt to changing conditions. That is, startup firms in innovative industries are likely to face more uncertainty in product markets and, thus, to reap greater benefits from broader skillsets. In this section, we test the prediction directly by examining differences in the relation between the diversity of team skills and firm growth as a function of the ex-ante uncertainty facing the firm.

V.1 Industry Shocks

First, we measure the uncertainty facing new businesses by exploiting differences in the industry-level persistence of sales. To measure sales persistence, we use the firm-level sales information available in the Census's Standard Statistical Establishment List (SSL) for the ten-year sample from 2000 to 2009. We run a separate firm-year level regression for each 3-digit NAICS industry using sales as the dependent variable and the lag of sales as the independent variable. We obtain a measure of the AR(1) coefficient, rho, for each industry from these regressions. We then rank industries according to rho and define an indicator variable that takes the value 1 if the industry has an estimated rho in the bottom quartile of the distribution (*D_Volatile*). In these industries, market conditions are less predictable based on prior year information, suggesting that new entrants would face greater uncertainty in projecting revenue and formulating a business plan. To test whether the diversity of the initial team's prior industry experience is more relevant under these conditions, we estimate Equation 2 using *DIV_Last* and *DIV_Worker* as the background diversity measures and including an interaction of each measure with the indicator variable for low industry-level sales persistence. Because the regressions include industry-state fixed effects, we cannot identify the level effect of the low persistence indicator. We report the results in Table 8. In Column 1, the dependent variable is the three-year cumulative employment growth rate, and in Column 2, it is the three-year sales growth rate. We find that cross-sectional diversity in team members' last industries prior to joining the startup has a positive association with employment and sales growth among firms in both low- and high-uncertainty industries. However, the association is stronger economically and statistically among startups in more uncertain industries. Economically, a one standard deviation increase in diversity is associated with a 3.5 (2.2) percentage point larger increase in employment (sales) growth among new firms in industries with more volatile sales. We also observe a significant positive association between the average diversity of individual team members' industry experience (*DIV_Worker*) and employment growth, but do not observe differences in the relation across industries with different levels of uncertainty.

V.2 Business Cycle Shocks

Second, we measure uncertainty using variation in the business cycle. To perform this test, we first extend our sample of startups to include all new firms that were founded between 2006 and 2010.[23] We then exploit the presence of the Great Recession during our sample period, distinguishing between firms founded in 2008 and 2009 (the NBER recession window runs from December of 2007 to June of 2009) and firms founded in the remaining sample years. Our hypothesis is that new firms founded during the recession period face greater ex ante uncertainty about the business's future prospects. We estimate Equation 2 on the full 2006 to 2010 sample using *DIV_Last* and *DIV_Worker* as the team diversity measures and including interactions of both measures with an indicator variable that takes the value of one if the firm was founded in 2008 or 2009 (*D_Recession*). We include year fixed effects to capture macroeconomic trends in growth rates and, as a result, cannot identify the level effect of the recession-start indicator. We report the results in Table 9. Again, the dependent variable is three-year cumulative employment growth rates in Column 1 and three-year sales growth rates in Column 2. Consistent with the patterns in Table 8, we estimate positive and significant general associations between the diversity of team members' last industry experiences before founding the startup and both measures of growth, regardless of the timing of the firm start. However, we find a

---

[23] We do not use the extended sample for our main analysis because some of our demographic variables are taken from the 2010 Decennial Census. As we go further back in time, there are more workers whom we cannot match to the Decennial Census, potentially introducing measurement error (e.g., one or two out of 10 team members in a firm may not have data). Nevertheless, all of our key results go through on the extended sample.

significantly stronger positive association among firms that start during the recession years. Here, we also estimate a significantly more positive association between the average diversity of individual industry experiences and startup growth among recession startups.

Overall, our evidence is consistent with greater adaptability in the face of uncertainty among startups with more diverse pre-startup work experience. The results suggest that having different experience across team members is particularly valuable, though there is some evidence that "jack of all trades" individual workers might also be beneficial when we use recession-year starts to measure heightened economic uncertainty facing new firms.

VI. Identification Concerns

Our analysis uncovers a strong positive association between the diversity of founding team members' prior industry experience and startup growth. However, there are several challenges to a causal interpretation of the evidence. It is important to note that we do not require random assignment for the estimated relations between diversity and growth to be economically important. If founders select either the locations for their firms or their fellow team members because of the diversity of their industry experience, then we can still interpret such diversity to be necessary to startup success, despite its endogeneity. Moreover, even if founders with the best ideas are able to attract better collaborators or workers to join their teams, the fact that they disproportionately form teams with more diverse industry experience indicates that they believe that such teams will add more value to the firm. Nevertheless, in this section, we discuss the most prominent identification concerns and provide additional analysis to explore their relevance to the interpretation of our results.

VI.1. Selection

Identifying a causal effect of the diversity of founding team industry experience on growth is subject to two different selection concerns. First, founders are unlikely to randomly select the locations in which they found their firms. The characteristics of residents (and potential workers) in different locations are likely to differ. For example, skilled workers could be drawn to locations in which business opportunities are the best. Then, startups could have diverse, skilled founding teams because they start in areas with strong business opportunities, which are subsequently reflected in future growth rates. Second, founding team members themselves are not randomly assigned to startups. Startups with the best growth prospects could be the most attractive to potential workers. In either case, causality could run in the reverse direction from growth prospects to the characteristics of team members.

To begin, we explore the selection of the locations in which new firms start. First, it is important to note that our baseline specification in Equation 2 already limits the scope for selection on this dimension to confound our results. We include industry by state fixed effects, so that we identify the coefficient estimates on team characteristics using only variation across startups in the same industry and state. Particularly among large states such as Texas or California, one could worry that the estimates are still confounded by within-state variation in business conditions and population characteristics. However, recall that our estimates are robust to instead including industry by county fixed effects. Moreover, the coefficient estimates barely change. For example, the coefficient estimate on *DIV_Last* when we consider 5-year cumulative employment (sales) growth as the dependent variable is 0.146 (0.178). Both estimates are significant at the 1% level and are nearly identical to the corresponding estimates in Tables 3 and 5. If nonrandom selection of locations were driving our results, we would expect to observe changes in the estimates from narrowing the comparison group to a finer geographic partition. Finally, note that it is not necessary to consider nonrandom differences in the timing of firm starts because all startups in the sample were founded in the same year.

To further reduce concerns about selection, we re-estimate our regression models among the set of firms that start in the county in which the highest-paid founding team member resided at the time of the 2000 Decennial Census (roughly ten years before founding the firm). Among these firms, it is plausible that the founder chose the location of the firm because it is where she lives, not because of other characteristics that could correlate with performance. While we could still be concerned that the timing of the firm start is not random, recall that we consider only a single cohort of new firms. Thus, the comparison is between firms started in the same year by local founders. We report the results in Table 10. The reported coefficients come from estimating Equation 2 on the full sample of startups, but allowing all independent variables and fixed effects to differ between firms with local and non-local founders. Thus, the estimates are equivalent to those we would obtain from estimating Equation 2 separately on the two subsamples. Again, for brevity, we report only the results using 3-year cumulative growth rates as dependent variables. Generally, we estimate similar associations between our team diversity measures and growth among firms with local and non-local founders. Focusing on the former set, we confirm positive and significant associations between *DIV_Last* (or the diversity of team members' most recent industry experiences in the cross-section) and both employment and sales growth among the set of firms that is least likely to be affected by location selection concerns.

We also perform additional analysis to mitigate the effect of team member selection on our estimates. Our strategy is again to identify a subset of firms in which we can reasonably infer the reason for selection and, therefore, create apples-to-apples comparisons across firms with similar selection criteria. In this case, we focus on family firms. We use information from the 2000 and 2010 Decennial Censuses to measure family links between members of the founding teams of the firms in our sample. Specifically, we classify a firm as a "family firm" if we observe at least two members of the founding team that were also members of the same household in either the 2000 or the 2010 Decennial Census. As a first step, we estimate Equation 2, including the family firm measure as an additional independent variable. In Column 1 of Table 11, we report the results using three-year cumulative employment growth as the dependent variable; in Column 2, the dependent variable is three-year cumulative sales growth. We find significantly lower growth rates among family firms than among non-family firms. Economically, employment (sales) growth is roughly 3 (5.5) percentage points lower among family firms. However, we do not observe that the inclusion of the family firm variable has any significant effect on the estimated coefficients on the diversity of team experience. Thus, a (lack of) diversity among founding team members in founding firms is not itself an explanation for our baseline estimates. Next, we include interactions of the family firm indicator with the *DIV_Last* and *DIV_Worker* measures. These specifications allow us to isolate the relations between diversity and growth among the set of family firms, in which family membership, rather than other characteristics, is likely to be the determining factor in selecting workers to the founding team. In Column 3, we report the results using three-year employment growth as the dependent variable. We find a negative and significant coefficient on the interaction term with *DIV_Last*. That is, diversity of the industry experiences of team members prior to joining family firms is less associated with employment growth than it is among non-family firms. However, the effect of diversity remains positive and significant (at the 10% level) even among family firms.[24] We observe statistically indistinguishable relations between *DIV_Worker* and employment growth among the two sets of firms. In Column 4, we report the results using three-year sales growth as the dependent variable. Here, we do not observe any significant differences between the coefficients on *DIV_Last* or *DIV_Worker* among family and non-family firms. Thus, even in a sample in which we break the link between the firm's growth prospects and the criteria by which workers are selected to the founding team, we estimate nearly identical associations between the diversity of workers' industry experience and firm sales growth. Given this result, the weaker relation between diversity and employment growth among family firms may reflect differences in hiring processes in family and non-family firms, rather than differences in profitability or growth opportunities. Overall, our results suggest that it is unlikely that the association between the diversity of the team's experience and growth is driven by selection.

VI.2. Omitted Variable Concerns

A related, but distinct endogeneity concern is that our measures of the diversity of team members' industry backgrounds correlate with omitted factors relevant to the performance of newly founded firms. Omitted variables could undermine the causal interpretation of our estimates even if the locations of firms and workers were randomly assigned. For example, suppose that variation in the diversity of team members' industry experience comes from the supply side of the labor market. In particular, suppose that local economic shocks cause firms to layoff workers and that more severe shocks cause more broad-based layoffs. In addition, suppose that only entrepreneurs with the best ideas can access funding to start new firms in bad economic times. Then, even if the entrepreneur randomly selected team members from the local supply of (laid-off) workers, she may build a team with more diverse industry experience. And, her firm would have stronger than average growth prospects, even though the two factors are unconnected. Of course, our industry by state (or industry by county) fixed effects may largely address this specific story – we compare only startups exposed to the same local market conditions. But, the more general omitted variable concern still remains. For example, diversity

[24] The estimated effect of experience diversity on growth for family firms is 0.119 – 0.0778 = 4.12%, with a p-value of 0.056.

of industry experience could correlate with other worker characteristics that themselves cause greater startup success and that are not reflected in workers' prior compensation, for which we control. We construct two strategies to address this potential consequence of the endogeneity of team industry experience.

VI.2.1. Instrumental Variable Strategy

First, we develop an instrumental variables strategy. To the extent that we can identify exogenous instruments for the diversity of team members' work experience, our results not only address the omitted variables concern, but also provide additional evidence against the selection stories we described in the prior section. We consider two sources of plausibly exogenous variation in the diversity of team members' past industry experience.

First, we exploit variation in the importance and composition of the mining industry across counties, building on the strategy from Glaeser, Kerr, and Kerr (2015). Mining is one of the oldest industries within the United States, having developed before the Second Industrial Revolution. Due to high transportation costs, mining typically became the central activity of the localities where it occurred (i.e., the extraction and transformation of mined commodities typically collocated in the same regions). Thus, mining and associated activities absorbed much of the local capital and also local workers, who tended to invest in skills relevant to the industry. Moreover, the activities associated with mining require high fixed investments, so that these industrial structures, once in place, were long-lasting. Glaeser et al argue that these factors hindered the development of industrial diversity in the locations in which mining is present. For our purposes, we rely on an additional implicit assumption that labor markets are at least partially segmented. Consistent with this assumption, Tate and Yang (2015) show that less than 5% of U.S. workers migrate across states, even in the case of forced employment discontinuity following plant closure. Under this assumption, the lack of local industrial diversity due to the deep-rooted presence of the mining industry will affect the diversity of founding team members' pre-startup work experience.

To construct an instrument from this source of variation, we obtain data on mines within the U.S. – both active and inactive – from the Mineral Resources Online Spatial Data, which is maintained by the U.S. Geological Survey's Mineral Resources Program.[25] We consider only mines that were discovered prior to 2002, eight years before the founding of our sample of startups.[26] The data provide the latitude and longitude of each mine, which we use to compute the distance of the mine from the centroid of each U.S. county. As our instrument, we calculate the natural logarithm of the number of mines located within 50 miles of the center of the county in which each sample startup firm operates. Based on the discussion above, we predict less diversity of the industry experience of founding team members among startups in counties with a larger historical presence of the mining industry. To be valid, the instrument must be excludable from our second-stage regression of startup performance on instrumented team diversity. That is, the historical strength of the mining industry in the county should explain the performance of new startup firms only through its effect on the industry diversity of workers' pre-startup job experiences. An immediate threat to the exclusion criterion is that mines tend to be located outside of urban centers. However, startups in urban locations are likely to have different growth prospects from startups founded in other locations, independent from the industry experience of their founders. To minimize this threat, we exploit only variation in the historical importance of mining to the county on the intensive margin. That is, we exclude counties from the analysis in which no mines were ever present. We also include a direct control for the population of the county, measured in log form as of 2010. In addition, we continue to control for industry fixed effects (crossed with state fixed effects) so that our results cannot be explained by differences in the industries in which new firms start across counties that were more or less historically mining intensive.

Second, we exploit cross-county variation in the organizational structures of the firms that operate local establishments, building on evidence from the recent literature on internal labor markets. Diversified firms and business groups redeploy labor internally in response to industry shocks (Tate and Yang, 2015; Cestone et al, 2017). Moreover, displaced workers from diversified firms make easier transitions to other industries operated by the firm than displaced workers from focused firms making the same transition, consistent with the development of

[25] The data are publicly available at https://mrdata.usgs.gov/.

[26] Our results are qualitatively similar if we count only mines that were active as of 1900, confirming that our identification comes from stable, long-lived differences across counties.

broader cross-industry skillsets inside diversified firms (Tate and Yang, 2015). Then, if labor markets are partially segmented, the prevalence of diversified firms in the local economy will affect the amount of cross-industry experience team members obtain prior to founding a startup.

To construct our instrument, we consider the full set of firms that were operating as of 2005 in each county in which we observe a 2010 new firm start. We then calculate the fraction of diversified firms (operating in multiple 3-digit NAICS industries). We predict a positive relation between the diversity of team members' industry experience and the fraction of the firms operating in the county that were diversified five years prior to the new firm's start date. In this case, the exclusion restriction requires that the historical fraction of diversified firms in a county does not predict startup performance except through its effect on the diversity of the founding team members' career experiences. New startups are unlikely to compete directly with large, diversified firms. Nevertheless, a potential source of concern is that the fraction of diversified firms could be related to county growth rates and business opportunities. To address this possibility, we include direct controls for county-level changes in aggregate employment and payroll measured over the 2002 to 2005 time period. Reassuringly, we do not estimate a strong association between these added controls and startup growth. In addition, we confirm that our results are robust to adding a control for the total number of firms in the county, which could also capture the vibrancy of local opportunities.

To implement our instrumental-variable strategy, we estimate the following regression system on the subsample of startups located in counties in which we observe at least one active or inactive mine:

$$Team\ Diversity_{fks} = v_1 \ln(Mines_f) + v_2\ PctDiv_f + \boldsymbol{X}'_{fks}\boldsymbol{\gamma_1} + \eta_{ks} + \epsilon_{fks} \tag{5}$$

$$Startup\ Performance_{fks} = \beta\ \widehat{Team\ Diversity}_{fks} + \boldsymbol{X}'_{fks}\boldsymbol{\gamma_2} + \eta_{ks} + \epsilon_{fks} \tag{6}$$

Because we do not have distinct sets of instruments for our different measures of the diversity of team members' industry experience, we consider only one measure of team diversity at a time (i.e., the system has only a single endogenous variable and first stage regression). The matrix $\boldsymbol{X}$ includes the same set of control variables as Equation 2, with the addition of the extra controls described above. We use three-year cumulative employment growth as the measure of startup performance in Equation 6. We also continue to include industry by state fixed effects and to cluster standard errors at the industry-state level.

In Table 12, we report the results of estimating Equations 5 and 6. In Panel A, the endogenous variable is our comprehensive measure of the diversity of team members' prior industry experience, *DIV_All*. Column 1 reports the first stage estimates. We find, as predicted, that team members have significantly less diverse industry histories among startups that are in counties with a stronger historical presence of the mining industry. On the other hand, a larger fraction of firms operating in multiple industries is associated with more diverse industry experience among the founding team. We find a Kleibergen-Paap (2006) F-statistic value of 14.73, comfortably rejecting the null that the instruments are not relevant in the first stage. Moreover, the Hansen J test has a p-value of 0.76 and, therefore, fails to reject the overidentifying restrictions of the model or the validity of our set of instruments at conventional significance levels. In Column 2, we report the second stage estimates. We confirm a significant positive relation between *DIV_All* and three-year startup employment growth.

Notably, the estimated effect in Column 2 is larger than the corresponding OLS estimates from Table 3. Here, a one standard deviation increase in *DIV_All* predicts a 32 percentage point higher three-year employment growth rate. Though endogeneity could magnify the estimated relation between team diversity and growth, it is also possible that endogeneity could cause the OLS estimates to understate the true effect. 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. Moreover, given the sizes of firms in the sample, this growth rate is not unreasonably high (it is roughly half of a standard deviation of the dependent variable). The median firm in the sample has 4 workers when it is founded, so that a one standard deviation increase in diversity implies the addition of roughly one more worker through three years. Nevertheless, the larger IV estimates suggest that we interpret the results with some caution.

For these tests, we do not consider sales growth as an alternative dependent variable because doing so would require us to restrict our sample even further. When we do so, the first stage estimates are not sufficiently strong for us to feel comfortable proceeding with the IV strategy. However, we do perform additional analyses to assess the source of the relation between our instruments and *DIV_All*. Specifically, we assess whether the predictive power comes from diversity of industry experience in the cross-section of workers or from diversity of the average worker's individual industry experience. In Panel B of Table 12, we report the results of estimating Equations 5 and 6 using *DIV_Worker* as the diversity measure. We find similar point estimates for the relations between the instruments and *DIV_Worker* to those we report in Column 1. However, the instruments are statistically stronger (here, the Kleibergen-Paap F-statistic is 21.56). As in Column 1, the Hansen J test does not reject exogeneity of the instruments (p-value = 0.78). In the second stage, we confirm a significant positive effect of the diversity of the average worker's personal industry experience on startup three-year employment growth. A one standard deviation increase in diversity increases growth by 22 percentage points, or roughly one-third of a standard deviation. If we instead estimate Equation 5 using *DIV_Last* as the dependent variable, we do not have enough statistical power to credibly estimate the second stage (i.e., the Kleibergen-Paap F-statistic is well below 10). Thus, our IV strategy can confirm the effect of diverse individual skill sets on startup growth; however, it cannot independently confirm that diversity across workers in the cross-section affects growth (the *DIV_All* estimates mix the two sources of variation together).

VI.2.2. Shocks to Team Composition

As a second approach to address omitted variable concerns, we consider shocks to team composition during the first year of startup operation. In this context, we focus explicitly on changes in team level industry experience in the cross-section so that our strategy complements the analysis in Section VI.2.1.

An ideal event to use for treatment would be the sudden death of a worker whose industry expertise is not replicated among her colleagues on the team. Unfortunately, we cannot observe worker deaths directly in our sample. As an alternative, we identify workers who exit from startups during the first full year of operation who are not subsequently reemployed by another firm through the end of the LEHD data sample in 2014.[27] Given the length of the

[27] Startups in our sample can be founded at any point during the year beginning in April, 2009 and ending March, 2010. To allow for at least one year of operations during the window in which we measure exits, we consider exits that occur in 2011 in our baseline analysis. Because our LEHD sample includes all 50 U.S. states, we can

observed unemployment spells, these exits from paid employment are likely to occur for reasons exogenous to startup performance. Possibilities include deaths, retirements, or family-motivated exits. Nevertheless, the timing of some of these events – notably retirement – could be influenced by forecasts of future startup performance. Thus, we do not compare the performance of startups with a team member who "permanently" exits paid employment to startups with a team that remains intact. Instead, we look within the set of startups that experienced the exit of a team member and compare cases in which the exiting team member's industry experience is replicated by another team member to cases in which it is not.

To perform the comparison, we estimate Equation 2 including the full set of controls and fixed effects and adding (1) an indicator variable for firms that experienced an exit of a team member whose experience overlapped with other team members (*Overlap*) and (2) an indicator variable for firms that experienced an exit of a team member whose experience did not overlap with other team members (*No-Overlap*). In Figure 2, we report the coefficient estimates on these indicator variables. The reported growth rates are differences relative to the baseline set of startups in which no initial employees exited the firm, estimated within groups of firms in which team members have prior experience in exactly the same number of industries.[28] Recall our baseline fixed effects also imply comparisons within sets of firms with the same initial team size and within firms in the same industry by state pair. We estimate separate regressions that measure the dependent variable at different horizons, ranging from one year to five years.

In the graph on the left, we use firm survival as the outcome variable. We find that the exit of a team member is costly: in both the overlap and non-overlap groups, we observe significant declines in survival probabilities relative to firms that did not experience an exit. However, exits are significantly more costly if they reduce the diversity of the team's industry experience. We estimate a significant difference of 4.2 percentage points at the end of the second year, following the exit events. Moreover, we do not observe differences at the end of

measure reemployment after exits without error. Our results are similar if we instead include exit events that occur in either 2010 or 2011.

[28] That is, we add an additional set of fixed effects to Equation 2 for the number of industries in which team members have prior experience.

year 1 between the survival rates of groups that experience the loss of a team member with experience that overlaps and does not overlap with the experience of other team members, confirming that the firms are on otherwise similar trajectories prior to the shock. We see a slight convergence in the relative survival rates over time, but the cross-group difference remains statistically significant even at the five-year horizon and both groups remain more likely to have failed than baseline firms with no exit events (all differences are significant at the 1% level).

In the graph on the right, we report the results from a parallel set of regressions in which we use conditional employment growth rates as the dependent variables. Given the survival results, it is plausible that we would not observe additional differences in conditional employment growth rates. That is, we may only observe the growth rate following the exit events among a set of firms that are able to replace the exiting team member successfully. Nevertheless, we do observe some evidence that employment grows significantly more slowly following the team member exits compared to firms that do not experience losses of initial team members. Similar to the survival results, we find that this slower growth is more pronounced among firms that lose a team member whose experience does not overlap with remaining team members' experience. The differences in growth rates slowly diminish beginning in year 3. Here, we do see a modest difference in year one growth rates between groups; however, the gap appears to widen over the subsequent one to two years. We also perform a similar set of estimations using sales growth as the dependent variables. We do not find evidence of significant differences in conditional sales growth between firms that experience exits of team members with industry experience that overlaps with their remaining colleagues and firms that lose team members whose industry experience is unique. However, it is worth noting that the power of the tests is low given the additional sample attrition from missing sales data.

Overall, the bulk of the effect of the loss of team members on the startup appears to manifest in higher failure rates. Consistent with a causal effect of the diversity of team industry experience on startup performance, we find that exits that reduce team diversity are associated with significantly worse performance.

VII. Economic Mechanisms

As a final step, we consider several possible economic mechanisms that could explain the effect of the diversity of team members' industry experience on startup performance.

VII.1. Worker Skills

Our extension of the Lazear (2005) framework operates through the channel of team members' skills. In our main analysis, we use diversity of initial employees' prior industry experience as our measure of the skill diversity that is part of the theory. In Section IV.2, we found that the link between the diversity of industry experience and performance is concentrated among startups that operate in high-wage industries, consistent with a link to worker skills. In this section, we tighten the link between industry experience and skills by exploiting variation in the ease with which workers in the general labor market move between industries. Our approach builds on recent work that uses the frequency of worker job changes between industry pairs in the general labor market to measure the transferability of workers' skills between those industries (Neffke, Otto, and Weyh, 2017; Tate and Yang, 2015; Neffke and Hanning, 2013).

Thus far, we have treated all prior industry experience as essentially equivalent. However, in our context, a reasonable hypothesis is that the skills that founding team members bring to a startup will prove more valuable if they are more transferable to the industry in which the startup operates. For example, even in a case in which two team members are electrical engineers but come from different prior industries, the unique combinations of their engineering skills with industry-specific knowledge can allow the startup to more easily pivot in response to changes in business conditions and opportunities. To test this hypothesis, we use a random sample of job changes from the LEHD data to compute a human capital transferability (HCT) index at the 3-digit NAICS industry level for our sample period. We describe the construction of the index in detail in the Appendix. For each founding team member, we consider her last industry experience prior to joining the startup. We use the HCT index to measure the transferability of human capital between this industry and the industry in which the startup operates. We then compute two separate diversity measures for each startup team. *DIV_Last_High_HCT* is computed using Equation 1 on the subset of industries for which the HCT index with respect to the startup's industry is above the sample median.

DIV_Last_Low_HCT is the corresponding measure for the subset of prior industries for which the HCT index is below the sample median. We then estimate Equation 2, considering both *DIV_Last_High_HCT* and *DIV_Last_Low_HCT* as measures of the diversity of the team's prior industry experience, together with the full set of controls and fixed effects.

We report the results in Panel A of Table 13. We find that both diversity measures have positive and significant associations with three-year employment growth (Column 1) and sales growth (Column 2). However, we find that the diversity of experience in industries from which skills transfer more easily to the startup's industry has a significantly more positive relation with both performance measures. It is notable that diversity is positively associated with startup performance even among the industries with low human capital transferability to the startup's industry. Given the uncertainty that new businesses face, diversity of skills, even when those skills are peripheral to the business, can be beneficial. However, skillsets that are relevant to the startup's core business have the most value.

We also use the HCT index to refine the link between team industry experience and diverse skillsets on a second dimension. Our baseline measure identifies diversity of industry experience when team members worked in different industries before joining the startup, without regard for potential overlap in the skillsets required in those industries. As a result, we could overestimate skill diversity among teams in which workers have histories in such industries. To tighten the link between diverse industry experience and diverse skillsets, we construct an alternative diversity measure in which we downweight industry pairs that have high values of the HCT index, assuming that observed worker mobility between industries positively correlates with overlapping skill requirements. Specifically, we consider the full set of industries in which team members had prior experience before founding the startup. We modify the Herfindahl calculation in Equation 1 by first accounting for the transferability of human capital from each industry to each of the other industries in which team members have prior experience. We then calculate an HCT-weighted version of the overall diversity index as follows:

$$DIV\_All\_HCTWeight = 1 - \sum_{i=1}^{N} w_i p_i$$

where $w_i = \sum_{j=1}^{N} m_{ij} p_j$ and $p_i = \frac{q_i}{\sum_{i=1}^{N} q_i}$. By pre-multiplying the fraction of quarters in industry j by the transferability of human capital between industries i and j, we effectively down-weight the contributions of high transferability pairs to the diversity measure *DIV_All_HCTWeight*. Likewise, we overweight the contributions of industries between which we rarely observe worker moves in the job market, suggesting that the industries employ truly distinct skillsets. We also modify the calculations of our measure of the diversity of team members' final industry experience prior to joining the firm and the average diversity of workers' individual industry experiences using the same approach. We denote the resulting measures as *DIV_Last_HCTWeight* and *DIV_Worker_HCTWeight*, respectively.

In Panel B of Table 13, we report the results of estimating Equation 2 using *DIV_Last_HCTWeight* and *DIV_Worker_HCTWeight* as the measures of team diversity and including all of the standard controls and fixed effects. We consider three-year cumulative employment growth as the dependent variable in Column 1 and three-year sales growth in Column 2. We find in both cases that cross-sectional diversity in team members' most recent industry experiences has a significant positive relation with startup growth. Consistent with the results in Panel A, we find that the economic magnitudes of the estimates are smaller than the corresponding estimates in Tables 3 and 5, which use unweighted versions of the measures. We find broadly similar results when we consider *DIV_Worker_HCTWeight*. The estimates are positive for both dependent variables and smaller in magnitude than the corresponding estimates using the unweighted version of the measure. Here, the estimate is insignificant in Column 2, though it is marginally significant in Column 2 of Table 5. Overall, our results confirm a positive association with growth, even if we concentrate on industry differences that are likely to entail truly distinct skillsets.

VII.2. Leadership

Another possible channel through which diversity of initial team members' experience could affect startup performance is the evolution of the leadership of the firm. One possibility is that a stronger initial team leads to less turnover at the top of the firm. Another possibility is that a more diverse set of initial team members provides a stronger talent pool from which to draw a new manager if the top executive of the firm exits. It is also possible that having a stronger team in place allows the firm to attract a higher quality manager from outside the firm if there is a transition in the leadership of the firm.

We use the worker-level information in the LEHD data to track the leadership of our baseline sample of 2010 startups through the end of 2014 (the final year in which the LEHD data is available). Because we cannot observe job titles in the LEHD data, we proxy for the manager of the firm in each year by identifying the worker with the highest annualized earnings. We estimate a series of regressions within the framework provided by Equation 2 (i.e., using the same set of fixed effects and controls and different combinations of our team diversity measures). However, we consider a set of dependent variables related to managerial traits in place of the growth measures we used in the rest of our analysis.[29]

Having identified the "manager" of each startup year-by-year, we begin by testing whether our main measure of the breadth of team skills, *DIV_Last*, could simply be a noisy measure of the breadth of the manager's skills. We replicate the analyses from Tables 3 through 5, but including a measure of the diversity of the manager's individual industry experience as an additional control. We use the Herfindahl-based approach from which we calculate *DIV_Worker* to construct the measure. Alternatively, we construct an indicator variable that equals one if the manager has prior experience in at least two distinct 3-digit NAICS industries. We find no evidence that our estimates of the coefficients on *DIV_Last* capture uncontrolled variation in managerial experience. The managerial experience variables themselves are sometimes positive, but are less reliably significant than the team measure. Thus, our analysis does capture different dynamics from the baseline Lazear (2005) model.

Next, we consider the evolution of firm leadership over time. We define an indicator variable that equals one if the manager of the firm is the same individual in 2014 as in 2010, at the time the firm was founded. We then estimate Equation 2 as a linear probability model, using this indicator as the dependent variable and our team diversity measures (*DIV_Last* and *DIV_Worker*) as key explanatory variables. We find that both diversity measures have a significant negative relation with the likelihood that the initial manager remains in place in

[29] We omit tables from this subsection for brevity; however, they are available from the authors upon request.

2014. A one standard deviation increase in *DIV_Last*, for example, is associated with a 2.4 percentage point lower likelihood that the initial manager still leads the firm in 2014.

We also test for differences in the traits of the manager in 2014 as a function of initial team diversity, conditional on a leadership change. First, we test whether there are differences in the likelihood that the new manager is promoted from within the firm, again using a linear probability model to estimate Equation 2. We find that both measures of the diversity of the experience of the initial team are associated with a higher likelihood that the new leader of the firm was hired from outside the firm. For example, a one standard deviation increase in *DIV_Last* is associated with a 4.5 percentage point higher likelihood of an external hire. We also find that firms with greater cross-sectional diversity in industry experience (*DIV_Last*) pay their new managers significantly higher salaries, controlling for the salary of the initial manager. If wages reflect general ability, then this evidence suggests that firms with more diverse initial teams, if anything, attract more competent new managers than their peers, conditional on a succession event. However, we do not observe a significant relation between the average individual experience of initial workers (*DIV_Worker*) and the new manager's pay.

For both diversity measures, we also find a significant positive association with the diversity of the new manager's personal industry experience, controlling for the diversity of the initial manager's industry experience. That is, firms with more diverse initial teams are more likely to hire new managers who are generalists, even accounting for whether the initial manager was a generalist or specialist. Similarly, using either diversity measure, we find a negative association with the likelihood that the new manager's last job prior to joining the firm was in the industry in which the firm operates, controlling for whether the initial manager of the firm was an industry insider.

Overall, we estimate significant differences in the evolution of the leadership of the firm across startups with more and less diverse initial teams. Our results do not support the hypothesis that initial team diversity leads to more stability of leadership (i.e., fewer succession events and more internal succession). However, together with the evidence that firms with diverse teams have higher employment and sales growth than other startups, our analysis of leadership changes suggests that firms with more diverse initial teams graduate to professional management more quickly than other startups. That is, the quicker transition to skilled, generalist managers could be another reflection of the stronger performance of this set of firms. Alternatively, startups with more diverse founding teams could develop cultures that are more open and thus are more attractive to external, out-of-industry, generalist managers.

VII. Conclusion

We use comprehensive data on a full cohort of U.S. startups matched with detailed individual-level data on employment histories and demographics to assess the role of founding teams' skills in early-stage firm growth. 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 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 several index measures of the diversity of the founding teams' pre-startup industry experience. We also distinguish between the diversity of experience across team members and the presence of team members with generalist skills.

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 and sales growth significantly increase with our measures of team diversity. The pattern appears to be primarily driven by the breadth of industry experience in the cross-section of team members and not by the presence of workers with more generalist skillsets. We find that the patterns are particularly pronounced among firms in innovative industries, which are more likely to become high-growth firms that are engines of job creation. Moreover, the results are particularly strong among startups that face the most ex ante uncertainty, suggesting that diversity enables teams to be more adept at responding to changing conditions. This ability can be particularly important among startup firms in which the exact set of skills that will be required may not be clear ex ante (particularly for firms that are founded around an innovative idea) and the ability to change team composition over time is constrained (e.g., by finances).

We take a variety of approaches to mitigate the effects of endogeneity on the interpretation of our results. We show that our results are robust to focusing on subsamples of firms in which the selection of startup location is unlikely to be driven by local economic conditions (startups with "local" managers) and in which the selection of team members into the firm is unlikely to be due to their prior industry experience (family firms). We also use plausibly exogenous, predetermined variation in county characteristics (intensity of the presence of the mining industry; prevalence of diversified firms) to instrument for team industry experience and consider shocks to team composition. Again, we confirm our conclusions.

Overall, our analysis suggests a fruitful endeavor in moving beyond the analysis of entrepreneurial characteristics to the question of how entrepreneurs construct optimal teams and in testing not whether teams matter, but instead which types of teams produce the greatest success.

Appendix: Computation of the Human Capital Transferability Index

We use a random sample of job changes from the LEHD data to construct an index of human capital transferability (HCT) following the general approach from Tate and Yang (2015). Following Tate and Yang, we consider only job changes in the external market (i.e., in which workers move to a new firm). For each pair of 3-digit NAICS industries i and j, we define the expected labor flow from industry i to j as $\widehat{F_{ij}} = \frac{M_i \times F_j}{\sum_j F_j}$ where M_i is the number of job changers in industry i and F_j is the number of jobs in industry j. 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 and end up accepting jobs in industry j should equal the fraction of the overall jobs in the economy that are in industry j. We then compute the ratio between the actual and expected flows as $r_{ij} = \frac{F_{ij}}{\widehat{F_{ij}}}$. r_{ij} greater than (less than) 1 indicates that we observe more (fewer) flows between i and j than we would expect under random assignment of job changers to new industries.

Because the measure of unexpected flows $\boldsymbol{R}$ is strongly right-skewed, we transform it according to the formula from Neffke, Otto, and Weyh (2017). Specifically, we calculate $\overline{r_{ij}} = \frac{r_{ij}-1}{r_{ij}+1}$. The resulting measure $\overline{\boldsymbol{R}}$ 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 of the flows in each direction: $h_{ij} = \frac{\overline{r_{ij}}+\overline{r_{ji}}}{2}$. By construction, the resulting matrix $\boldsymbol{H}$ is symmetric; i.e., $h_{ij} = h_{ji}$ for all i and j. To compute the final HCT Index, we take a three-year average of the annual values of $\boldsymbol{H}$. A higher value of the index h_{ij} suggests greater transferability of human capital between the industries.

References

Adams, R. and D. Ferreira. 2009. "Women in the Boardroom and their Impact on Governance and Performance," *Journal of Financial Economics* 94: 291-309.

Azoulay, P., Graff Zivin, J., and J. Wang. 2010. "Superstar Extinction," *Quarterly Journal of Economics* 125(2): 549-589.

Azoulay, P., B. Jones, J. D. Kim, and J. Miranda, 2017. "Age and high-growth entrepreneurship", *American Economic Review: Insights,* 2(1): 65-82.

Babina, T. and S. Howell, 2018. "Entrepreneurial Spillovers from Corporate R&D", Working Paper, Columbia University.

Berstein, S., A. Korteweg, and K. Laws, 2017. "Attracting Early-Stage Investors: Evidence from a Randomized Field Experiment", Journal of Finance 72 (2), 509 - 538

Bertrand, M., and A. Schoar. 2003. "Managing with Style: The Effect of Managers on Firm Policies," *Quarterly Journal of Economics,* 118(4): 1169-1208.

Borjas, G. and K. Doran. 2014. "Which Peers Matter? The Relative Impacts of Collaborators, Colleagues, and Competitors," NBER Working Paper 20026.

Campell, B., Sexton, B., and P. Banerjee. 2014. "Resetting the Shot Clock: The Effect of Comobility on Human Capital," *Journal of Management* 40(2): 531-556.

Cestone, G., C. Fumagalli, F. Kramaz, and G. Pica, 2017. "Insurance between Firms: The Role of Internal Labor Markets," Working Paper, City University of London.

Custodio, C., Ferreira, M., and P. Matos. 2013. "Generalists versus Specialists: Lifetime Work Experience and Chief Executive Officer Pay," *Journal of Financial Economics.* 108(2): 471-492.

D'Acunto, F., Tate, G., and Liu Yang. 2017. "Correcting Market Failures in Entrepreneurial Finance," Working Paper, University of Maryland.

Decker, R., J. Haltiwanger, R. Jarmin, and J. Miranda, 2014. "The Role of Entrepreneurship in US Job Creation and Economic Dynamism," *Journal of Economic Perspectives* 28(3): 3-24.

Fisman, R., Paravisini, D., and V. Vig. 2017. "Cultural Proximity and Loan Outcomes," *American Economic Review.* 107(2): 457-492.

Glaeser, E., S.P. Kerr, and W.R. Kerr, 2015. "Entrepreneurship and Urban Growth : An Empirical Assessment," *The Review of Economics and Statistics* 97(2): 498-520.

Glover, D., Pallais, A., and W. Pariente. 2017. “Discrimination as a Self-Fulfilling Prophecy: Evidence from French Grocery Stores,” *Quarterly Journal of Economics,* 132(3): 1219-1260.

Goldschlag, N. and J. Miranda, 2020. “Business Dynamics of High-Tech Industries,” *Journal of Economics & Management Strategy* 29(1): 3-30.

Gompers, P., W. Gornall, S. Kaplan, and I. Strebulaev, 2020, “How Do Venture Capitalists Make Decisions”, *Journal of Financial Economics*, forthcoming.

Gompers, P., Lerner, J., Scharfstein, D., and A. Kovner. 2010. “Performance Persistence in Entrepreneurship and Venture Capital,” *Journal of Financial Economics* 96(1): 731-764.

Graham, J., Harvey, C., and M. Puri. 2013. “Managerial Attitudes and Corporate Actions,” *Journal of Financial Economics,* 109: 103-121.

Groysberg, B. and L. Lee. 2009. “Hiring Stars and their Colleagues: Exploration and Exploitation in Professional Service Firms,” *Organization Science* 20(4): 740-758.

Hacamo, I., and K. Kleiner. 2020. “Confidence Spillovers: Evidence from Entrepreneurship” Working Paper.

Hayes, R., Oyer, P., and S. Schaefer. 2006. “Coworker Complementarity and the Stability of Top-Management Teams,” *Journal of Law, Economics and Organization* 22(1): 184-212.

Hecker, D., 2005. “High-technology employment: A NAICS-based update,” *Monthly Labor Review* 128: 57.

Hjort, J. 2014. “Ethnic Divisions and Production in Firms,” *Quarterly Journal of Economics,* 129(4): 1899-1946.

Hyatt, H., S. Murray, and K. Sandusky. 2018 “Business Ownership Dynamics and Labor Market Fluidity”, Working Paper, Census Bureau.

Jaravel, X., Petkova, N., and A. Bell. 2018. “Team-specific Capital and Innovation,” *American Economic Review* 108(4-5): 1034-1073.

Jones, B., and L. H. Summers. 2020. “A Calculation of the Social Returns to Innovation,” NBER Working Paper 27863.

Jones, C. 2016. “The Facts of Economic Growth”, in *Handbook of Macroeconomics* 2(A): 3-69.

Kaplan, S., Klebanov, M., and M. Sorensen. 2012. “Which CEO Characteristics and Abilities Matter?” *Journal of Finance,* 67(3): 973-1007.

Kerr, S. P., and Kerr, W. R. 2017. “Immigrant Entrepreneurship”, Measuring Entrepreneurial Business: Current Knowledge and Challenges.

Kerr, S. P., W. R. Kerr, and T. Xu. 2017. "Personality Traits of Entrepreneurs: A Review of Recent Literature", NBER Working Paper 24097.

Lazear, E. 2005. "Entrepreneurship," *Journal of Labor Economics,* 23(4): 649-680.

Lazaer, E. 2009. "Firm-specific Human Capital: A Skill-Weights Approach," *Journal of Political Economy,* 117(5): 914-940.

Lerner, J. and U. Malmendier. 2013. "With a Little Help from My (Random) Friends: Success and Failure in Post-Business School Entrepreneurship," *Review of Financial Studies* 26(10): 2411-52.

Levine, R., and Y. Rubinstein. 2017. "Smart and Illicit: Who Becomes and Entrepreneur and Do They Earn More?" *Quarterly Journal of Economics,* 132(2): 963-1018.

Liang, J., H. Wang, and E.Lazear. 2018. "Demographics and Entrepreneurship", *Journal of Political Economy,* 126(1): 140-196.

Lyons, E. 2017. "Team Production in International Labor Markets: Experimental Evidence from the Field," *American Economic Journal: Applied Economics*, 9(3): 70-104.

Mailath, G. and A. Postlewaite. 1990. "Workers versus Firms: Bargaining over a Firm's Value," *Review of Economic Studies* 57(3): 369-380.

Malmendier, U., and G. Tate. 2005. "CEO Overconfidence and Corporate Investment," *Journal of Finance,* 60(6): 2661-2700.

Malmendier, U., and G. Tate. 2008. "Who Makes Acquisitions? CEO Overconfidence and the Market's Reaction," *Journal of Financial Economics,* 89(1): 20-43.

Malmendier, U., Tate, G., and J. Yan. 2011. "Overconfidence and Early-life Experiences: The Effect of Managerial Traits on Corporate Financial Policies," *Journal of Finance*, 66(5): 1687-1733.

Neal, D., 1995. "Industry-Specific Human Capital: Evidence from Displaced Workers," *Journal of Labor Economics* 13(4): 653-677.

Neffke, F. and M. Henning. 2013. "Skill Relatedness and Firm Diversification," *Strategic Management Journal* 34: 297-316.

Neffke, O., Otto, A., and A. Weyh. 2017. "Inter-industry Labor Flows," *Journal of Economic Behavior and Organization,* 142(C): 275-292.

Oettl, A. 2012. "Reconceptualizing Stars: Scientist Helpfulness and Peer Performance," *Management Science* 58(6): 1122-1140.

Ouimet, P. and R. Zarutskie. 2016. "Acquiring Labor," Working Paper, University of North Carolina.

Parrotta, P., Pozzoli, D., and M. Pytlikova. 2014. "Labor Diversity and Firm Productivity," *European Economic Review,* 66(C): 144-179.

Rajan, R. G., 2012, Presidential address: The corporation in finance, *Journal of Finance* 57, 1173–1217.

Roach, M., and H. Sauermann. 2015. "Founder or Joiner? The Role of Preferences and Context in Shaping Different Entrepreneurial Interests", 61(9): 2013-80.

Tate, G., and L. Yang. 2015. "The Bright Side of Corporate Diversification: Evidence from Plant Closure," *Review of Financial Studies,* 28(8): 2203-2249.

Tate, G. and L. Yang. 2015. "Female Leadership and Gender Equity: Evidence from Plant Closure," *Journal of Financial Economics* 117(1): 77-97.

Tate, G., and L. Yang. 2015. "The Human Factor in Acquisitions: Cross-industry Labor Mobility and Corporate Diversification," Working Paper, University of Maryland.

Waldinger, F. 2010. "Quality Matters: The Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany," *Journal of Political Economy* 118(4): 787-831.

Waldinger, F. 2012. "Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany," *Review of Economic Studies* 79(2): 838-861.

Wernerfelt, B., 1984, A resource-based view of the firm, *Strategic Management Journal* 5, 171–180.

Figure 2. Firm Survival and Growth around Worker Exits that Increase/Reduce Diversity of Team Experience

The table plots coefficient estimates from ordinary least squares regressions. Each plot reports results from five separate regressions, in which outcomes are measured 1, 2, 3, 4, or 5 years following the founding of the firm. The dependent variable is either an indicator for firm survival or the cumulative employment growth rate, as indicated in the plot title. The regression samples are subsets of the 2010 cohort of new firm starts in which necessary covariates are observed and match the samples in Table 3 reported over the same horizons. All regressions include the full set of controls from Table 3. In addition we include fixed effects for the number of industries in which team members have pior experience. The "No Overlap" series plots coefficient estimates on an indicator variable that equals one if a worker left the firm in 2011 whose most recent prior industry experience before joining the startup is not replicated by any of the other founding team members. The "Overlap" series plots coefficient estimates on an indicator variable that equals one if a worker left the firm in 2011 whose most recent prior industry experience before joining the firm is shared with another founding team member.

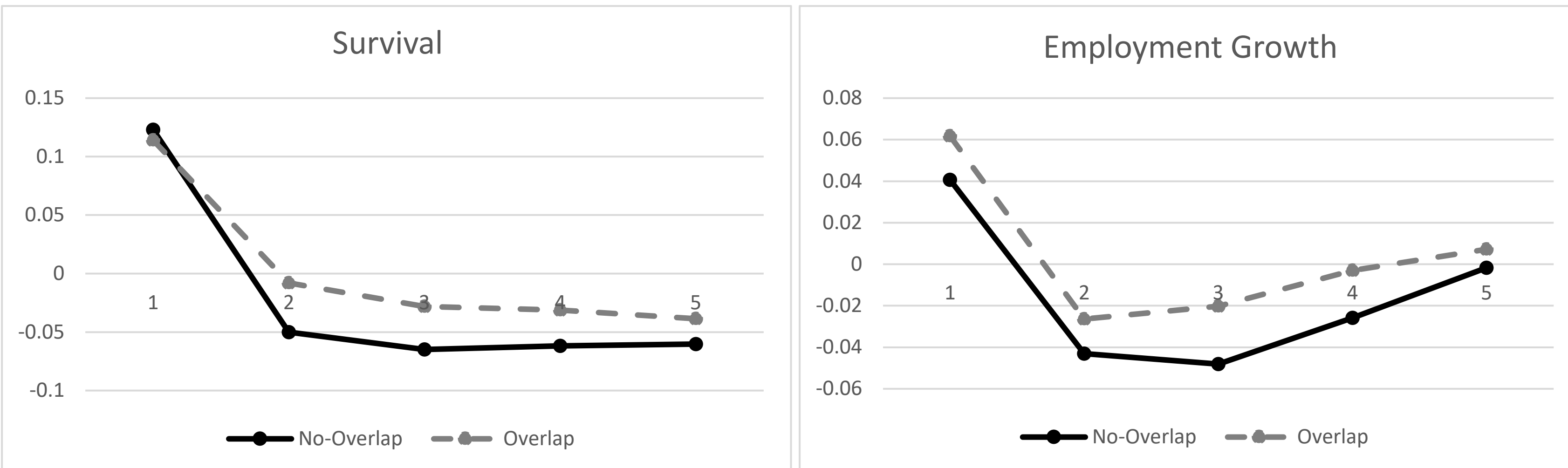

Table 1. Summary Statistics of Firm and Worker Characteristics

This table reports summary statistics for the samples we use in the analysis. Panel A reports the distribution across 2-digit NAICS industries, Census Divisions, and by the number of initial employees. Panel B reports statistics at the firm level. Family Firm is an indicator equal to one if at least two members of the initial set of employees were members of the same household at the time of the 2000 or 2010 Decennial Census. Local Founder is an indicator equal to one if the highest paid inital employee resided in the county in which the firm operates at the time of the 2000 Decennial Census. Survive_Year*t* is an indicator varaible equal to one if the firm survives to the end of year t, where year 0 is the year of founding. EmpGrowth_Year*t* (SalesGrowth_Year*t*) is the growth rate of employment (sales) from year 0 to year t. Age is the average age of the firm's workers. Demographic variables (Female, White, Black, Hispanic, Asian, Foreign) are the fraction of workers in the firm falling into the category.

Panel A. Distribution of Firms

	Overall Sample	Regression Sample
Industry	**Percentage**	**Percentage**
Accommodation	10.1%	12.0%
Administrative	5.3%	5.3%
Agriculture	0.3%	0.3%
Arts and Entertainment	1.6%	1.5%
Construction	10.4%	10.7%
Education	1.3%	1.3%
Finance	4.5%	4.2%
Healthcare	10.9%	11.1%
Information	1.4%	1.3%
Management	0.2%	0.2%
Manufacturing-1	0.7%	0.8%
Manufacturing-2	0.8%	0.8%
Manufacturing-3	1.5%	1.6%
Mining	0.4%	0.3%
Other svc	8.0%	8.2%
Professional service	16.2%	13.2%
Real Estate	4.7%	4.2%
Retail-1	9.9%	11.3%
Retail-2	3.2%	3.4%
Transportation-1	3.1%	2.7%
Transportation-2	0.3%	0.3%
Utilities	0.1%	0.2%
Wholesale	5.2%	5.0%
Observations	191,000	118,000

	Overall Sample	Regression Sample
Census Division	**Percentage**	**Percentage**
East North Central	12.3%	12.3%
East South Central	4.7%	5.0%
Middle Atlantic	16.4%	15.8%
Mountain	7.9%	7.9%
New England	2.1%	1.9%
Pacific	17.5%	17.9%
South Atlantic	22.3%	21.5%
West North Central	4.9%	5.0%
West South Central	12.0%	12.6%
Observations	191,000	118,000

Employment	**Percentage**
1	30.7%
2	21.5%
3	13.1%
4	9.1%
5	5.9%
6	4.4%
7	3.2%
8	2.7%
9	2.0%
10	1.8%
10+	5.5%
Observations	191,000

Panel B. Firm and Worker Characteristics

	Observations	Mean	Standard Deviation
Firm Characteristics			
# of Employees	118,000	4.034	2.215
Wage (in $1000s)	118,000	29.900	50.070
Family Firm	118,000	0.192	0.394
Local Founder	118,000	0.392	0.488
Survive_Year1	118,000	0.877	0.328
Survive_Year2	118,000	0.776	0.417
Survive_Year3	118,000	0.690	0.463
Survive_Year4	118,000	0.590	0.492
Survive_Year5	118,000	0.528	0.499
EmpGrowth_Year1	104,000	0.024	0.518
EmpGrowth_Year2	91,500	0.088	0.627
EmpGrowth_Year3	81,500	0.142	0.691
EmpGrowth_Year4	69,500	0.184	0.721
EmpGrowth_Year5	62,500	0.234	0.756
SalesGrowth_Year1	72,500	0.102	0.573
SalesGrowth_Year2	62,500	0.194	0.678
SalesGrowth_Year3	54,000	0.271	0.745
SalesGrowth_Year4	48,000	0.338	0.808
SalesGrowth_Year5	42,500	0.407	0.831
Worker Characteristics			
Age	118,000	39.730	9.272
Female	118,000	0.439	0.379
White	118,000	0.760	0.357
Black	118,000	0.059	0.187
Asian	118,000	0.125	0.293
Hispanic	118,000	0.138	0.278
Foreign	118,000	0.252	0.370

Table 2: Summary Statistics for Measures of Diversity of Experience

This table reports summary statistics for the indices of experience diversity used in the analysis. DIV_All is one minus the Herfindahl index of the number of quarters workers spent in different 3-digit NAICS industries between 2002 and the founding of the firm. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. HCT weighted versions of the indices are calculated by taking one minus the sum over all industries i of the product of the fraction of quarters spent in industry i and the weighted sum of the fraction of quarters spent in each industry j Weights are a measure of the transferability of human capital between the industries i and j, calculated following the approach in Tate and Yang (2020) and Neffke, Otto, and Weyh (2017). In all cases, industry spells lasting fewer than four quarters are exluded from the calculations.

	Mean	Standard Deviation
Unweighted		
DIV_All	0.466	0.287
DIV_Last	0.220	0.253
DIV_Worker	0.267	0.205
Mobility Weighted		
DIV_All_HCTWeight	0.739	0.315
DIV_Last_HCTWeight	0.489	0.238
DIV_Worker_HCTWeight	0.526	0.248

Table 3: Diversity of Team Industry Experience and Employment Growth

This table reports the results from ordinary least squares regressions of employment growth on measures of the diversity of founding workers' past industry experience. The dependent variable is the cumulative employment growth rate measured 1, 3, or 5 years after founding, as indicated in the column header. DIV_All is one minus the Herfindahl index of the number of quarters workers spent in different 3-digit NAICS industries between 2002 and the founding of the firm. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_AllButLast is one minus the Herfindahl index of the complementary set of job spells. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Div (X) is one minus the Herfindahl index of characteristic X among the startups' initial workers. All specifications include state by industry (3-digit NAICS) fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

	Year 1	Year 3	Year 5	Year 1	Year 3	Year 5	Year 1	Year 3	Year 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(9)
DIV_All	0.0240***	0.0662***	0.107***						
	(0.007)	(0.012)	(0.014)						
DIV_Last				0.0757***	0.104***	0.149***	0.0769***	0.105***	0.147***
				(0.008)	(0.014)	(0.017)	(0.008)	(0.014)	(0.016)
DIV_AllButLast				0.00134	0.0338***	0.0409***			
				(0.007)	(0.010)	(0.013)			
DIV_Worker							-0.0089	0.0463***	0.0661***
							(0.009)	(0.013)	(0.016)
Same Ind	0.001	-0.009	-0.010	0.0122***	0.00294	0.00465	0.0117***	0.00533	0.00793
	(0.004)	(0.006)	(0.008)	(0.004)	(0.007)	(0.008)	(0.004)	(0.007)	(0.008)
Ln(Avg. Wage)	0.00370*	0.0165***	0.0200***	0.00471**	0.0178***	0.0219***	0.00482**	0.0174***	0.0213***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Ln(Avg. Age)	-0.108***	-0.252***	-0.360***	-0.107***	-0.253***	-0.366***	-0.108***	-0.251***	-0.361***
	(0.008)	(0.012)	(0.015)	(0.008)	(0.012)	(0.015)	(0.008)	(0.012)	(0.015)
Ln(Avg. Education)	-0.0000757	0.00799**	0.0137***	-0.00024	0.00770**	0.0131***	-0.000291	0.00778**	0.0132***
	(0.002)	(0.003)	(0.005)	-0.00243	-0.00341	-0.00476	-0.00242	-0.00341	-0.00476
Pct(Female)	0.0380***	0.0225**	-0.00347	0.0391***	0.0242**	-0.000289	0.0393***	0.0240**	-0.001
	(0.006)	(0.010)	(0.013)	(0.006)	(0.010)	(0.013)	(0.006)	(0.010)	(0.013)
Pct(White)	0.0173	0.00883	0.0124	0.0168	0.00861	0.0124	0.0168	0.00859	0.0122
	(0.012)	(0.015)	(0.023)	(0.012)	(0.015)	(0.023)	(0.012)	(0.015)	(0.023)
Pct(Black)	0.0073	-0.0349	-0.00453	0.00626	-0.0355	-0.00374	0.00659	-0.0361	-0.00547
	(0.016)	(0.023)	(0.033)	(0.016)	(0.023)	(0.033)	(0.016)	(0.023)	(0.033)
Pct(Asian)	0.0233*	0.00307	-0.0143	0.0223*	0.00174	-0.0161	0.0220*	0.00261	-0.0153
	(0.013)	(0.018)	(0.027)	(0.013)	(0.018)	(0.027)	(0.013)	(0.018)	(0.027)
Pct(Hispanic)	0.0211***	0.013	0.0182	0.0208***	0.0125	0.0171	0.0207***	0.0129	0.0176
	(0.008)	(0.012)	(0.015)	(0.008)	(0.012)	(0.015)	(0.008)	(0.012)	(0.015)
Pct(Foreign)	-0.0258***	-0.0330***	-0.0289**	-0.0264***	-0.0348***	-0.0322**	-0.0269***	-0.0335***	-0.0303**
	(0.008)	(0.011)	(0.015)	(0.008)	(0.011)	(0.014)	(0.008)	(0.011)	(0.015)
Div (Wage)	0.0284***	0.0347***	0.0411***	0.0248***	0.0305***	0.0355***	0.0247***	0.0309***	0.0360***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)	(0.002)	(0.004)	(0.005)
Div (Age)	0.0899***	0.0706***	0.0508***	0.0920***	0.0737***	0.0556***	0.0920***	0.0737***	0.0556***
	(0.008)	(0.013)	(0.017)	(0.008)	(0.013)	(0.017)	(0.008)	(0.013)	(0.017)
Div (Education)	0.136***	0.133***	0.119***	0.136***	0.132***	0.117***	0.136***	0.133***	0.119***
	(0.009)	(0.013)	(0.016)	(0.009)	(0.013)	(0.016)	(0.009)	(0.013)	(0.016)
Div (Race)	0.0644***	0.0612***	0.0656***	0.0637***	0.0606***	0.0650***	0.0637***	0.0607***	0.0653***
	(0.010)	(0.016)	(0.019)	(0.010)	(0.016)	(0.019)	(0.010)	(0.016)	(0.019)
Div (Region Of Birth)	0.0311***	0.0702***	0.0631***	0.0318***	0.0723***	0.0662***	0.0320***	0.0713***	0.0648***
	(0.009)	(0.014)	(0.017)	(0.009)	(0.014)	(0.017)	(0.009)	(0.014)	(0.017)
Observations	104000	81500	62500	104000	81500	62500	104000	81500	62500
Adj. R-Squared	0.155	0.137	0.137	0.156	0.137	0.137	0.156	0.137	0.137

Table 4: Diversity of Team Industry Experience and Outlier Employment Growth

This table reports the results from ordinary least squares regressions of employment growth on measures of the diversity of founding workers' past industry experience. The dependent variable is an indicator variable that equals 1 if the cumulative employment growth rate measured 1, 3, or 5 years after founding, as indicated in the column header, lies in the top 10% of the distribution among startups in the same 3-digit NAICS industry. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Standard controls are the full set of controls from Table 3. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

	Year 1 (1)	Year 3 (2)	Year 5 (3)
DIV_Last	0.0578***	0.0738***	0.0886***
	(0.006)	(0.007)	(0.007)
DIV_Worker	-0.00702**	0.0074	0.00313
	(0.003)	(0.005)	(0.006)
Standard Controls	Yes	Yes	Yes
Observations	104000	81500	62500
Adj. R-Squared	0.275	0.177	0.138

Table 5: Diversity of Team Industry Experience and Sales Growth

This table reports the results from ordinary least squares regressions of sales growth on measures of the diversity of founding workers' past industry experience. The dependent variable is the cumulative growth rate measured in year 1, 3, or 5, as indicated in the column header. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Div (X) is one minus the Herfindahl index of characteristic X among the startups' initial workers. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

	Year 1	Year 3	Year 5
	(1)	(2)	(3)
DIV_Last	0.0444***	0.101***	0.162***
	(0.012)	(0.018)	(0.021)
DIV_Worker	-0.0191*	0.0329*	0.0557**
	(0.011)	(0.018)	(0.022)
Same Ind	0.002	-0.008	-0.004
	(0.006)	(0.009)	(0.011)
Ln(Avg. Wage)	0.0108***	0.0150***	0.0178***
	(0.003)	(0.005)	(0.005)
Ln(Avg. Age)	-0.100***	-0.260***	-0.423***
	(0.010)	(0.019)	(0.022)
Ln(Avg. Edu)	0.00677**	0.0131***	0.0248***
	(0.003)	(0.005)	(0.006)
Pct(Female)	-0.0188**	-0.0503***	-0.0871***
	(0.008)	(0.014)	(0.019)
Pct(White)	0.0126	0.0287	0.00447
	(0.017)	(0.026)	(0.031)
Pct(Black)	-0.0203	-0.0326	-0.0562
	(0.023)	(0.034)	(0.043)
Pct(Asian)	0.0306	0.0416	0.00626
	(0.020)	(0.029)	(0.035)
Pct(Hispanic)	-0.00135	-0.00177	-0.000864
	(0.012)	(0.017)	(0.023)
Pct(Foreign)	0.00307	0.00726	0.0252
	(0.010)	(0.014)	(0.019)
Div (Wage)	0.0145***	0.0236***	0.0134*
	(0.004)	(0.006)	(0.007)
Div (Age)	0.0131	0.009	0.00669
	(0.013)	(0.020)	(0.024)
Div (Edu)	0.0236**	-0.0156	-0.0128
	(0.011)	(0.018)	(0.022)
Div (Race)	0.0490***	0.0508**	0.0542**
	(0.013)	(0.022)	(0.026)
Div (POB)	0.00967	0.0249	0.00477
	(0.015)	(0.021)	(0.026)
Observations	72500	54000	42500
Adj. R-Squared	0.0266	0.0372	0.0584

Table 6: Diversity of Team Industry Experience and Survival

This table reports the results from ordinary least squares regressions of firm survival on measures of the diversity of founding workers' past industry experience. The dependent variable is an indicator variable that equals one if the firm suvived to the end of year 1, 3, or 5, as indicated in the column header. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Div (X) is one minus the Herfindahl index of characteristic X among the startups' initial workers. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Panel A. Team and Worker Diversity of Experience

	Year 1	Year 3	Year 5
	(1)	(2)	(3)
DIV_Last	0.0148**	-0.0222**	-0.0560***
	(0.006)	(0.009)	(0.012)
DIV_Worker	-0.0391***	-0.0748***	-0.0802***
	(0.007)	(0.009)	(0.014)
Same Ind	0.0285***	0.0514***	0.0527***
	(0.006)	(0.011)	(0.010)
Ln(Avg. Wage)	-0.000615	0.00667**	0.00881**
	(0.002)	(0.003)	(0.003)
Ln(Avg. Age)	0.0177*	0.0240**	0.0387***
	(0.010)	(0.012)	(0.014)
Ln(Avg. Edu)	0.00428*	0.00397*	0.00466**
	(0.002)	(0.002)	(0.002)
Pct(Female)	0.0228***	0.0269**	0.0261
	(0.006)	(0.013)	(0.016)
Pct(White)	0.00589	0.0166*	0.0103
	(0.008)	(0.009)	(0.010)
Pct(Black)	-0.0288**	-0.0673***	-0.0897***
	(0.014)	(0.016)	(0.018)
Pct(Asian)	0.0117	0.0179**	-0.00189
	(0.009)	(0.008)	(0.013)
Pct(Hispanic)	-0.0106**	-0.00789**	-0.0106
	(0.004)	(0.004)	(0.009)
Pct(Foreign)	0.0135**	0.0168	0.00481
	(0.006)	(0.012)	(0.013)
Div (Wage)	0.00687***	0.00760***	0.0113***
	(0.001)	(0.002)	(0.002)
Div (Age)	0.00534	0.00573	0.00343
	(0.004)	(0.007)	(0.009)
Div (Edu)	0.0727***	0.0895***	0.0780***
	(0.007)	(0.008)	(0.006)
Div (Race)	0.00411	-0.00441	-0.00994
	(0.007)	(0.011)	(0.016)
Div (POB)	0.00233	0.00377	0.0155
	(0.006)	(0.009)	(0.010)
Observations	118000	118000	118000
Adj. R-Squared	0.0338	0.0407	0.0457

Panel B. Interaction between Worker and Team Diversity

	Year 1	Year 3	Year 5
	(1)	(2)	(3)
DIV_Last	0.0293***	0.0104	-0.0211
	(0.008)	(0.015)	(0.015)
DIV_Worker	-0.0326***	-0.0601***	-0.0644***
	(0.007)	(0.008)	(0.013)
DIV_Last * DIV_Worker	-0.0471**	-0.106***	-0.114***
	(0.019)	(0.030)	(0.029)
Standard Controls	Yes	Yes	Yes
Observations	118000	118000	118000
Adj. R-Squared	0.0338	0.0408	0.0458

Table 7: Diversity and Firm Growth - Innovative Entrepreneruship vs. Small Businesses

This table reports the results from ordinary least squares regressions of firm growth on measures of the diversity of founding workers' past industry experience and several indicators of entrepreneurial industries. In Panel A, we consider three measures of industry-level innovation, indicated in the column headers. BDS_HT is an indicator of high-tech industries from Goldschlag and Miranda (2020). HCI is an indicator of a higher than expected flow of research-trained new graduates into the industry. D_R&D is an indicator variable that equals 1 if the average ratio of R&D spending in the industry (defined as R&D spending over sales in the 3-digit NAICS industry) is in the top quartile and zero otherwise. In Panel B, we distinguish between industries that employ more and fewer high wage workers. D_HighWage is an indicator equal to 1 if more than 75% of the workers in the industry have salaries in the top quartile across all firms in the LEHD sample and zero otherwise. In both panels, the dependent variable is the cumulative employment growth rate measured in year 3 in odd numbered columns and sales growth rate in even numbered columns, as indicated in the column headers. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Standard controls are the full set of controls from Table 3. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Panel A. Innovative Industries

	BDS_HT		**HCI**		**D_R&D**	
	Emp	Sales	Emp	Sales	Emp	Sales
	(1)	(2)	(3)	(4)	(5)	(6)
DIV_Last	0.0811***	0.0945***	0.0795***	0.0970***	0.0605***	0.0885***
	(0.014)	(0.019)	(0.017)	(0.020)	(0.015)	(0.019)
DIV_Worker	0.0541***	0.0262	0.0525***	0.0366*	0.0543***	0.0211
	(0.013)	(0.019)	(0.015)	(0.020)	(0.014)	(0.019)
DIV_Last x D_Innovation	0.212***	0.196**	0.150***	0.0212	0.312***	0.167**
	(0.052)	(0.088)	(0.028)	(0.038)	(0.038)	(0.065)
DIV_Worker x D_Innovation	-0.183***	-0.0527	-0.0376	-0.0194	-0.0823*	0.0246
	(0.066)	(0.098)	(0.034)	(0.042)	(0.048)	(0.061)
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81500	54000	81500	54000	81500	54000
Adj. R-Squared	0.153	0.054	0.138	0.0372	0.154	0.054

Panel B. High Wage Industries

	Emp	Sales
	(1)	(2)
DIV_Last	0.0227	0.0465**
	(0.016)	(0.020)
DIV_Worker	0.0424***	0.0222
	(0.015)	(0.020)
DIV_Last x D_HighWage	0.361***	0.230***
	(0.034)	(0.049)
DIV_Worker x D_HighWage	0.00479	0.0363
	(0.039)	(0.053)
Standard Controls	Yes	Yes
Observations	81500	54000
Adj. R-Squared	0.140	0.038

Table 8: Diversity and Firm Growth - Industry Uncertainty

This table reports the results from ordinary least squares regressions of firm growth on measures of the diversity of founding workers' past industry experience, allowing for difference across industries by the volatility of sales. The dependent variable is the cumulative employment growth rate measured in year 3 in Column 1 and sales growth rate in Column 2. D_Volatile is an indicator variable that equals 1 for industries in which the persistence of industry sales (measured by an AR(1) process over the prior 10 years) is in the bottom quartile and zero otherwise. Industries are defined by 3-digit NAICS codes. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Standard controls are the full set of controls from Table 3. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

	Emp (1)	Sales (2)
DIV_Last	0.0476***	0.0650***
	(0.017)	(0.023)
DIV_Worker	0.0564***	0.0167
	(0.017)	(0.023)
DIV_Last x D_Volatile	0.140***	0.0850***
	(0.023)	(0.028)
DIV_Worker x D_Volatile	-0.0264	0.0375
	(0.027)	(0.035)
Standard Controls	Yes	Yes
Observations	81500	54000
Adj. R-Squared	0.138	0.037

Table 9: Diversity and Firm Growth - All Years

This table reports the results from ordinary least squares regressions of firm growth on measures of the diversity of founding workers' past industry experience for the full set of firms that start between 2006 and 2010. The dependent variable is the cumulative employment growth rate measured in year 3 in Column 1 and sales growth rate in Column 2. D_Recession is an indicator variable that equals 1 for firms that start in 2008 or 2009. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Standard controls are the full set of controls from Table 3. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. We also incude year fixed effects. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

	Emp (1)	Sales (2)
DIV_Last	0.0770***	0.115***
	(0.008)	(0.011)
DIV_Worker	0.0177**	0.0101
	(0.008)	(0.010)
DIV_Last x D_Recession	0.0460***	0.0677***
	(0.009)	(0.013)
DIV_Worker x D_Recession	0.0311***	0.0446***
	(0.010)	(0.016)
Standard Controls	Yes	Yes
Observations	471000	301000
Adj. R-Squared	0.146	0.059

Table 10: Diversity and Firm Growth - Local Founders

This table reports the results from ordinary least squares regressions of firm growth on measures of the diversity of founding workers' past industry experience, allowing for separate effects among "local" and "nonlocal" firms. The dependent variable is the cumulative employment growth rate measured in year 3 in Column 1 and sales growth rate in Column 2. Local Founder is an indicator variable that equals 1 if the highest paid initial emplyee of the startup resided in the county in which the startup operates at the time of the 2000 Decennial Census. Industries are defined by 3-digit NAICS codes. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Standard controls are the full set of controls from Table 3. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

	Emp	Sales
	(1)	(2)
DIV_Last x (Local Founder=1)	0.0703 ***	0.0903 ***
	(0.022)	(0.027)
DIV_Last x (Local Founder=0)	0.121 ***	0.107 ***
	(0.018)	(0.024)
DIV_Worker x (Local Founder=1)	0.0409 **	0.0167
	(0.019)	(0.027)
DIV_Worker x (Local Founder=0)	0.0475 ***	0.0386 *
	(0.018)	(0.023)
Standard Controls	Yes	Yes
Standard Controls * Local Founder	Yes	Yes
Observations	81500	54000
Adj. R-Squared	0.141	0.0414

Table 11: Diversity and Firm Growth - Family Firms

This table reports the results from ordinary least squares regressions of firm growth on measures of the diversity of founding workers' past industry experience, allowing for differences among family firms. The dependent variable is the cumulative employment growth rate measured in year 3 in odd numbered columns and sales growth rate in even numbered columns. Famly Firm is an indicator variable equal to one if the firm has at least two founding team members that resided in the same household as of the 2000 or 2010 Decennial Census. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. Standard controls are the full set of controls from Table 3. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

	Emp (1)	Sales (2)	Emp (3)	Sales (4)
DIV_Last	0.104***	0.100***	0.119***	0.105***
	(0.014)	(0.018)	(0.015)	(0.021)
DIV_Worker	0.0436***	0.0267	0.0460***	0.0247
	(0.013)	(0.017)	(0.015)	(0.019)
Family Firm	-0.0280***	-0.0553***	-0.00842	-0.0527***
	(0.006)	(0.008)	(0.009)	(0.011)
Family Firm x DIV_Last			-0.0778***	-0.0221
			(0.023)	(0.035)
Family Firm x DIV_Worker			-0.0108	0.00937
			(0.028)	(0.038)
Standard Controls	Yes	Yes	Yes	Yes
Observations	81500	54000	81500	54000
Adj. R-Squared	0.138	0.0381	0.138	0.0381

Table 12: Diversity of Industry Experience and Employment Growth - IV Estimates

This table reports the results from IV regressions of employment growth on measures of the diversity of founding workers' past industry experience. We restrict the sample to counties in which there is at least one active mine located within 50 miles of the county center as of 1990. The dependent variable is the cumulative employment growth rate measured 3 years after founding. The endogenous variable is DIV_All in Panel A and DIV_Worker in Panel B. DIV_All is one minus the Herfindahl index of the number of quarters workers spent in different 3-digit NAICS industries between 2002 and the founding of the firm. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. We use two instruments. Num. Mines is the number of mines within 50 miles of the county center. Pct(Div. Firms) is the percentage of firms in the county that operate in multiple 3-digit NAICS industries in 2005. Div (X) is one minus the Herfindahl index of characteristic X among the startups' initial workers. Chg.(Emp) (Chg.(Pay)) is the log difference in aggregate employment (payrolls) in the county between 2002 and 2005. Population is the total poluation in the county as of 2010. All specifications include state by industry (3-digit NAICS) fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

	Panel A. DIV_All		**Panel B. DIV_Worker**	
	First Stage	Second Stage	First Stage	Second Stage
	(1)	(2)	(3)	(4)
DIV_All		1.115**		
		(0.493)		
DIV_Worker				1.089**
				(0.468)
Ln(Num. Mines)	-0.00220*		-0.00238***	
	(0.001)		(0.001)	
Pct(Div. Firms)	2.730***		2.772***	
	(0.556)		(0.459)	
Same Ind	-0.190***	0.200**	-0.0796***	0.0743*
	(0.006)	(0.095)	(0.004)	(0.039)
Ln(Avg. Wage)	-0.00420**	0.0200***	0.00937***	0.00512
	(0.002)	(0.006)	(0.001)	(0.007)
Ln(Avg. Age)	-0.198***	-0.0635	-0.143***	-0.129*
	(0.009)	(0.102)	(0.007)	(0.071)
Ln(Avg. Edu)	-0.00600**	0.0195***	-0.00665***	0.0200***
	(0.003)	(0.007)	(0.002)	(0.007)
Pct(Female)	0.0105**	-0.00624	0.0108***	-0.00624
	(0.005)	(0.019)	(0.004)	(0.018)
Pct(White)	0.0141	0.0113	0.0112	0.0148
	(0.009)	(0.027)	(0.008)	(0.027)
Pct(Black)	0.0585***	-0.107**	0.0412***	-0.0863**
	(0.013)	(0.044)	(0.011)	(0.040)
Pct(Asian)	-0.0152	0.0597*	-0.016	0.0602*
	(0.011)	(0.032)	(0.011)	(0.032)
Pct(Hispanic)	0.00244	0.0147	-0.00062	0.0181
	(0.008)	(0.023)	(0.007)	(0.023)
Pct(Foreign)	-0.0419***	0.000124	-0.0355***	-0.00792
	(0.009)	(0.028)	(0.007)	(0.025)
Div (Wage)	0.0296***	0.0111	-0.00608***	0.0507***
	(0.002)	(0.016)	(0.002)	(0.007)
Div (Age)	0.0063	0.0630***	0.00627	0.0632***
	(0.007)	(0.022)	(0.006)	(0.022)
Div (Edu)	-0.00913	0.144***	-0.0174***	0.153***
	(0.008)	(0.022)	(0.007)	(0.023)
Div (Race)	0.0142*	0.0401	0.00541	0.0501**
	(0.008)	(0.025)	(0.006)	(0.023)
Div (POB)	0.0345***	0.0201	0.0164**	0.0408*
	(0.009)	(0.028)	(0.006)	(0.024)
Chg.(Emp.)	0.0286	0.113	0.00994	0.135
	(0.034)	(0.102)	(0.027)	(0.099)
Chg.(Pay)	-0.0234	-0.127*	-0.00672	-0.146**
	(0.028)	(0.075)	(0.023)	(0.073)
Ln(Population)	-0.00343***	0.0124***	-0.00330***	0.0122***
	(0.001)	(0.004)	(0.001)	(0.004)
Observations	34000	34000	34000	34000
Adj. R-Squared	0.406	0.039	0.11	0.066
Kleibergen-Paap F-stat	14.73		21.56	
Hansen J p-value	0.762		0.781	

Table 13: Diversity and Firm Growth - Mobility

This table reports the results from ordinary least squares regressions of firm growth on measures of the diversity of founding workers' past industry experience. The dependent variable is the cumulative employment growth rate measured in year 3 in Column 1 of each Panel and sales growth rate in Column 2. DIV_Last is one minus the Hefindahl index of the number of quarters workers spent in different 3-digit industries between 2002 and the founding of the firm, but considering only the most recent job spell for each worker. DIV_Worker is the firm-level average of one minus the Herfindahl indices of each worker's cross-industry experience, measured between 2002 and the founding of the firm. In Panel A, we adjust the DIV_Last measure for common skills between the industries in which founding team members have prior experience and the industry in which the startup operates. DIV_Team_High_HCT (DIV_Team_Low_HCT) follows the construction of DIV_Last on only the set of industries in which founding team members have prior expeirence that have HCT values higher (lower) than the median. HCT is a measure of the transferability of human capital between the industries i and j, calculated following the approach in Tate and Yang (2015) and Neffke, Otto, and Weyh (2017). In Panel B, we adjust for common skills in the industries in which founding team members have prior experience by adjusting for worker mobility between each industry pair. HCT weighted versions of the indices are calculated by taking one minus the sum over all industries i of the product of the fraction of quarters spent in industry i and the weighted sum of the fraction of quarters spent in each industry j. Weights are measured using HCT. In all cases, industry spells lasting fewer than four quarters are exluded from the calculations. Standard controls are the full set of controls from Table 3. All specifications include state by industry fixed effects and fixed effects for the number of initial employees. Standard errors clustered at the industry-state level are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Panel A. Diversity Weighted by HCT to Startup Industry

	Emp	Sales
	(1)	(2)
DIV_Last_High_HCT	0.147***	0.112***
	(0.017)	(0.028)
DIV_Last_Low_HCT	0.0802***	0.0766***
	(0.014)	(0.020)
DIV_Worker	0.0474***	0.0349**
	(0.013)	(0.018)
Standard Controls	Yes	Yes
Observations	81500	54000
Adj. R-Squared	0.138	0.037

Panel B. Diversity Weighted by HCT Among Experience Industry Pairs

	Emp	Sales
	(1)	(2)
DIV_Last_HCTWeight	0.0524***	0.0589***
	(0.009)	(0.013)
DIV_Worker_HCTWeight	0.0331***	0.0205
	(0.011)	(0.015)
Standard Controls	Yes	Yes
Observations	81500	54000
Adj. R-Squared	0.137	0.037