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Research Experience as Human Capital in New Business Outcomes

Nathan Goldschlag, Ron Jarmin, Julia Lane, and Nikolas Zolas

6.1 Introduction

Start-ups and entrepreneurial firms contribute disproportionately to job creation and productivity growth (Decker et al. 2014; Acemoglu et al. 2018). The workforce composition of young firms plays an equally important role in shaping dispersion in start-up outcomes (Audretsch, Keilbach, and Lehmann 2006; McGuirk, Lenihan, and Hart 2015). Human capital, whether acquired through experience (Glaeser, Kerr, and Ponzetto 2010), on-the-job training (Lazear and Shaw 2007; Bender et al. 2016; Bloom et al. 2014), or university-based research experience, is an important determinant

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of growth and survival for young firms. Moreover, this relationship may be particularly salient for innovative, R&D-intensive, and high-tech firms, who increasingly demand a highly trained workforce. This chapter contributes to this literature by developing new measures of workplace experience, particularly within R&D-intensive and high-tech firms. We also make use of an entirely new data source that directly measures research experience. We examine the relationship between those measures and start-up survival, growth, and innovative activities such as patenting and trademarking.

We describe the construction of four new human capital measures derived from two different sources. The first is a direct measure of research experience derived from a new dataset drawn from the human resource files of a set of research-intensive universities. The data capture all payroll transactions for all individuals—including undergraduate students, graduate students, and postdoctoral fellows—employed on funded scientific projects at 22 major universities (Lane et al. 2015). These data are the first to directly measure the human capital developed through project-level investments in university science. The second, third, and fourth measures are indirect in nature. They are drawn from LEHD (Longitudinal Employee-Household Dynamics) and W-2 data and create new worker-level measures of human capital based on whether each worker has worked in R&D labs, high-tech businesses, or universities.

We also describe the construction of two new datasets on start-ups. The first of these is a Startup Firm History File drawn from the Longitudinal Business Database (LBD), supplemented with additional information from the Census Bureau's Business Register. In addition, we create a Startup Worker History File derived from worker-level data on jobs and earnings. These new files provide a national frame of start-ups, their survival, and their growth between the years 2005 and 2015, as well as a national frame of all workers affiliated with these start-ups.

Our results suggest that a one-worker increase in the number of high-human-capital employees in a start-up firm's workforce is associated with a lower probability of survival to the next period by 0.74 to 4.8 percentage points, depending on the experience type. However, for start-ups that do survive to the first period, the hiring of one of these workers in the founding year is associated with a 1.3 to 4 percentage point increase in employment growth and a 2.2 to 5 percentage point increase in revenue in the following year. This is suggestive evidence that high-human-capital employees elect to go to more high-risk start-ups that exhibit "up or out" dynamics—either exiting or growing quickly. On the innovation side, the addition of one high-human-capital individual is positively related to patent and trademark outcomes in the next period, with patent filings increasing by 0.5 to 9.2 percentage points and trademark filings increasing by 1.5 to 7.5 percentage points in the following year. Our measures of human capital also explain a significant amount of the variation in innovation outcomes, where the inclusion of our basic measures of human capital help explain an additional 40 percent of variation in patenting outcomes and 11 percent of variation in trademarking outcomes.

The direction of causality may be complex in this setting. Start-ups with inherently risky ideas or production technologies may exhibit higher demand for high-human-capital workers. Moreover, there may be several important channels through which high-human-capital workers impact young firms. First, high-human-capital workers may simply represent an important input to the firm's production technology. Alternatively, there may be important interaction effects between high-human-capital workers and the tacit knowledge they bring to the firm. Regardless of the mechanism, the results presented in this chapter are consistent with the view that there is a positive and significant relationship between workforce experience and business start-up outcomes.

6.2 Background

Our focus on start-ups is informed by literature that suggests that young entrepreneurial businesses are important for introducing and diffusing innovations in the economy. Several authors have shown indirect linkages between formal investments in research and innovation and entrepreneurship and economic growth (Bania, Eberts, and Fogarty 1993; Lowe and Gonzalez-Brambila 2007; Hausman 2012). In particular, the work of Akcigit and Kerr (2018) shows that the relative rate of major inventions is higher in small firms and new-entrant firms. Guzman and Stern (2016) note that the early-stage choices of start-ups—their "digital signatures"—are particularly important in predicting their future success.

There is a growing literature linking human capital to the survival and growth of such new businesses (Audretsch, Keilbach, and Lehmann 2006; McGuirk, Lenihan, and Hart 2015). In particular, the decision to start a business and its subsequent productivity and success are associated with having an entrepreneurial workforce (Glaeser, Kerr, and Ponzetto 2010; Syverson 2010). Related work also suggests that highly innovative individuals make "exceptional" contributions to economic growth (Kerr et al. 2016). Indeed, the personnel economics and management literatures draw on extensive studies of businesses and human resource practices, which suggest that many productive businesses either invest in job-based training or seek to hire well-trained individuals (Lazear and Shaw 2007; Bender et al. 2016; Bloom et al. 2014). A related literature links external R&D investment and the success of the R&D efforts of individual firms (Tambe 2014). In-depth studies of the components of intangible assets in contributing to firm productivity and success invariably mention the importance of training (Corrado, Hulten, and Sichel 2005). In addition to affecting innovative outcomes, human capital measures such as on-the-job training have also been linked to firm productivity (Black and Lynch 1996; Bartel et al. 2014).

For our purposes of measuring the relationship between human capital and start-up outcomes, we draw on two sets of literature. The first has studied human capital acquisition through learning by doing and experience. The second addresses the transmission of new knowledge through the flows of individuals from one business to another.

The role of experience in terms of learning how to perform complex new tasks through trial and error has been extensively discussed in the endogenous technical change literature (Romer 1990). There is also a great deal of evidence to support the notion that past experience imparts valuable business skills (Lafontaine and Shaw 2016) and that firm growth can be significantly affected by workers with experience in R&D activities (Jones 2002; Acemoglu et al. 2013).

The role of university research training specifically on innovative activity and business start-ups is supported by compelling anecdotal evidence. This includes linking the growth of Silicon Valley to the presence of Stanford, the success of Boston to the excellent set of universities in the area, and the arising of the Research Triangle to the research activity of Duke University, the University of North Carolina, and North Carolina State. An extensive literature ties regional economic development clusters to the presence of active research universities, suggesting that research-trained individuals flow into innovative new businesses (Hausman 2012; Glaeser, Kerr, and Ponzetto 2010; Kantor and Whalley 2013, 2014). To this end, Corrado and Lane note that the data needed to determine the economic and social value created by innovation in organizations should include "detailed data on workers—their skills, their responsibilities, and their knowledge—including their flows across companies were desired for transformative research on the combined process of entrepreneurship and innovation" (Corrado and Lane 2009).

Taken together, these various literatures are consistent with the notion that hiring workers with experience is a way firms gain tacit knowledge, particularly when ideas are complex (Duranton and Puga 2004; Gertler 2003). The work of Lee Fleming and coauthors, for example, suggests that if there are impediments to research-experienced workers moving from one firm to another, less innovation occurs (Fleming, King, and Juda 2007; Marx, Singh, and Fleming 2015). Our own work suggests that research-trained workers are more likely to work at firms with characteristics closely linked to productivity (Zolas et al. 2015).

However, there has been little work done in terms of measuring the experience of workers at different types of firms. The Annual Survey of Manufactures provides counts of production and nonproduction workers; most other business data sources simply provide counts of employees. In principle, a particularly useful source of evidence in this context is economy-wide linked employer-employee data, such as the LEHD data (Abowd, Haltiwanger, and Lane 2004). Abowd, Haltiwanger, and Lane (2005) have used linked data to compute person-specific measures of human capital but do not directly compute measures of research experience. While some work has shown that there are returns to experience at R&D-performing firms (Barth, Davis, and Freeman 2016), there has been no study to our knowledge that directly measures experience in high-tech firms, R&D labs, universities, or scientific projects and ties it to start-up outcomes. In this chapter, we analyze the link between these types of experience and among workers at start-ups and the outcomes of those start-ups, including survival, growth, and innovative activity.

6.3 Framework, Data, and Measurement

We follow much of the literature (Lazear and Shaw 2007; Bender et al. 2016; Bloom et al. 2014) in adopting a simple reduced-form framework to examine outcomes for start-ups in terms of their survival, employment and revenue growth, and innovative activities, such as being granted patents and registering trademarks. Conceptually, outcomes (Y) for start-up firm f at time t are driven by the quantity and quality of human capital (HK) it employs as well as standard controls such as capital (K), technology (A), and external factors (X) such as macroeconomic conditions and industry factors:

$$Y_{ft} = F(A_{ft}, K_{ft}, HK_{ft}, X_{ft}). \tag{1}$$

There is some evidence that the effect of human capital will be important for businesses whose production processes involve performing complex tasks (Ichniowski, Shaw, and Prennushi 1997). As a result, the analysis that follows provides separate analyses for high-tech businesses; the scale of the data permits such detailed analyses. The rest of this section describes how such businesses are identified, how the human capital measures are constructed, and how start-up outcomes are measured.

6.3.1 Identifying and Classifying Start-Ups

The Startup History file is constructed as an unbalanced panel dataset. The primary frame for the data is the LBD, supplemented with additional information from the Census Bureau's Business Register, upon which the LBD is based. We utilize this file to identify start-ups as age-zero firms. Once the start-ups have been identified, we supplement the data with geocodes (state- and county-level FIPS, along with Census Tract information if available) and Employer Identification Numbers (EINs) taken from the Business Register. These variables are used to subsequently characterize the workforce associated with each start-up gathered from both LEHD and W-2 records. The full file contains data on employment, payroll, industry, geography, firm type, and birth/death of the firm.

For the purpose of characterizing worker experience, firms are classified as R&D labs, high-tech, or universities. The R&D lab measure is created by identifying R&D laboratories within R&D-performing firms. First, we identify R&D-performing firms using the Business R&D and Innovation Survey (BRDIS) and the Survey of Industrial Research and Development (SIRD).[1] A firm is classified as an R&D-performing firm if it has positive R&D expenditures during the year the employee was affiliated with the firm. R&D laboratories are identified by establishment-level industry codes, specifically North American Industry Classification System (NAICS) 5417, which is defined as "Scientific Research and Development Services." The high-tech definition is based on the relative concentration of science, technology, engineering, and math (STEM) employment by industry as in Hecker (2005) and Goldschlag and Miranda (2020). We use the high-tech classification to both subset the universe of start-ups within a year and to characterize worker experience, identifying individuals with prior experience in high-tech industries. The university measure is derived from Integrated Postsecondary Education Data System (IPEDS) and Carnegie Institute data, which provide a frame of universities in the United States. We use the national university research outlays collected by the National Center for Science and Engineering Statistics at the National Science Foundation to subset our sample of universities to the top 130 research universities, which account for 90 percent of total federally funded university-based R&D expenditures.

While capital, financing, management, and macroeconomic conditions are not directly measured in the data, because the data are longitudinal, we can include firm and time/industry/geography fixed effects.

6.3.2 Human Capital Measures

The first three human capital measures are derived from a new dataset called the Startup Worker History File, which characterizes the workforce associated with each start-up in its first year. It is created from the universe worker-level data on jobs derived from administrative records in both the LEHD and W-2 records and covers the period 2005–15.

The frame covers each paid job for each worker from 2005 to 2015 as reported at both the EIN level via Internal Revenue Service (IRS) form W-2 and state-level unemployment insurance wage records. The latter underlie the core LEHD infrastructure (Abowd, Haltiwanger, and Lane 2004) used to generate the Quarterly Workforce Indicators (QWI) and are necessary to identify the establishment for the bulk of multiunit firms (Abowd et al. 2009). The combined data includes more than 3 billion person-EIN-year observations (approximately 70 percent match across the W-2 and LEHD universes, 20 percent are found only in the W-2 records, and 10 percent are only found in LEHD). These data are enhanced with the LEHD Individual Characteristics File (ICF), which includes demographic data on

1. We use the SIRD to identify R&D firms between 2005 and 2007 and BRDIS for 2008–14. Firms with positive expenditure in R&D in a given year are classified as R&D performing.

persons, including sex, age, race, and place of birth. We are able to link 43 million of the 3 billion person-EIN-year observations to start-ups in their birth year, giving us an average of nearly 4.5 million person-start-up observations each year.[2]

The first three measures of human capital are indirect in nature, since they do not directly measure research experience. They are derived from an individual's work history in the years prior to being employed at a given start-up in its first year and capture employment experience in R&D labs, high-tech businesses, and universities. In the case of R&D labs, we include all workers employed in an R&D-performing firm in an R&D lab (2007 NAICS code 5417). We classify workers as having high-tech experience if they have worked in a high-tech industry and their earnings in those positions fall within the top half of the earnings distribution within that industry for a given year. This earnings condition minimizes the likelihood of classifying workers in support or administrative roles as having high-tech experience. We use a similar approach to classify workers with experience at national research universities.

The fourth, more direct measure is derived from UMETRICS data (Lane et al. 2015), which include, at the time of writing, 22 universities accounting for about 26 percent of all federally funded research.[3] The data are derived from universe personnel and financial records of participating universities. Although four files are provided by each university, the key file of interest in this project is the employee file. These individuals will compose a subset of the university experienced workers described previously. For each funded research project, both federal and nonfederal, the file contains all payroll charges for all pay periods (identified by period start date and period end date). This includes links to both the federal award ID (unique award number) and the internal university identification number (recipient account number). In addition to first name, last name, and date of birth, the data include the employee's internal deidentified employee number and the job title (which we map into broad occupational categories). The Catalog of Federal Domestic Assistance (CFDA), which is included in each award identifier, allows us to classify projects by the funding agency. The years covered by each university's data vary, as each university provided data as far back as their record keeping allowed.

6.3.3 The Start-Up Worker History File

The start-up worker history file, from which our human capital measures are derived, is constructed in three steps. The first step involves identifying

2. This figure differs from the reported Business Dynamics Statistics (BDS), which calculate employment at start-ups at a specific point in time (March 12). Our figures are higher, reflecting employee-employer transitions (i.e., workers who work briefly for a start-up and then move to a different job). The 48 million observations represent 37.8 million unique individuals.

3. UMETRICS stands for Universities: Measuring the Impacts of Research on Innovation, Competitiveness and Science.

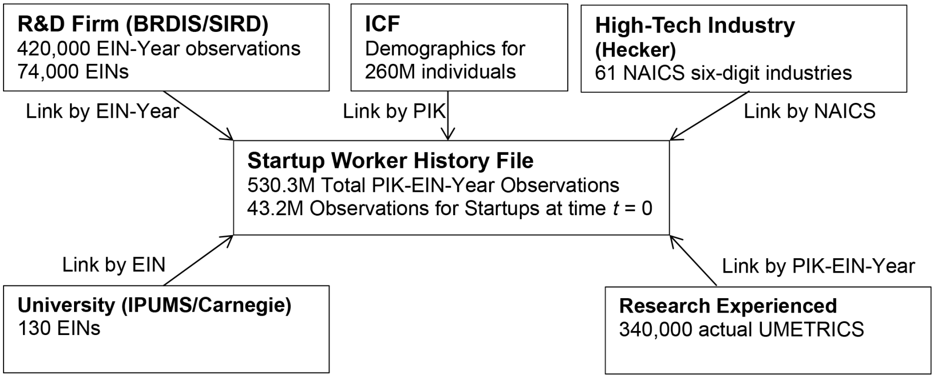

Fig. 6.1 Start-up worker history file

person and firm characteristics in the years prior to start-up. The LEHD and W-2 data provide worker histories for 260 million individuals for each employer (at the EIN level) for each year in the period 2005–15. Their individual characteristics are captured by matching to the ICF, which provides information on date of birth, foreign-born status, and sex.

The EIN of their employers is then matched to the BRDIS/SIRD data to determine whether the employer is an R&D-performing firm. There are 74,000 of those EINs and 420,000 resulting EIN-year observations. A subset of these records will be associated with the R&D lab NAICS industry. The EIN is also matched to firms in 61 six-digit high-tech industries. Employment on a grant is determined by a match to UMETRICS data; there are 340,000 research-experienced individuals between 2005 and 2015.

Start-ups are identified as firms of age zero. The total worker history file thus has 530.3 million protected identification key (PIK)-EIN-year start-up observations. Of those, 43.2 million observations are associated with start-ups in year zero.

Figure 6.1 provides a graphical illustration of the process.

The second step involves measuring human capital at the start-up level. There are 4.9 million EINs associated with age-zero firms in the data, of which about 35,000 have hired individuals with work experience in R&D-performing labs—the number of such employees totals 67,000. About 371,000 EINs have hired at least one individual with high-tech experience—the number of these employees totals 806,000. About 442,000 EINs have hired at least one university-experienced employee; the number of these totals 882,000. There are about 11,000 start-ups that have hired a total of 13,000 individuals with research experience at the UMETRICS universities. The process is described graphically in figure 6.2.

The third and final step involves merging the start-up EIN file with the

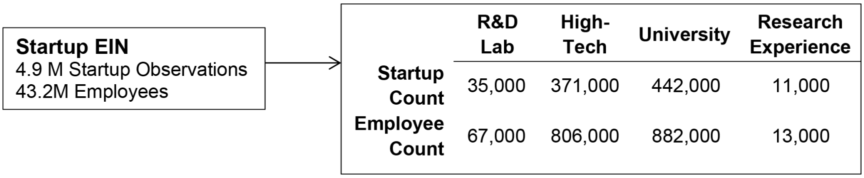

Fig. 6.2 Creating start-up file

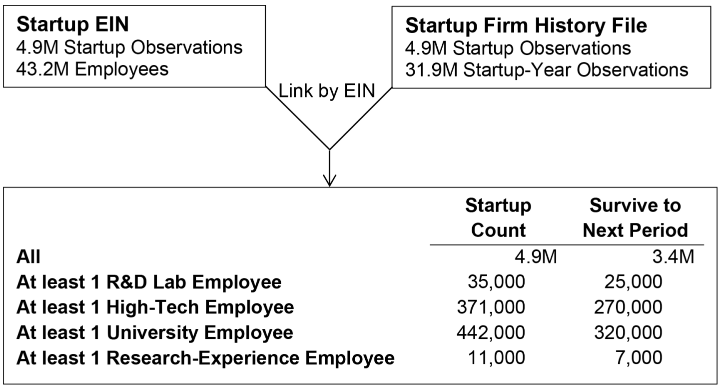

Fig. 6.3 Start-up history file

Start-Up Firm History File, classifying start-up types and outcomes at time $t = 0$ and calculating how many survive to the year subsequent to their birth. That information is graphically presented in figure 6.3. Of the 4.9 million start-ups we observe, 3.4 million survive to the next period, or about 69 percent. This compares to 71 percent for start-ups with at least one employee with R&D lab experience, 72 percent for high-tech and university experience, and 64 percent for research experience.

6.3.3 Start-Up Outcomes

While a wide variety of outcome measures can be generated, here we focus on survival to period $t + 1$, employment growth between t and $t + 1$, revenue growth between t and $t + 1$, patenting in $t + 1$, and trademarking in $t + 1$.[4] Survival is a binary indicator for start-ups that have positive employment in $t + 1$. Employment growth and revenue growth are calculated as the log difference of employment between t and $t + 1$, which can be interpreted as a percentage change. Patenting and trademarking in $t + 1$ is measured

4. We track outcomes only to $t + 1$ due to limitations on how far back in time each UMETRICS institution's data goes. Outcomes measured further in the future would limit the sample of start-ups and individuals under consideration.

as applying for a patent in $t + 1$ that is eventually granted and filing for a trademark in $t + 1$ that is eventually registered.

Start-ups are linked to patent grants and trademark filings through existing crosswalks between United States Patent and Trademark Office (USPTO) and Census data. Patent linkages are based on a triangulation methodology first described in Graham et al. (2018). Their linkage methodology simultaneously leverages information on both patent inventors and assignees in combination with job-level information from the LEHD to distinguish between true and false matches. By using more information than traditional patent-linkage efforts (e.g., fuzzy business name and geography), the triangulation match produces more and higher-quality linkages. Trademarks are matched to start-ups using the match described in chapter 5 of this volume (Dinlersoz et al.). The business name and address information found in the USPTO's Trademark Case File Database are used to create firm-trademark linkages. To measure innovative outcomes of start-ups, we identify whether a start-up applied for a patent in the year after its birth ($t + 1$) that was eventually granted. Similarly, we identify whether each start-up filed for a trademark in $t + 1$ that was eventually registered.

6.4 Basic Facts

This section establishes some basic facts on the human capital composition of start-ups and their outcomes.

6.4.1 Start-Up Facts

We begin by highlighting some facts regarding start-ups and their outcomes. Between 2005 and 2015, one-year survival rates typically hover around 68 percent but are higher for high-tech start-ups in every year. As is well known, the number of start-ups dropped in 2007 by 25 percent (relative to 2005) and by 33 percent the following year—by 2013, the start-up count was still at the same level. High-tech start-up employment follows a similar pattern: the total number of employees at $t = 0$ declined by more than 30 percent between 2005 and 2014.

It is rare for start-ups to have high-human-capital workers as employees in their first year.[5] Approximately 0.25 percent of employees at start-ups have experience working in an R&D laboratory, around 2.5 percent have experience working at a high-tech firm, and 2 percent have been linked through their earnings with a research university. The proportion of start-ups that have individuals formerly paid on research grants is even smaller, with fewer

5. It is important to keep in mind that the results are left-censored, as the LEHD has somewhat limited coverage prior to 2000.

Table 6.1 **Start-up statistics at year 0**

All start-ups	Mean	Fuzzy median	Standard deviation
Employment	5.6	2.0	16.5
Payroll per employee (thousands)	29.6	17.7	84.0
Revenue (thousands)	540.2	232.5	958.7
Patents	0.02	—	3.1
Trademarks	0.06	—	0.7
High-Tech Start-ups	**Mean**	**Fuzzy median**	**Standard deviation**
Employment	4.0	1.5	14.4
Payroll per employee (thousands)	54.4	39.8	64.8
Revenue (thousands)	428.9	181.2	824.4
Patents	0.11	—	10.2
Trademarks	0.20	—	1.2

Notes: Statistics calculated pooling 2005–15 start-ups in the LBD and tabulating the first-year statistics. Because employment figures are captured at a stationary point in time (March 12), if a firm is shown to have zero employment in their birth year, then the following year's employment is taken as the employment at $t = 0$. Fuzzy medians are calculated by taking the mean of firms between the 45th and 55th percentile levels. Real revenue is in 2009 dollars.

than 0.05 percent of employees being linked to a research grant from one of the 22 UMETRICS universities.

Table 6.1 provides some information about the characteristics of start-ups in their initial year of existence. The vast majority of start-ups, across all start-up types, start off very small in their first year: 75 percent of all start-ups have fewer than 5 employees at time $t = 0$; more than 50 percent of start-ups have 2 or fewer employees. Fewer than 5 percent of start-ups have more than 20 employees in the initial period. While the average revenue for start-ups exceeds half a million dollars per year, this measure is somewhat skewed, as the median start-up generates less than a quarter million dollars in its first year, with the median revenue being even smaller in high-tech firms. While these size characteristics are mostly consistent across firm types, the payroll per employee and innovation measures are quite different. High-tech firms offer the highest mean payroll per employee, paying nearly twice as much as a typical start-up, and have innovation rates (as measured by patents and trademarks) that are three to five times higher than the typical start-up.

The dataset also enables us to describe the human capital composition of the start-up workforce. Table 6.2 documents the employment composition of all start-ups in the left-hand panel and high-tech start-ups in the right-hand panel. Individuals in start-ups that have at least one high-tech-experienced employee are younger, less likely to be female or black, more likely to be foreign born, and more likely to be Asian than other start-ups. Individuals in start-ups that have at least one university- or research-experienced employee

Table 6.2 **Start-up employee mean demographic characteristics at time 0**

	All start-ups Start-ups with at least one worker with experience in:					High-tech Start-ups with at least one worker with experience in:				
	Total	R&D	High-tech	University	Research	**Total**	R&D	High-tech	University	Research
Count	**43.2M**	67,000	806,000	882,000	13,000	**1M**	21,000	416,000	48,000	1,000
Birth year	**1974**	1969	1970	1980	1982	**1971**	1965	1969	1980	1979
Female	**45%**	44%	32%	54%	54%	**30%**	36%	27%	31%	26%
Foreign	**21%**	24%	24%	14%	18%	**25%**	24%	28%	25%	29%
White	**73%**	75%	75%	75%	70%	**74%**	80%	74%	72%	69%
Black	**12%**	7%	7%	12%	8%	**6%**	3%	5%	5%	2%
Hispanic	**16%**	10%	9%	8%	6%	**9%**	13%	8%	7%	4%
Asian	**6%**	13%	13%	8%	13%	**12%**	13%	15%	17%	19%
Other	**7%**	4%	4%	4%	8%	**7%**	2%	5%	5%	8%
duration		4.73	5.29	2.46	1.85		5.93	6.05	2.42	2.20

Source: LBD combined with Individual Characteristics File (ICF)

Notes: Statistics calculated pooling 2005–15 start-ups in the LBD and tabulating the first-year demographic statistics. Figures have been rounded for disclosure purposes. (D) indicates that the number has been suppressed for disclosure. Note that counts in this and subsequent tables are rounded for disclosure limitation reasons.

Table 6.3 **Distribution of start-ups hiring research experienced workers by funding source**

	NIH	NSF	DOD	DOE	Other federal	Nonfederal
Number of start-ups hiring UMETRICS workers	3,500	1,900	700	400	5,400	3,000
Proportion of start-ups in high-tech (%)	7.2	16.8	21.0	17.4	6.4	9.4
Ratio relative to proportion of all start-ups in high-tech (4.4%)	1.64	3.82	4.77	3.95	1.45	2.14

Notes: Statistics calculated pooling 2005–15 start-ups in the LBD and tabulating the funding sources for each of the UMETRICS experienced workers. UMETRICS workers can be funded through multiple agencies and start-ups can hire multiple UMETRICS experienced workers, so that the counts are not mutually exclusive. Figures have been rounded for disclosure purposes. (D) indicates that the number has been suppressed for disclosure.

are even younger but are more likely to be female; research-experienced start-ups are more likely to be Asian and less likely to be black.

The demographic differences are even starker among start-ups in high-tech industries. Overall, employees in these start-ups are less likely to be female, more likely to be foreign born, much less likely to be black, and much more likely to be Asian. These patterns are even stronger for those with university and research experience.

The literature suggests that high levels of human capital should be disproportionately valued by firms with complex production processes (Abowd et al. 2005). That is borne out by our data. Even though high-tech start-ups account for only 4.4 percent of all start-ups in the United States, they account for 17 percent of start-ups hiring at least one R&D-experienced worker, 36 percent of start-ups hiring high-tech workers, 6 percent of start-ups hiring university-experienced workers, and 8 percent of start-ups hiring research-experienced workers.

Of course, the first three human capital measures, while extremely valuable in measuring potential research experience (in the same spirit, but in more detail, than older measures such as employment tenure and labor market experience), include a variety of workers.

The direct measures offered by UMETRICS enable us to tease out the relationships in more detail. Table 6.3 shows the subset of start-ups who hired workers employed on research grants in the 22 UMETRICS universities by funding source. In all cases, start-ups that hired funded researchers were more likely to be high-tech—the ratio is particularly high for those hiring individuals who worked on grants funded by the National Science Foundation, the Department of Defense, and the Department of Energy.

The detail included in the UMETRICS data allows us to similarly char-

Table 6.4 **Distribution of start-ups hiring research-experienced workers by occupation**

	Faculty	Graduate student	Postgraduate	Undergraduate	Other
Number of start-ups	3,500	1,900	700	400	5,400
Proportion of start-ups in high-tech (%)	12.0	15.2	9.8	6.0	8.3
Ratio relative to proportion of all start-ups in high-tech (4.4%)	2.73	3.45	2.23	1.36	1.89

Source: LBD combined with UMETRICS worker file.

Notes: Statistics calculated pooling 2005–15 start-ups in the LBD and tabulating the funding sources for each of the UMETRICS experienced workers. Start-ups can hire multiple UMETRICS experienced workers so that the counts are not mutually exclusive. Figures have been rounded for disclosure purposes. (D) indicates that the number has been suppressed for disclosure.

acterize the propensity to be in high-tech industries by the skill level of researchers, as reported in table 6.4. Start-ups hiring graduate students and faculty are much more likely to be high-tech than other start-ups; the pattern for undergraduate hiring is much more similar to the start-up distribution as a whole.

Finally, the data enable us to drill down into the more detailed industry distribution of start-ups. Table 6.5 shows vast compositional differences in the worker types of high-tech start-ups within narrowly defined industries. More than 85 percent of all high-tech start-ups are in the fields of computer design (NAICS 5415), engineering (NAICS 5413), or R&D laboratories (NAICS 5417). More than half of high-tech start-ups are in computer design. While there is some variation in the shares of each worker type across these industries, more than 80 percent of each of the worker types are affiliated with a start-up in one of those three industries. Although only 5 percent of high-tech start-ups are R&D labs, almost two-thirds of start-ups who hired workers with R&D experience and over one-third of start-ups hiring workers with research experience are R&D labs.

6.4.3 Start-Up Outcomes and Human Capital Composition

This section provides some initial descriptive results about the link between workforce experience and start-up outcomes (survival to period $t + 1$, employment growth to $t + 1$, Revenue growth to $t + 1$, patent in $t + 1$, and trademark in $t + 1$). We start by first exploring the proportion of start-ups that experiences each type of outcome considered.

Figure 6.4 provides some useful initial insights about start-up outcomes. Although, by and large, start-ups that hire workers with R&D, high-tech, and university experience are more likely to survive than those that do not, start-ups that hire UMETRICS-experienced individuals show about the same survival rate as the typical start-up. Moreover, in the analyses

Table 6.5 Industry sector of high-tech start-ups at year 0

Start-up sector	All start-ups Counts	All start-ups Distribution (%)	Start-ups hiring workers with R&D experience (%)	High-tech experience (%)	University experience (%)	Research experience (%)
AERO MANU	700	0.30	0.18	0.36	0.34	(D)
COMM MANU	700	0.30	0.27	0.36	0.34	(D)
COMP DESIGN	128,100	54.28	14.64	53.80	46.21	40.83
COMP MANU	800	0.34	0.27	0.29	0.34	(D)
DATA PROCESS	6,700	2.84	1.00	2.99	4.14	4.17
ENGINEER	61,500	26.06	6.36	28.47	20.69	14.17
INFO SERVICE	8,800	3.73	0.91	1.82	5.86	5.00
INSTRUM MANU	1,800	0.76	0.91	1.02	1.03	1.67
INTERNET	1,300	0.55	0.18	0.58	0.69	(D)
ISP	2,600	1.10	0.18	1.09	0.69	(D)
OIL GAS	4,500	1.91	0.18	2.04	1.03	(D)
PHARMA	1,100	0.47	1.64	0.58	1.03	1.67
RD LAB	12,900	5.47	67.82	3.80	14.14	28.33
SEMI MANU	1,600	0.68	0.91	0.88	1.03	1.67
SOFTWARE	3,500	1.48	0.82	1.75	2.76	4.17
Total	**236,000**		**11,000**	**137,000**	**29,000**	**1,200**

Notes: Statistics calculated pooling 2005–15 start-ups in the LBD. Figures have been rounded for disclosure purposes. (D) indicates that the number has been suppressed for disclosure.

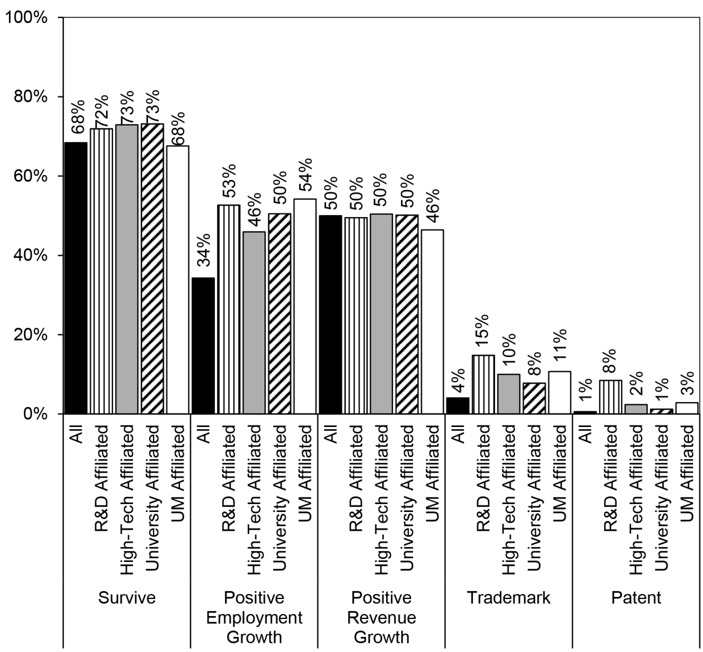

Fig. 6.4 Outcomes of all start-ups, $t + 1$

Notes: Figure shows the share of each start-up sample that experiences each outcome.

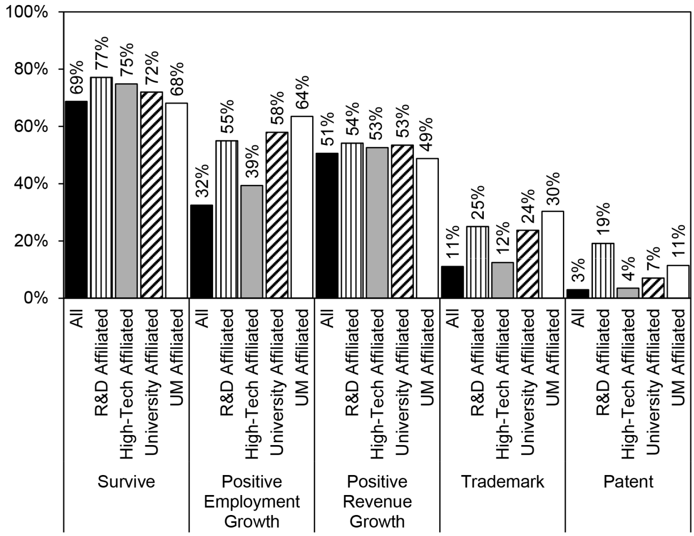

Fig. 6.5 Outcomes of high-tech start-ups, *t* + 1

Notes: Figure shows the share of each start-up sample within high-tech industries that experiences each outcome.

that follow, we find that the higher survival rates for firms that hire high-human-capital workers are primarily a compositional effect. Controlling for other characteristics of the start-up, such as industry and size, these firms are generally less likely to survive. Consistent with an "up or out" dynamic, start-ups hiring high-human-capital individuals are more likely to see employment growth than those in the economy at large, and this is particularly true for UMETRICS start-ups. The picture is a little different for revenue growth—UMETRICS start-ups have lower revenue growth. Patent and trademark activity are consistently substantially higher for all start-ups hiring experienced workers—and UMETRICS start-ups are second only to start-ups that hire R&D-experienced workers in both of these dimensions of innovation. As figure 6.5 shows, an almost identical pattern holds true, albeit at different levels, for high-tech start-ups.

For high-tech start-ups, we see a greater proportion of firms patenting and trademarking, especially among start-ups with high-human-capital workers. The "up-or-out" dynamic is even clearer for start-ups with research-trained workers in high-tech industries, which are less likely to survive, more likely to hire additional employees, and more likely to trademark.

6.5 Analysis

In this section, we expand on the framework provided in equation (1) and formalize our model to control for a number of nonhuman capital characteristics. We assume that the functional form of equation (1) is a linear combination of exponential functions, allowing us to use a log-linear estimation and calculate multiple outcome measures for each start-up (survival, employment growth, revenue growth, patenting, and trademarking) one year after the birth of the firm. We regress these outcomes against the start-up's workforce and other characteristics in the year of firm birth ($t = 0$).

Our main empirical specification is as follows:

$$(2)\quad Y_f = \alpha + \beta_1 \ln EARN_{f0} + \sum_{k=1}^{9} \delta_k SIZE_{kf0} + \beta_2 \ln \overline{AGE_{f0}} + \beta_3 \ln FEMALE_{f0} + \beta_4 \ln FOREIGN_{f0} + \beta_5 \ln RD_{f0} + \beta_6 \ln HT_{f0} + \beta_7 \ln UNI_{f0} + \beta_8 \ln Research\ Experience_{f0} + \varepsilon.$$

The key measures of interest are the workforce human capital measures—the number of workers who have worked in R&D-performing firms, high-tech firms, and universities—as well as the number who have direct research experience. As noted above, survival is a binary measure capturing whether a start-up had positive employment in $t + 1$, employment and revenue growth is calculated as the log differences in the values between t and $t + 1$, and patenting and trademarking is a binary measure capturing whether the start-up applied for a patent that was eventually granted or filed for a trademark that was eventually registered. The earnings variable is the inverse hyperbolic sine transformation of the start-up worker's earnings (collected from the W-2 or LEHD).[6] The size categories consist of six separate groupings: 1 employee, 2–5 employees, 6–9 employees, 10–19 employees, 19–49 employees, and 50 or more employees. For worker types, we take the inverse hyperbolic sine transformation of the number of each type of worker at the start-up at time $t = 0$. Other controls include zip code-year fixed effects and industry fixed effects.

The richness of the data permits the introduction of many controls. In particular, we can include mean earnings of the firm workforce as well as firm employment size categories. We interact demographics with each of the R&D worker types to identify potential nonlinearities of being a certain type of worker (e.g., female university worker).[7]

Since the Census Bureau data does not have direct measures of technology, we control for industry, detailed geography, and year using fixed effects. External macroeconomic conditions are proxied by zip code-year fixed effects and industry fixed effects.

6. We use the inverse hyperbolic sine transformation to address the fact that many start-ups have zero high-human-capital workers.

7. Note that these interaction terms are the result of multiplying continuous counts of employees falling into each group and that any given employee may belong to any number of designated groups.

6.5.1 Baseline Results

We begin by simply describing the contribution of each factor to start-up outcomes. Table 6.6 describes the explanatory power of a group of covariates to the start-up outcomes of survival, employment growth, revenue growth, patenting, and trademarking in the next period. Table 6.6 shows that just controlling for location and industry fixed effects can explain a small share of the variance in outcomes. Including initial firm characteristics, such as employment size and mean earnings at $t = 0$, contributes significantly to the share of variance explained in all the outcomes. Including demographic controls—such as the mean age of the employees, number of female employees, foreign-born status, and race—increases the explanatory power for future employment growth but has little effect on revenue, survival, and innovation. Including our basic human capital measures leads to an insignificant increase in the explanatory power of the model in survival and employment growth across all firms but does have significant power in our model for revenue growth, patenting, and trademarking. In particular, the human capital elements contribute an additional 40 percent in explanatory power for patenting outcomes in the following period and an additional 10 percent in explanatory power for trademarking. These patterns continue to hold for high-tech start-ups, with human capital contributing an additional 25 percent in explanatory power for patents and an additional 4.5 percent in revenue and 4.7 percent in trademarking. Table 6.6 highlights the explanatory power of human capital in relation to start-up growth and innovative outcomes.

Table 6.7 provides the key results associated with the full regression. Briefly, the relationship between the different measures of human capital and start-up survival and growth (in terms of both employment and revenue) is measurable and quite large. Start-ups that employ workers with experience working in R&D labs, high-tech, and universities are less likely to survive. Our human capital measures are clearly associated with positive employment and revenue growth. Using the fully controlled specification, our results suggest that employing one additional R&D worker is associated with a 1.4 percentage point increase in employment growth (conditional on survival).[8] This figure increases to 4 percentage points for one additional high-tech worker and 3.6 percentage points for a former university employee.[9] We see similar patterns in revenue growth. For all start-ups, the hiring of one additional high-human-capital worker is associated with a 1.4 to 4 percentage point increase in employment growth and a 2.3 to

8. Note that the coefficient interpretation is based on adding a single worker of a given type to the mean number of workers of that type at time $t = 0$ across all start-ups.

9. Again, it is important to note that we are not making claims about the direction of causality. Start-ups with more volatile ideas or production technologies may be more likely to hire high-human-capital workers.

Table 6.6 **Explanatory power (R^2) of start-up covariates**

All start-ups	Survival, $t+1$	Employment growth, $t+1$	Revenue growth, $t+1$	Patent, $t+1$	TM, $t+1$
Geography-year and industry dummies only	0.230	0.019	0.026	0.014	0.041
Geography-year and industry dummies + initial firm characteristics	0.342	0.184	0.027	0.016	0.049
Geography-year and industry dummies + initial firm characteristics + Demographics	0.344	0.303	0.031	0.017	0.050
Geography-year and industry dummies + initial firm characteristics + Demographics + human capital	0.344	0.303	0.032	0.029	0.056
Share of explained variance explained by human capital	**0.1%**	**0.3%**	**3.1%**	**41.4%**	**10.7%**

High-tech start-ups	Survival, $t+1$	Employment Growth, $t+1$	Revenue Growth, $t+1$	Patent, $t+1$	TM, $t+1$
Geography-year and industry dummies only	0.248	0.071	0.067	0.058	0.084
Geography-Year and industry dummies + initial firm characteristics	0.354	0.218	0.07	0.072	0.113
Geography-year and industry dummies + initial firm characteristics + demographics	0.355	0.371	0.085	0.078	0.123
Geography-year and industry dummies + initial firm characteristics + demographics + human capital	0.358	0.377	0.089	0.104	0.129
Share of explained variance explained by human capital	**0.8%**	**1.6%**	**4.5%**	**25.0%**	**4.7%**

Notes: Table reports changes in R^2 using different sets of covariates. The first specification regresses outcomes on geography, year, and industry dummies. Each subsequent specification adds additional covariates such as firm characteristics, worker demographics, and finally our human capital measures.

Table 6.7 OLS on all start-up outcomes, 2005–15

	Survival, $t+1$	Employment growth, $t+1$	Revenue growth, $t+1$	Patent, $t+1$	TM, $t+1$
ln RD_{f0}	−0.0481***	0.0156*	0.0456***	0.105***	0.0849***
	(0.00407)	(0.00717)	(0.0127)	(0.0136)	(0.0134)
ln HT_{f0}	−0.0268***	0.0474***	0.0596***	0.0121***	0.0488***
	(0.00333)	(0.00415)	(0.00384)	(0.000772)	(0.00311)
ln UNI_{f0}	−0.0177***	0.0431***	0.0282***	0.00541***	0.0299***
	(0.00215)	(0.00416)	(0.00536)	(0.000915)	(0.00319)
Observations	4,930,000	3,370,000	1,910,000	4,930,000	4,930,000
R^2	0.344	0.303	0.032	0.029	0.056
Start-ups that hired UMETRIC university employees:					
Overall					
ln $RESEARCH_{f0}$	−0.00902*	0.0204*	0.0272+	0.0139***	0.0180***
	(0.00357)	(0.00858)	(0.0161)	(0.00175)	(0.00396)
Observations	68,000	45,000	17,000	68,000	68,000
R^2	.567	.397	.148	.109	.146
Start-ups that hire UMETRIC university employees:					
Decomposed by funding source					
NIH	−0.00662	0.0440**	−0.00850	0.0141***	0.0210**
	(0.00612)	(0.0144)	(0.0262)	(0.00299)	(0.00679)
NSF	−0.00852	0.0432*	0.0506	0.0259***	0.0313**
	(0.00864)	(0.0204)	(0.0381)	(0.00420)	(0.00954)
DOD	−0.00217	−0.0158	0.0615	0.0528***	0.0235
	(0.0134)	(0.0313)	(0.0551)	(0.00649)	(0.0147)
DOE	−0.0127	−0.0222	0.174*	0.0452***	−0.0432*

	(0.0177)	(0.0415)	(0.0787)	(0.00865)	(0.0196)
Other federal funding	−0.00594	0.0192+	−0.0109	−0.00605*	−0.00507
	(0.00486)	(0.0115)	(0.0212)	(0.00237)	(0.00538)
Nonfederal funding	0.000349	0.0108	0.0558+	0.00217	0.0225**
	(0.00670)	(0.0161)	(0.0309)	(0.00326)	(0.00740)
R^2	.567	.397	.148	.109	.146
Start-ups that hire UMETRIC university employees: Decomposed by occupation					
Faculty	−0.0143	−0.0926**	−0.0151	0.0566***	0.00230
	(0.0146)	(0.0338)	(0.0586)	(0.00708)	(0.0161)
Graduate student	−0.0204*	0.0225	0.0578	0.0416***	0.0289**
	(0.00921)	(0.0223)	(0.0429)	(0.00449)	(0.0102)
Postgrads	−0.00804	−0.127***	−0.0297	0.0430***	−0.00418
	(0.0164)	(0.0383)	(0.0692)	(0.00800)	(0.0182)
Undergraduate	−0.00713	0.0784***	0.0461+	0.00192	0.00889
	(0.00525)	(0.0126)	(0.0241)	(0.00257)	(0.00583)
Other (admin, technician)	−0.00605	0.0251*	0.0237	0.00658**	0.0242***
	(0.00499)	(0.0118)	(0.0213)	(0.00244)	(0.00554)
R^2	.567	.397	.148	.109	.146

Notes: Observations are start-up-year combinations. Clustered robust standard errors in parentheses (by four-digit industry-year). + $p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$; controls included for size and average earnings, proportion of workforce that is female, foreign born, and interactions of female, foreign born with all the different types of research experience (e.g., foreign female R&D lab workers). In order to account for zeros in our logged counts of high-human-capital workers, we implement an inverse hyperbolic sine transformation. Interpretation of coefficients is based on the addition of one worker of a given type to the mean of that type of worker across all start-ups at time $t = 0$. The mean number of R&D workers, high-tech workers, and university workers at time $t = 0$ is 0.0114, 0.1534, and 0.1686, respectively. Observations have been rounded for disclosure purposes.

5 percentage point increase in revenue growth (conditional on survival). We see fairly large coefficients on the patenting and trademarking outcomes for R&D lab workers, with the addition of one R&D lab worker contributing a 9.2 percentage point increase in patent filing and a 7.5 percentage point increase in trademark filing.

The second panel of table 6.7 reports the results for the subset of start-ups that hired employees from the 22 institutions that provided UMETRICS data. The interpretation of the coefficient is thus relative to the effects of hiring an individual trained on a research grant over and above those who simply have experience working in one of these 22 universities. The results are consistent. Start-ups that hired research-trained individuals were more likely to fail than those who only hired university-experienced individuals (which are in turn more likely to fail than other start-ups, as established in the first panel). However, those that survive are more likely to create jobs, have higher revenue, and file more patents and trademarks. However, those that survive have higher revenue and file more patents and trademarks relative to start-ups that hired university-experienced workers.

The third and fourth panel of table 6.7 delves more deeply into the types of projects and skill embodied within our direct measure of human capital. Start-ups that hire workers funded by Department of Defense (DOD) and Department of Energy (DOE) grants are much more likely to patent, again relative to start-ups that hire nonresearch-trained workers at these universities. Start-ups that hire workers trained on National Institutes of Health (NIH)- and National Science Foundation (NSF)-funded grants see greater employment growth. Interestingly, faculty, graduate students, and postgrads contribute more to patenting and trademark activity, while undergraduates are associated with greater employment growth.

Table 6.8 reports estimates similar to the top panel of table 6.7 (with the full set of controls) but for start-ups in high-tech industries. The results are substantively unchanged. The magnitude of the coefficients is also significantly larger than the coefficients in the previous table, which confirms our hypothesis that the relationship with measures of human capital is more sensitive among high-tech start-ups. In the case of employment growth, increasing the number of high-human-capital workers by 10 percent is associated with a 0.29 to 0.93 percentage point increase in employment growth and a 0.63 to 0.88 percentage point increase in revenue growth for high-tech firms. The same increase in R&D-lab-experienced workers is associated with a 1.82 percentage point increase in patenting and a 1.14 percentage point increase in trademarking.[10]

In addition to these tables, we have estimated the same specification over different-size groups of start-ups and find that the results are robust and do

10. Disclosure limitation protocols preclude us from doing a deeper dive using UMETRICS-only data.

Table 6.8 **OLS on high-tech start-up outcomes, 2005–15**

	Survival, $t+1$	Employment growth, $t+1$	Revenue growth, $t+1$	Patent, $t+1$	TM, $t+1$
ln RD_{f0}	−0.0515***	0.0287	0.0632*	0.182***	0.114***
	(0.00706)	(0.0146)	(0.0305)	(0.0211)	(0.0239)
ln HT_{f0}	0.0423***	0.0823***	0.0865***	−0.00551*	0.00308
	(0.00549)	(0.00366)	(0.00638)	(0.00234)	(0.00417)
ln UNI_{f0}	−0.00633	0.0933***	0.0879***	0.0142*	0.0711***
	(0.00429)	(0.00748)	(0.0127)	(0.00648)	(0.0137)
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	210,000	140,000	95,000	210,000	210,000
R^2	0.358	0.377	0.089	0.104	0.129

Notes: Observations are start-up-year combinations. Robust standard errors in parentheses. *p <.05, **p <.01, ***p < .001; controls included for size and average earnings, proportion of workforce that is female, foreign born, and interactions of female, foreign born with research experience.

not differ greatly. To summarize our empirical findings, with the exception of survival, we find mostly positive and significant associations between R&D experience, high-tech experience, university experience, and research-trained experience and start-up performance. These human capital measures are associated with much riskier outcomes: survival of such start-ups is significantly less likely. However, conditional on survival, these basic measures of human capital have positive and significant effects on employment growth and revenue growth for the following period. The explanatory power of these measures is surprisingly high, contributing more than 15 percent to the cumulative explanatory power of high-tech start-up employment growth.

6.6 Conclusion

This chapter leverages new data about workforce human capital that can be used to provide more insights into the survival, growth, and innovative activity of new businesses. Our human capital measures have a negative impact on survival but a significant and positive association with employment growth and revenue growth conditional on survival. These results are consistent with the view that there is a relationship between workforce experience and business start-up outcomes. While it is important to note that the cumulative magnitude of the effects of these human capital measures on start-up outcomes is relatively small, it is also important to consider that these are very basic measures of human capital (binary and extensive margin type measures).

Overall, these findings point to the important role human capital plays in the outcomes of young businesses. While we neglect to say that the relationship is causal, there are multiple mechanisms that may suggest this is the case. One mechanism by which these human capital measures might affect start-up outcomes is through knowledge diffusion. A worker's experience in university-based research activities and the experience individuals gain by working in different types of environments (R&D laboratories, high-tech industries, and/or universities) might transmit tacit knowledge that is valuable to firms. Moreover, the importance of tacit knowledge may vary by the types of tasks workers perform, which is consistent with the evidence that our human capital measures are relatively more important in high-tech industries. A firm's investment in technology may also affect the value of human capital, making some types of knowledge more valuable through complementarities and others less valuable through substitutability. These types of interactions provide scope for future research using these data.

As always, there is much more to be done with these data, particularly as the time series grows. It should be possible to include more information about the project level factors identified by Corrado and Lane as important, such as "the roles of: organizational practices (employment and management); organizational characteristics (employee knowledge and skills, business model, IT use); environmental and cultural factors (location and networks); entrepreneurial factors (firm age and origin)" (Corrado and Lane 2009). In future work, we will do just that. We will expand the analysis of research experience to capture network effects as well as the effects of intensive exposure to research-intensive environments. We will also examine a broader set of outcome measures, including for start-ups that went public or became exceptionally large. It is always difficult to identify causal relationships, but we have begun to investigate the effects of sharp changes in funding, such as the 2009 American Recovery and Reinvestment Act (ARRA), as well as changes in funding to different research areas.

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