Research Experience as Human Capital in New Business Outcomes[1]

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Abstract

Human capital is typically cited as an important contributor to the survival, growth and innovative activity of new businesses. This paper contributes to the literature by both developing novel measures of human capital and examining the link between those measures and the outcomes of young firms.   It builds on several strands of the literature which emphasize the importance of employee workplace experience as a dimension of human capital. It shows that the effects of work experience differ substantially by where an employee worked and is valued differently by firms in different sectors. This is particularly true for research experience, which is consistent with the notion that on the job training in complex tasks should be valuable to firms with complex production technologies.

1. Introduction

This paper contributes to the literature on the link between human capital and the survival, growth and innovative activity of new businesses. We develop 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 startup survival, growth and innovative activities such as patenting and trademarking.

We describe the construction of four new human capital measures derived from two 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(*1*) 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 W2 data and create new worker-level measures of human capital based on whether each worker has worked in R&D labs, High-Tech businesses and universities.

We also describe the construction of two new datasets on startups. 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 startups, their survival and their growth between the years 2005 and 2015, as well as a national frame of all workers affiliated with these startups.

Our results suggest that a one-worker increase in the number of high human capital employees in a startup 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 startups 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 startups 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 points in the following year. Our measures of human capital also explain a significant amount of the known variation in innovation outcomes, where the inclusion of our basic measures of human capital helps explain an additional 40% of known variation in patenting outcomes and 11% of known variation in trademarking outcomes. These results are consistent with the view that there is a positive and significant relationship between workforce experience and business startup outcomes.

2. Background

Our focus on startups is informed by literature that suggests 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 (*2–4*). In particular, the work of Akcigit and Kerr(*5*) shows that the relative rate of major inventions is higher in small firms and new entrant firms. Scott Stern and coauthors note that the early stage choices of startups – their "digital signature" - is particularly important in predicting their future success.(*6*)

There is a growing literature linking human capital to the survival and growth of such new businesses (*7*, *8*). In particular, the decision to start a business, and its subsequent productivity and success is associated with having an entrepreneurial workforce (*9*, *10*). Related work also suggests that highly innovative individuals make "exceptional" contributions to economic growth (*11*). 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 (*12–14*). A related literature links external R&D investment and the success of the R&D efforts of individual firms (*15*). In depth studies of the components of intangible assets in contributing to firm productivity and success invariably mention the importance of training (*16*). In addition to affecting innovative outcomes, human capital measures such as on-the-job training have also been linked to firm productivity (*17*, *18*).

For our purposes of measuring the relationship between human capital and startup 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 do complex new tasks through trial and error has been extensively discussed in the endogenous technical change literature (*19*). There is also a great deal of evidence to support the notion that past experience imparts valuable business skills(*20*), and that both firm growth can be significantly affected by workers with experience in R&D activities (*21*, *22*).

The role of university research training specifically on innovative activity and business startups 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 with the presence of active research universities, suggesting that research trained individuals flow into innovative new businesses (*4*, *9*, *23*, *24*) . 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"(*25*).

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 (*26, 27*). The work of Lee Fleming, for example, suggests that if there are impediments to research-experienced workers moving from one firm to another, less innovation occurs. (*28, 29*). Our own work suggests that that research trained workers are more likely to work at firms with characteristics closely linked to productivity (*30*).

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 non-production 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 (*31*). Abowd et al. have used linked data to compute person specific measures of human capital (*32*), 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 (*33*), there has been no study to our knowledge that directly measures experience in High-Tech firms, R&D labs, universities or in scientific projects and ties them to startup outcomes. In this paper we analyze the link between these types experience and among workers at startups and the outcomes of those startups, including survival, growth, and innovative activity.

3. Framework, Data and Measurement

We follow much of the literature (*12–14*) in adopting a simple reduced form framework to examine outcomes for startups in terms of their survival, employment and revenue growth, and innovative activities such as being granted patents and registering trademarks. Conceptually, outcomes (Y) for startup 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.

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

There is some evidence that the effect of human capital will be important for businesses whose production processes involve performing complex tasks (*34*). 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 startup outcomes are measured.

3.1 Identifying and classifying startups

The Startup History file is constructed as an unbalanced panel dataset. The primary frame for the data is the Longitudinal Business Database (LBD), supplemented with additional information from the Census Bureau's Business Register, upon which the LBD is based. We utilize this file to identify startups at age zero firms. Once the startups have been identified, we supplement the data with geocodes (state and county-level FIPS, along with Census Tract information if

available) and EINs taken from the Business Register. These variables are used to subsequently characterize the workforce associated with each startup gathered from both LEHD and W2 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 Innovation and Research and Development Survey (BRDIS) and Survey of Industrial Research and Development (SIRD)[4]. 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 NAICS 5417, which is defined as "Scientific research and development services". The High-Tech definition is based on the relative concentration of STEM employment by industry as in Hecker(*35*, *36*). We use the High-Tech classification to both subset the universe of startups within a year and to characterize worker experience, identifying individuals with prior experience in High-Tech industries. The university measure is derived from IPEDS and Carnegie Institute data, which provide a frame of universities in the United States. We use the national university research outlays collected by 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% 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.

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 startup in its first year. It is created from the universe worker level data on jobs derived from administrative records in both the LEHD and W2 records and covers the period 2005-2015.

The frame covers each paid job for each worker from 2005-2015 as reported at both the Employer Identification Number (EIN) level via IRS form W2 and state-level Unemployment Insurance wage records. The latter underlie the core LEHD infrastructure (*31*) used to generate the Quarterly Workforce Indicators (QWI) and are necessary to identify the establishment for the bulk of multi-unit firms (*37*). The combined data includes more than 3 billion person-EIN-year observations (approximately 70% match across the W2 and LEHD/UI universes, 20% are found only in the W2 records and 10% are only found in LEHD). These data are enhanced with the LEHD Individual Characteristics File (ICF), which includes demographic data on 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 startups in their birth year, giving us an average of nearly 4.5 million person-startup observations each year.[5]

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 startup 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 (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 High-Tech 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(*1*), which includes 22 universities accounting for about 26% of all federally funded research. 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 comprise 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 de-identified employee number, and the job title (which we mapped 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 varies as each university provided data as far back as their record keeping allowed.

3.3 The Startup Worker History File

The startup worker history file, from which our human capital measures are derived, is constructed in three steps. The first step involves identifying person and firm characteristics in the years prior to startup. The LEHD and W2 data provide worker histories for 260 million individuals for each employer (at the EIN level) for each year in the period 2005-2015. Their individual characteristics are captured by matching to the Individual Characteristics File (the ICF) – this file 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

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

industry. The EIN is also matched to firms in 61 High-Tech industries (6-digit NAICS). Actual employment on a grant is determined by a match to UMETRICS data; there are 340,000 research experienced individuals between 2005 and 2015.

Startups are identified as firms of age zero. The total worker history file thus has 530.3 million PIK-EIN-Year startup observations. Of those, 43.2 million observations are associated with startups in year 0.

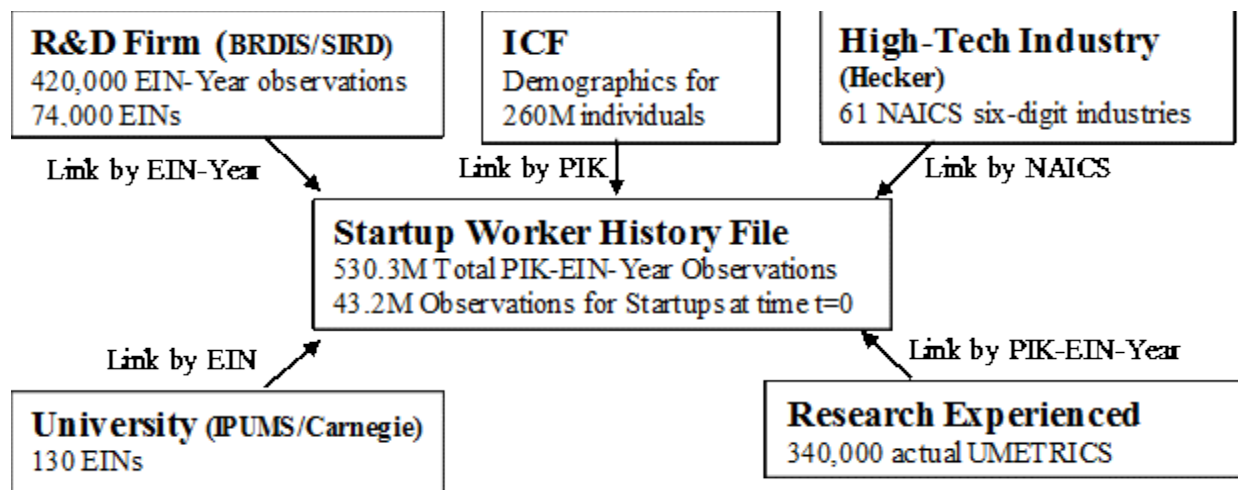Figure 1 provides a graphical illustration of the process.

Figure 1: The startup worker history file

The second step involves measuring human capital at the startup-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. 371,000 EINs have hired at least one individual with High Tech experience – the number of these employees total 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 startups that have hired a total of 13,000 individuals with research experience.at the UMETRICS universities. The process is described graphically in Figure 2.

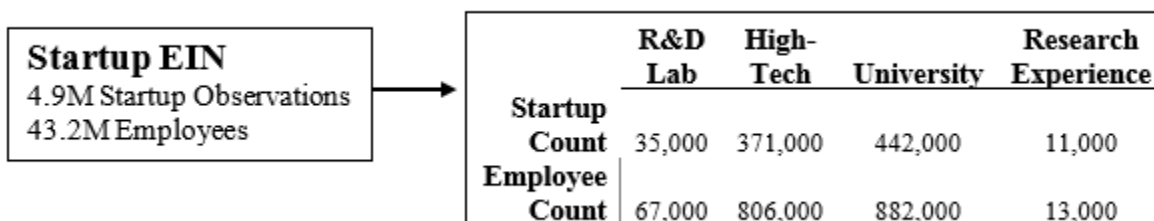| Startup EIN 4.9M Startup Observations 43.2M Employees		R&D Lab	High-Tech	University	Research Experience
	Startup Count	35,000	371,000	442,000	11,000
	Employee Count	67,000	806,000	882,000	13,000

Figure 2: Creating the Startup file

The third and final step involves merging the startup EIN file with the Startup Firm History File, classifying startup 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 3. Of the 4.9 million startups we observe, 3.4 million survive to the next period, or about 69%. This compares to 71% for startups with at least one employee with R&D lab experience, 72% for High-Tech and University experience, and 64% for research experience.
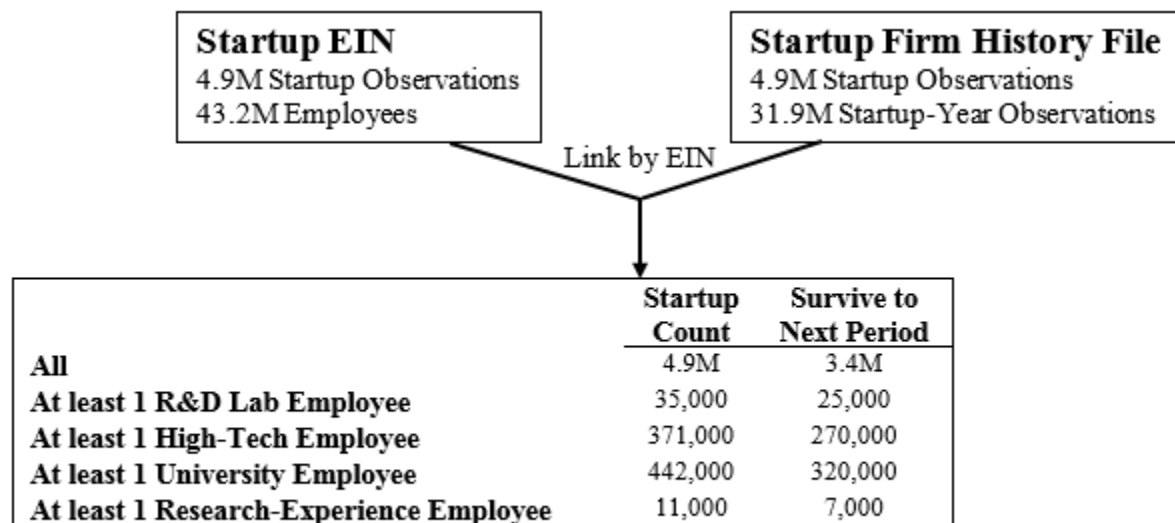

	Startup Count	Survive to Next Period
All	4.9M	3.4M
At least 1 R&D Lab Employee	35,000	25,000
At least 1 High-Tech Employee	371,000	270,000
At least 1 University Employee	442,000	320,000
At least 1 Research-Experience Employee	11,000	7,000

Figure 3: The Startup History file

3.3 Startup 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 $t+1$.[6] Survival is a binary indicator for startups 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 as applying for a patent in $t+1$ that is eventually granted and filing for a trademark in $t+1$ that is eventually registered.

Startups are linked to patent grants and trademark filings through existing crosswalks between USPTO and Census data. Patent linkages are based on a triangulation methodology first described in Graham et. al.(*38*) 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 startups using the match described in Dinlersoz et. al. (*39*). 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 startups we identify whether a startup applied for a patent in the year

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

after its birth (t+1) that was eventually granted. Similarly, we identify whether each startup filed for a trademark in t+1 that was eventually registered.

4. Basic Facts

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

4.1 Startup Facts

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

It is rare for startups to have high-human capital workers as employees in their first year[7]. Approximately 0.25% of employees at startups have experience working in an R&D laboratory, around 2.5% have experience working at a High-Tech firm and 2% have been linked through their earnings with a research university. The proportion of startups that have individuals formerly paid on research grants is even smaller, with fewer than 0.05% of employees being linked to a research grant from one of the 22 UMETRICS universities.

Table 1 provides some information about the characteristics of startups in their initial year of existence. The vast majority of startups, across all startup types, start off very small in their first year: 75% of all startups have fewer than 5 employees at time *t=0*; more than 50% of startups have 2 or fewer employees. Fewer than 5% of startups have more than 20 employees in the initial period. While the average revenue for startups exceeds half a million dollars per year, this measure is somewhat skewed as the median startup generates less than a quarter million dollars in their 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 startup and have innovation rates (as measured by patents and trademarks) that are 3-5x higher than the typical startup.

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[7] It is important to keep in mind that the results are left-censored as the LEHD has somewhat limited coverage prior to 2002

Table 1: Startup Statistics at Year 0

All Startups	Mean	Fuzzy Median	Standard Deviation
Employment	5.6	2.0	16.5
Payroll per Employee (000s)	29.6	17.7	84.0
Revenue (000s)	540.2	232.5	958.7
Patents	0.02	-	3.1
TMs	0.06	-	0.7
High-Tech Startups	Mean	Fuzzy Median	Standard Deviation
Employment	4.0	1.5	14.4
Payroll per Employee (000s)	54.4	39.8	64.8
Revenue (000s)	428.9	181.2	824.4
Patents	0.11	-	10.2
Trademarks	0.20	-	1.2

Note: Statistics calculated pooling 2005-2015 startups 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 the 45th and 55th percentile levels.

The dataset also enables us to describe the human capital composition of the startup workforce. Table 2 documents the employment composition of all startups in the left-hand panel and High-Tech startups in the right hand panel. Individuals in startups 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 startups. Individuals in startups that have at least one university or research experienced employee are even younger but are more likely to be female; research experienced startups are more likely to be Asian and less likely to be Black.

The demographic differences are even starker among startups in High-Tech industries. Overall employees in these startups 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.

Table 2: Startup Employee Mean Demographic Characteristics at time 0

	All Startups					High-Tech				
		Startups with at least one worker with experience in:					Startups 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

Note that counts in this and subsequent tables are rounded for disclosure limitation reasons

Source: LBD combined with Individual Characteristics File (ICF)

Note: Statistics calculated pooling 2005-2015 startups 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.

The literature suggests that high levels of human capital should be disproportionately valued by firms with complex production processes (32). That is borne out by our data. Even though

High-Tech startups account for only 4.4% of all startups in the US, they account for 17% of startups hiring at least one R&D experienced worker, 36% of startups hiring High Tech workers, 6% of startups hiring university experienced workers and 8% of startups 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. As such, a startup that hired a secretary who had been at an R&D lab would be classified as having hired an R&D experienced worker.

The direct measures offered by UMETRICS enable us to tease out the relationships in more detail. Table 3 shows the subset of startups who hired workers employed on research grants in the 22 UMETRICS universities, by funding source. In all cases, startups 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.

Table 3: Distribution of Startups hiring research experienced workers by funding source

	NIH	NSF	DOD	DOE	Other Federal	Non-Federal
Number of startups hiring UMETRICS workers	3,500	1,900	700	400	5,400	3,000
Proportion of startups in High-Tech	7.2%	16.8%	21.0%	17.4%	6.4%	9.4%
Ratio relative to proportion of all startups in High-Tech (4.4%)	1.64	3.82	4.77	3.95	1.45	2.14

Note: Statistics calculated pooling 2005-2015 startups in the LBD and tabulating the funding sources for each of the UMETRICS experienced workers. UMETRICS workers can be funded through multiple agencies and startups 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.

The detail included in the UMETRICS data allows us to similarly characterize the propensity to be in High-Tech industries by the skill level of researchers, as reported in Table 4. Startups hiring graduate students and faculty are much more likely to be High-Tech than other startups; the pattern for undergraduate hiring is much more similar to the startup distribution as a whole.

Table 4: Distribution of Startups hiring research experienced workers by Occupation

	Faculty	Graduate Student	Post Graduate	Undergraduate	Other
Number of startups	3,500	1,900	700	400	5,400
Proportion of startups in High-Tech	12.0%	15.2%	9.8%	6.0%	8.3%
Ratio relative to proportion of all startups in High-Tech (4.4%)	2.73	3.45	2.23	1.36	1.89

Source: LBD combined with UMETRICS worker file
Note: Statistics calculated pooling 2005-2015 startups in the LBD and tabulating the funding sources for each of the UMETRICS experienced workers. Startups 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.

Finally, the data enable us to drill down into the more detailed industry distribution of startups. Table 5 shows vast compositional differences in the worker types of High-Tech startups within narrowly defined industries. More than 85% of all High-Tech startups are in the fields of Computer Design (NAICS "5415"), Engineering (NAICS "5413") or R&D laboratories (NAICS "5417"). More than half of High-Tech startups are in computer design. While there is some variation in the shares of each worker types across these industries, more than 80% of each of the worker types is affiliated with a startup in one of those 3 industries. Although only 5% of High-Tech startups are R&D labs, almost two thirds of startups who hired workers with R&D experience and over one third of startups hiring workers with research experience are R&D labs.

Table 5: Industry sector of High-Tech startups at Year 0

	All Startups		Startups hiring workers with			
Startup Sector	Counts	Distribution	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**

Note: Statistics calculated pooling 2005-2015 startups in the LBD. Figures have been rounded for disclosure purposes. (D) indicates that the number has been suppressed for disclosure.

4.3 Startup Outcomes and Human Capital Composition

This section provides some initial descriptive results about the link between workforce experience and startup 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 startups that experience each type of outcome considered.
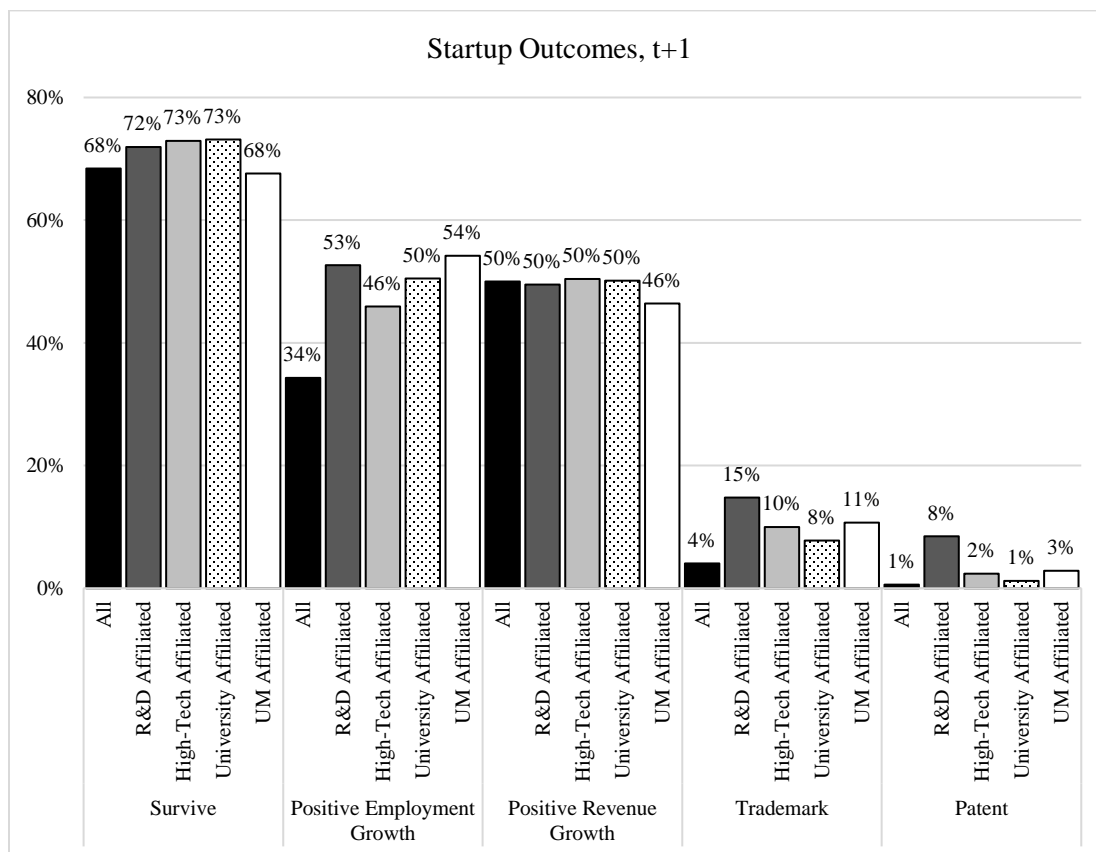

Figure 4: Outcomes of All Startups

Notes: Figure shows the share of each startup sample that experience each outcome.

Figure 4 provides some useful initial insights about startup outcomes. Although, by and large, startups that hire workers with R&D, High-Tech, and University experience are more likely to survive than those that do not, startups that hire UMETRICS experienced individuals show about the same survival rate as the typical startup. Moreover, in the analyses that follow we find that higher surival rates for firms that hire high human capital workers is primarily a compositional effect. Controling for other characteristics of the startup, such as industry and size, these firms are generally less likely to survive. Consistent with an "up or out" dynamic, startups 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 startups. The picture is a little different for revenue growth –UMETRICS startups have lower revenue growth. Patent and trademark activity are consistently substantially higher for all startups hiring experienced workers – and UMETRICS startups are second only to startups that hire R&D experienced workers in both of

these dimensions of innovation. As Figure 5 shows, an almost identical pattern holds true, albeit at different levels, for High-TechTech startups.
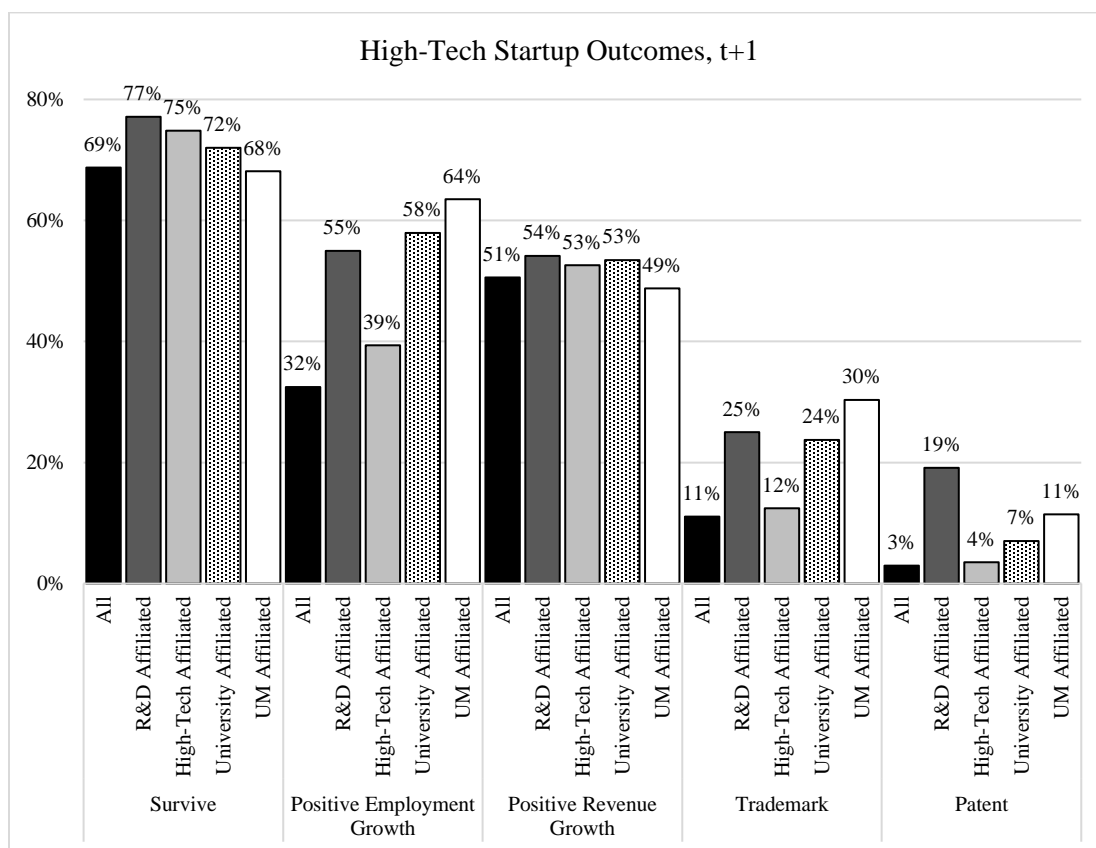

Figure 5 Outcomes of High-Tech startups

Notes: Figure shows the share of each startup sample within High-Tech industries that experience each outcome.

For High-Tech startups, we see a greater proportion of firms patenting and trademarking, especially among startups with high human capital workers. The "up-or-out" dynamic is even more clear for startups 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.

5. Analysis

In this section we expand on the framework provided in Equation (1) and formalize our model to control for a number of non-human 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 startup (survival, employment growth, revenue growth, patenting and trademarking) one year after the birth of the firm. We regress these outcomes against the startup's workforce and other characteristics in the year of firm birth (t=0).

Our main empirical specification is as follows:

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

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, universities – as well as the number who have direct research experience. As noted above, survival is a binary measure capturing whether a startup 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 startup 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 startup worker's earnings (collected from the W2 or LEHD).[8] The size categories consist of 6 separate groupings: 1 employee, 2-5 employees, 6-9 employees, 10-19 employees, 19-49 employees and 50 or greater. For worker types, we take the inverse hyperbolic sine transformation of the number of each type of worker at the startup at time t=0. Other controls include zip code-year fixed effects and industry fixed effects.

The richness of the data permit 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 non-linearities of being a certain type of worker (e.g. female University worker).[9]

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.

5.1 Baseline Results

We begin by simply describing the contribution of each factor to startup outcomes. Table 6 describes the explanatory power of a group of covariates to the startup outcomes of survival, employment growth, revenue growth, patenting and trademarking in the next period.
Table 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 of the outcomes. Including demographic controls, such as the mean age of the employees, number of female employees, foreign-born status and race, has large explanatory power in future employment growth, but relatively little explanatory power on revenue, survival and innovation. Including our basic human capital measures leads to an insignificant increase in the explanatory

[8] We use the inverse hyperbolic sine transformation to address the fact that many startups have zero high human capital workers.
[9] 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.

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% in explanatory power for patenting outcomes in the following period and an additional 10% in explanatory power for trademarking. These patterns continue to hold for High-Tech startups with human capital contributing an additional 25% in explanatory power for patents and an additional 4.5% in revenue and 4.7% in trademarking. This table highlights the explanatory power of human capital in relation to startup growth and innovative outcomes.

Table 6: Explanatory power (R^2) of Startup Covariates

All Startups	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 Startups	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 7 provides the key results associated with the full regression. Briefly, the relationship between the different measures of human capital and startup survival and growth (both in terms

of employment and revenue) is measurable and quite large. Startups 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 1 additional R&D worker is associated with a 1.4 percentage point increase in employment growth (conditional on survival).[10] This figure increases to 4 percentage points for one additional High-Tech worker, and 3.6 percentage point for a former university employee. We see similar patterns in revenue growth. For all startups, 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 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 7 reports the results for the subset of startups 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 simply with experience of working in one of these 22 universities. The results are consistent. Startups 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 startups, 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. Again, these results are over and above the relationship between university experienced workers.

The third and fourth panel of Table 7 delves more deeply into the types of projects and skill embodied within our direct measure of human capital. Startups that hire workers funded by DOD and DOE grants are much more likely to patent, again relative to startups that hire non-research trained workers at these universities. Startups that hire workers trained on NIH and NSF funded grants see greater employment growth. Interestingly, faculty, graduate students, and post-grads contribute more to patenting and trademark activity while undergraduates are associated with greater employment growth.

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[10] 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 startups.

Table 7: OLS on All Startup Outcomes, 2005-2015

	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-squared	0.344	0.303	0.032	0.029	0.056
Startups 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-squared	.567	.397	.148	.109	.146
Startups 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)
Non-Federal Funding	0.000349	0.0108	0.0558+	0.00217	0.0225**
	(0.00670)	(0.0161)	(0.0309)	(0.00326)	(0.00740)
R-squared	.567	.397	.148	.109	.146
Startups 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)
Post-Grads	-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-squared	.567	.397	.148	.109	.146

Notes: Observations are startup-year combinations. Clustered Robust Standard Errors in Parentheses (by 4-digit Industry-Year). + p<0.10, *p<0.05, **p<0.01, ***p<0.001; controls included for size and average earnings, proportion of workforce that is female, foreign born, and interactions of female, foreign born with all of 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 startups at time $t=0$. The mean number of R&D workers, High-Tech workers, and university at time t=0 is 0.0114, 0.1534, and 0.1686 respectively. Observations have been rounded for disclosure purposes.

Table 8 reports estimates similar to the top panel of Table 7 (with the full set of controls) but for startups in High-Tech industries. The results are substantively unchanged. The magnitude of the coefficients are also significantly larger than the coefficients in the previous table, which confirms our hypothesis that High-Tech startups are relatively more sensitive to measures of human capital. In the case of employment growth, increasing the number of high human capital workers by 10% 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 an 1.82 percentage point increase in patenting and an 1.14 percentage point increase in trademarking.[11]

Table 8: OLS on High-Tech Startup Outcomes, 2005-2015

	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-squared	0.358	0.377	0.089	0.104	0.129

Notes: Observations are startup-year combinations. Robust Standard Errors in Parentheses. *p<0.05, **p<0.01, ***p<0.001; controls included for size and average earnings, proportion of workforce that is female, foreign born, and interactions of female, foreign born with research experience.

In addition to these tables, we have estimated the same specification over different size groups of startups and find that the results are robust and do 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 with startup performance. These human capital measures are associated with much riskier outcomes: survival of such startups 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% to the cumulative explanatory power of High-Tech startup employment growth.

6. Conclusion

This paper 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 startup outcomes. While it is important to note that the cumulative magnitude of the effects of these

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[11] Disclosure limitation protocols preclude us from doing a deeper dive using UMETRICS only data.

human capital measures on startup outcomes is relatively small, it is 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. One mechanism by which these human capital measures might affect startup 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 or 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)"(25). 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 startups 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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