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Declining science-based startups: Strategic human capital and the value of working in startups versus established firms

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Abstract

Research Summary: We document that since 1997, the rate of startup formation has precipitously declined for firms operated by US PhD recipients in science and engineering. We explore how increasing knowledge complexity can be associated with fewer science-based startups. The decline in startup formation is accompanied by an earnings decline, increasing work complexity in R&D, and more administrative work for science-based founders. Founding a startup appears to have become increasingly harder over the past 20 years, while established firms are becoming more attractive workplaces for PhDs.

Managerial Summary: The increase in knowledge complexity has changed the balance of incentives between starting own business versus working for an incumbent firm in favor of the latter for PhDs. If maintaining a steady flow of new businesses in the high-tech sector is important to keep the flow of commercialization of new ideas coming, managerial practitioners and policy makers may need to find ways to make the job of the founder more attractive. The findings in this article point to the importance of secularly increasing value of complementary assets in work practices, especially for founders and employees that are high value generators. Alternatively, the increasing dominance of a few very large tech firms that the increasing burden of knowledge is fueling could be just fine, and startups need not play an important role in economic development.

KEYWORDS
entrepreneurship, knowledge complexity, science-based startups, strategic human capital, time trends

1 | INTRODUCTION

There is a deep concern that the United States has experienced a declining trend in entrepreneurship, as manifested in lower firm entry rates, falling employment share in new firms, and declining job mobility (e.g., Decker et al., 2014; Goldschlag & Miranda, 2020). The reasons for these trends are still being debated.

In this article, we employ the nationally representative Survey of Doctorate Recipients (SDR) to show a decline over the past 20 years in both the rate of startups founded and the share of employment at startups by the highest-educated science and engineering portion of the US workforce. The declines are wide-ranging and not driven by any particular demographic category or geographic region or scientific discipline.

Meanwhile, the burden/complexity of knowledge necessary for innovation has been on the increase (Bloom et al., 2020), as is the associated use and size of teams in science and invention (Jones, 2009; Wuchty et al., 2007). We conjecture that the increasing complexity of knowledge could be a salient source of the afore-mentioned decline. As an example from medicine, "It is estimated that the doubling time of medical knowledge in 1950 was 50 years; in 1980, 7 years; and in 2010, 3.5 years… What was learned in the first 3 years of medical school will be just 6% of what is known at the end of the decade from 2010 to 2020" (Densen, 2011).

We explore how the increasing complexity of knowledge may negatively impact science-based startup founders.[1] While startup founders as repositories of knowledge have been extensively examined (see literature review), the links between the troika of increasing complexity of knowledge over time, declining business dynamics, and startup founders' incentives and opportunities to be effective have not been clarified. The rich data available in SDR surveys provides us with an opportunity to explore these connections.

We use detailed individual-level job description data from these surveys to document changes in the allocation of human capital in the highest-educated, science-based part of the US workforce. In particular, we demonstrate that the differences in the nature of work, compensation, and allocation of talent have all changed dramatically between startups and large firms over time, and that these changes have over time increasingly favored working in established, and especially large firms, over startups. It is the differential ability of these two types of firms to rearrange their internal complementary assets to human capital that we think could be an important part of the increasing advantage of working in large firms over time, at the expense of declining startup creation. To the best of our knowledge, this study represents a first attempt to use rich individual-level data to examine how business dynamics in the knowledge-intensive and high-tech sectors may be affected by the changing nature of work.[2]

We document a decline of 38% in the rate of startup formation and a similar decline in the share of employment at startups by US PhD degree holders in science and engineering over the past 20 years. The declines are universal, observed across all demographic categories, geographic regions, occupations, and scientific disciplines in the United States.

We then turn to abductive reasoning to search for a plausible explanation of these trends.[3] For example, we show (a) a growing importance of work experience before becoming a founder; (b) an increase in the number of tasks that founders have to cope with; and (c) limitations faced by startups in utilizing efficient knowledge hierarchies. Workers in established firms have not experienced nearly as much increase in tasks and have instead experienced increasing relative wages. Other trends that we document in the organization of work imply that large firms have been better at adjusting to the increase in the complexity of innovation than startups. Hence, an increasing complexity of innovation appears to reduce the relative perceived value of founding new science-based firms.

Why should one care that innovative work has gotten, relatively, more comfortable in large firms? The concentration of innovative work in the already largest tech firms may be an efficient solution, after all. But, if one believes that it is new firms from which many new technologies and business opportunities typically originate (Schumpeter, 1942) so that "[a] country cannot be great over a sustained period without a steady flow of great new firms" (Klepper, 2016, p. 62), then these trends are of great concern. Concluding the article, we return to this debate and discuss various potential actions that could be taken by policy makers, universities, founders, and other start-up ecosystem builders to mitigate these trends.

The rest of the article is organized as follows. In Section 2, we provide a brief literature review. Section 3 describes the data, with more exhaustive information provided in Appendix S1. In Section 4, we present our key findings. Section 5 examines various trends in more detail. Section 6 focuses on the human capital of startup founders and their job satisfaction. Section 7 concludes.

2 | BRIEF LITERATURE REVIEW

The strategy literature has recognized human capital as a key source of firm competitive advantage (Agarwal et al., 2020; Campbell et al., 2012; Castanias & Helfat, 1991, 2001). This is especially true for startups (Carnahan, 2017; Klepper, 2016). As greater complexity of innovation causes greater coordination challenges (Nickerson & Zenger, 2004; Rivkin, 2000), a firm's capability to organize larger teams may become a crucial determinant for its success (Agarwal et al., 2016; Ganco, 2013; Jones, 2009). Work practices in science jobs have indeed been changing over time. For example, Jones (2009), and Wuchty et al. (2007) document an increasing preponderance of teamwork in science and invention.

Firms can implement a variety of human capital management practices to retain valuable human assets (see, e.g., Campbell et al., 2012; Campbell, Kryscynski & Olson, 2017; Carnahan et al., 2012; Gambardella et al., 2015; Wang et al., 2017; Zenger, 1992). However, if all firms follow these management practices, then nobody receives any competitive benefits in a general equilibrium. In our search for the best explanation for the observed relative decline in science-based startups, we explore how startups and large firms appear to *differ* in their ability to implement various human capital management practices to mitigate the impact of increasing knowledge complexity.

The literature on efficient knowledge hierarchies (Caliendo & Rossi-Hansberg, 2012; Garicano, 2000; Garicano & Rossi-Hansberg, 2004) can explain how large organizations, compared with startups, cope differentially with the increasing burden of knowledge. As the complexity of innovation increases, more innovation work exceptions are reported by lower-level workers to their managers, and ultimately to the C-suite. The firm can respond by either training workers to handle more of these exceptions or by increasing the number of layers to handle the increasing volume of reports, and by narrowing the variance in reports to allow greater job specialization. Indeed, Caliendo and Rossi-Hansberg (2012) show that larger firms are more likely to become hierarchically taller. Founders at startups should logically have less recourse to this mitigation strategy as they are typically financially constrained (Evans & Jovanovic, 1989) and hence, less likely to have the financial resources to pay for either additional layers of hierarchy or to pay for employee training.

In sum, this brief literature review suggests that we should explore the differential evolution of a number of human resource practices, including compensation, task allocation, and hierarchical design, to enlist evidence of why science-based startups have been falling in relative numbers.

3 | DATA

The (SDR) is a nationally representative SDR in science and engineering from US PhD-granting institutions. It is sponsored by the National Center of Science and Engineering Statistics (NCSES). We employ restricted-use data from all available surveys conducted (for the most part) biannually between 1995 and 2017 and report the results using NCSES-provided weights. The restricted SDR data provide detailed information including annual earnings, occupations, employment types, employer age and size, work activities, education background, and demographics. We limit the sample to individuals residing in the United States, employed full-time (working at least 48 weeks per year and at least 30 hours per week) with nonzero salaries, who either work at their own business, or whose principal employer is a private-sector for-profit company at the time of the survey. We discuss the construction of key variables as follows. A summary of key variables and definitions can be found in Table 1.

TABLE 1 Variable definitions and description.

Variable name	Definition/description
Young	Individuals below age 45, the median age in the sample
Experience	The number of years after receiving doctorate degree
Gender	Gender of the individual
Ethnicity	Ethnicity of the individual
Occupation	Occupation of the individual
US state of employment	The state of the individual's residence
Real earnings	Inflation-adjusted annual earnings reported by the individual
Startup	A business newly established within the past 5 years
Established firm	A business not newly established within the past 5 years
Founder (Startup founder, Science-based startups founder)	Indicator for respondents who report to be employed in own incorporated businesses newly established within the past 5 years
R&D-focused founder/owner/worker	Founders (established business owners/workers) who reported R&D to be their primary work activity in the SDR surveys
Employee of a startup	Indicator for individuals who are employees of incorporated businesses newly established within the past 5 years
Startup rate	Share of founders among all owners of incorporated businesses
Span of control	Number of people supervised directly by the individual
Depth of hierarchy	Number of people supervised indirectly by the individual
Time trend	Survey year minus 1997
Number of R&D tasks	Number of R&D tasks performed by the individual including basic research, applied research, development, and design
Number of management tasks	Number of managerial tasks performed by the individual including accounting, finance, contracts, human resources, management, quality management and sales
Firm size category	1: 10 or fewer employees; 2: 11–24 employees; 3: 25–99 employees; 4: 100–499 employees; 5: 500–999 employees; 6: 1000–4999 employees; 7: 5000–24,999 employees; 8: >25,000 employees
Large firm	Businesses in categories 7 and 8; with 5000 and more employees
Importance of job's degree of independence	1: very important; 2: somewhat important; 3: somewhat unimportant; 4: not important at all
Importance of job's salary	1: very important; 2: somewhat important; 3: somewhat unimportant; 4: not important at all
EJR	Dummy equal to one if the job and the highest degree reported as closely related; zero otherwise

Note: All individuals in the sample are PhD degree holders in science or engineering fields from a US institution. All the variables reflect SDR respondents' self-reported information.
Abbreviations: EJR, education-job related; SDR, Survey of Doctorate Recipients.

3.1 | Science-based startups and founders

Information about startups comes from answers to the question whether one's principal employer "c[a]me into being as a new business within the past five years." We call businesses that did not come into being within the prior 5 years "established firms." We split the data to show *the fraction* of the startups in the total number of all firms (the sum of startups and established firms). When we refer to the "rate" of startup formation we mean this fraction. This split is consistent with the commonly used way of measuring the fraction of new firms and their employment share in the economy (see, e.g., Decker et al., 2014). This rate aptly reflects the fundamental decision problem for a recent PhD that wants to do business: the choice of either starting or joining a startup, or joining an established firm.[4] We also sometimes use the term "startup rate" as a shortcut when referring to the share of founders among all incorporated business owners. To avoid possible confusion, we want to make clear that this concept of a startup rate is theoretically and empirically distinct from the concept of the self-employment rate, which instead represents the fraction of those who work at their own businesses in the total number of all workers. We do not have anything to say about this latter concept in this article.

The question about whether the business was new or not was not asked in the 1995, 2006, and 2008 surveys. Most of our analyses therefore start with the year 1997. In some illustrative graphs, we identify founders and workers of startups/established firms in 2006 and 2008 through a well-established imputation method (see, e.g., Little & Rubin, 2019). We do not employ this imputation method in regressions. The details of the imputation method are in Appendix B. We deliberately focus on PhDs, the upper tail of the distribution of scientists and engineers and their decisions on whether to found a startup. The sample therefore excludes other types of science-based firms; for example, those owned and operated by individuals with Bachelor's or Master's degrees in science and engineering, or those owned by individuals without degrees in science and engineering.

Self-employment is often associated with motivations other than launching high-opportunity startups (e.g., Hurst & Pugsley, 2011). Business incorporation has lately become a popular indicator of the growth potential of startups (see, e.g., Åstebro & Tåg, 2017; Levine & Rubinstein, 2017). Therefore, in our main analysis, we focus on owners of *incorporated* startups, whom we call "founders." This term refers to owners at the time observed in the data, whose incorporated startups were their full-time primary employer and who drew non-zero salaries. For further details, see Table 1.

3.2 | R&D and managerial tasks

To track the evolution of the number of R&D and managerial job tasks we use SDR data that contain responses to the question "Which of the following work activities occupied at least 10% of your time during a typical week on the job?" The list of possible alternatives includes 14 different activities. See Table A2 (all figures and tables starting with the letter "A" are in the Appendix S1). We call these "tasks" and follow the classification suggested by the SDR to identify four of those activities as "R&D" tasks: "basic research," "applied research," "development," and "design." We add up tasks in the R&D category to obtain the number of R&D tasks performed by founders and workers. We also follow the SDR-suggested classification to classify five work activities as management and administration (abbreviated as "management" tasks) as detailed in Appendix A. In addition to the list of work activities, SDR asks the question "On which work activity did you spend most of your time during a typical week on the job?" We call founders who listed R&D as their primary work activity "R&D-focused" founders and similar for owners of established businesses and workers at established firms.

3.3 | Span of control and depth of hierarchy

As in recent empirical work (e.g., Tåg et al., 2016), we infer firms' hierarchical structure based on microdata. SDR provides data on the number of people supervised directly and indirectly for those that respond to the survey.

Consistent with prior work we call the former "span of control" and the latter "depth of the hierarchy" as it relates to the respondents' job position (Guadalupe et al., 2014). Labor experience is measured as the number of years after receiving doctoral degree.

3.4 | Size category of employers

While SDR surveys do not collect rich firm-level information, they do contain responses to the question about broadly defined size categories of employers, measured by the responders' estimates of how many people worked for the principal employer across all locations. There are 8 categories, ranging from 10 or fewer employees to 25,000+ employees. We utilize this information for analysis related to firm size and startup growth. Specifically, we define firms in the two largest categories, 5000–24,999 employees and 25,000+ employees, as "large firms," and those with <25 employees as "small firms." It is noteworthy that "large firms" accounts for about half of the total employment at established firms in our sample.

3.5 | Job motivation and satisfaction

Some SDR surveys also contain questions about the importance of salary and degree of independence when thinking about a job, with the respondents asked to check one of the following boxes for each factor[5]: "very important," "somewhat important," "somewhat unimportant," and "not important at all." Similarly, the respondent is asked to rate his/her satisfaction with the salary and degree of independence for the principal job by choosing between "very satisfied," "somewhat satisfied," "somewhat dissatisfied," and "very dissatisfied." We utilize this information to measure motivation of science-based startup founders and to compare job satisfaction between founders and employed workers at established firms over time.

4 | THE STARTUP FOUNDING RATE AND THE DYNAMICS OF THE EMPLOYMENT SHARE AT STARTUPS

Figure 1 displays our key motivating findings for this study: a large decline over the past two decades in (1) the share of startup founders among all business owners, and (2) the share of workers employed at startups. Together, these imply a large decline in startup rates within the most science-intensive part of the workforce in the US economy. Specifically, in 1997, 34% of business owners reported that their businesses had been founded within the previous 5 years, but by 2017, this rate had declined to 21%, a decline of 38%. Meanwhile, the employment share of science and engineering PhDs at startups as a fraction of all employment opportunities in private firms had fallen from 12% in 1997 to 8% in 2017, despite two temporary employment spikes in 2001 and 2008.

The aforementioned spikes could potentially be related to abnormal events in computers and information technologies. But, as computer-related occupations[6] represent a relatively small minority of PhDs in our sample (Table A5), their impact on the overall trends is in fact marginal. We also reconstructed Figure 1 excluding computer-related occupations and found the same trends (Figure A9). It is still possible that the dot-com boom incentivized many recent PhDs with coding skills to work in startups, while the 2008 financial crisis may have temporarily pushed many recent graduates out of the banking and finance sectors and toward startups. Whatever the explanation, these temporary shocks appear not to have affected the overall declining trends in PhDs deciding to start or work for new firms.

Importantly, the downward trend is universal and found across all categories of PhDs in our data. The declines in the fractions of founders from 1997 to 2017 for some subcategories are 39% for males, 36% for Whites, 35% for

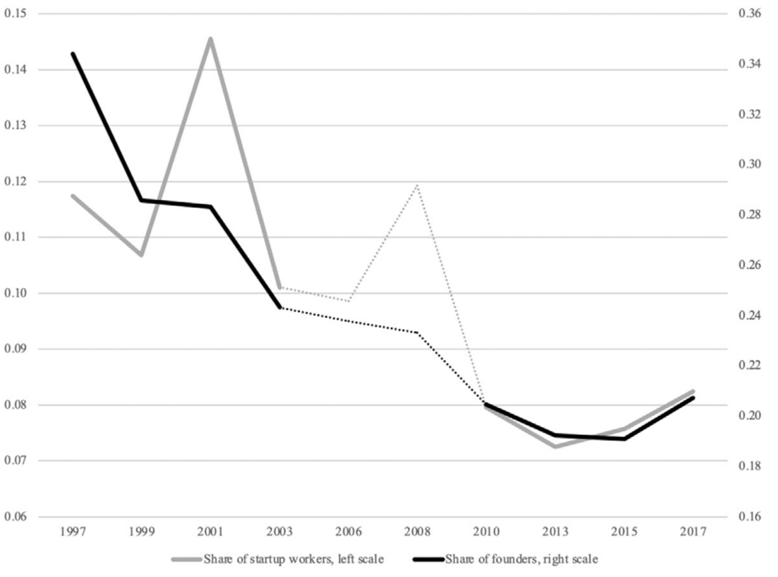


FIGURE 1 Dynamics of the share of PhDs who are founders of startups or employed at startups. Note that the figure reports the share of PhDs in science and engineering who are founders of startups working full-time with nonzero salaries in the total number of PhDs in science and engineering who are self-employed or owners of established businesses. It also reports the share of PhDs in science and engineering employed full-time with nonzero salaries in new (5 years old or less) private for-profit companies compared to the total number of PhDs in science and engineering employed full-time with non-zero salaries in all private for-profit businesses. "Founders" are owners/self-employed at an incorporated startup at the time observed in the data. The business age question was not asked in the 2006 and 2008 surveys. We have imputed the numbers for these years, according to the procedure described in the main text and in Appendix B. The imputed numbers are connected by dotted lines.

those residing in California, 41% for those whose work activity included computer-related tasks, and so on (Figures A2–A8). One category of founders that suffered an especially large decline is the non-US born PhD degree holders where the fraction of founders was higher than in the whole sample in 1997 (at 41.5%) but had fallen to about 21% by 2017 (a decline of almost 50%). This exaggerated drop may be associated with a tightening of US visa requirements (Roach & Skrentny, 2019) but notably, it is still in line with the overall trend.

We also examined the evolution over time of the composition of science-based startup founders in terms of their major PhD fields. Figure A10 compares the fraction of founders with different PhD backgrounds in 1997–1999 and in 2015–2017. There is some increase in the fraction of founders with majors in engineering, natural sciences, computer science, and mathematics, while the fraction of founders with backgrounds in life sciences, social sciences, and medicine has declined. But the changes are rather minor, and their magnitude cannot account for the sharp decline in the total fraction of startups. Furthermore, changes in founder demographics including race, gender, primary work activities, and state of residence are not nearly large enough to have a bearing on the overall decline in science-based startup rate (Figure A11).

Life sciences-related startups have perhaps undergone the most dramatic changes over the last 20 years so we thought that they may perhaps buck the overall trend. Slightly over 20% of founders in our data have PhD degrees in life sciences (including bioengineering and biomedical engineering). It turns out that the trend toward declining startup founding rate is similar and perhaps even more pronounced for startups with PhD founders in the life sciences. Specifically, the fraction of founders among PhD degree recipients in life sciences went down by almost 50% from 1997 to 2017 (Figure A12).

5 | A POTENTIAL EXPLANATION FOR THE DECLINE IN SCIENCE-BASED STARTUPS

5.1 | Some preliminary evidence

What is behind this drastic decline in science-based startups? Employing individual-level work data provides an opportunity to examine one explanation that has not yet attracted much attention in the literature. As mentioned in the introduction, there has been an increasing complexity in conducting science-based innovation (a.k.a. the "burden of knowledge"), documented in Jones (2009) and more recently in Bloom et al. (2020). We focus on the potential implications this may have for the attractiveness of founding a startup as opposed to working at an established firm. The underlying idea is that an increasing scientific complexity could be especially hard to handle by founders in science-based startups. In what follows, we tease out some more specific implications that can then be taken to our data.

We first note an increase in post-PhD experience for science-based startup founders, which goes up on average by more than a full year (from 16.4 to 17.5 years) from 1997 to 2017 in the raw data. Regression estimations controlling for gender, ethnicity, occupation, and the US state of employment imply that the average founder had about 15% longer post-PhD experience in 2017 than in 1997, and it is statistically highly significant (Table A6).

Figure 2 shows another closely related fact—there is a pronounced decline over time in the earnings of less experienced founders relative to their more experienced peers. Here, we separate founders by the median number of years after PhD (13 years), although other reasonable cutoffs lead to similar results. Between 1997 and 2001, founders with experience at or below the median earned more than the rest of the sample (consistent with Ouimet & Zarutskie, 2014), but by the 2010s, the situation is reversed, with less experienced founders earning on average 30%–40% less than experienced founders. The earnings of less experienced founders declined also in

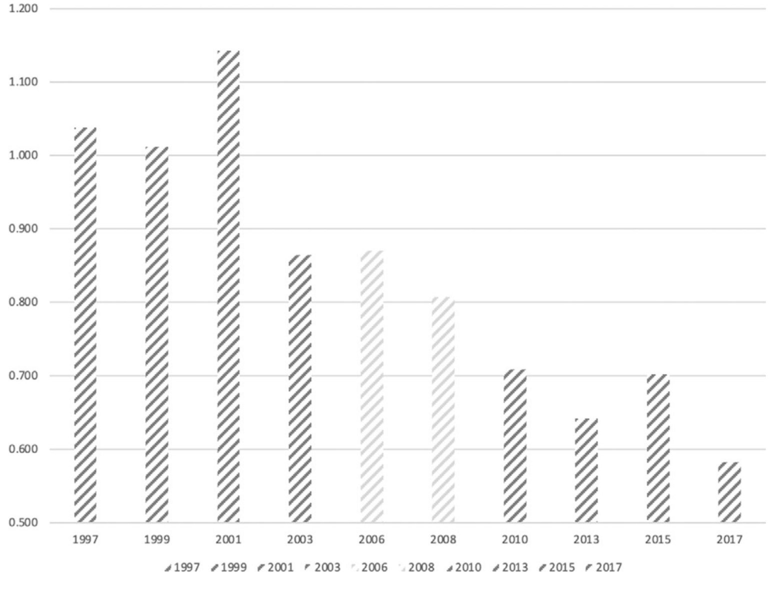


FIGURE 2 Dynamics of relative earnings of founders with below the median years after PhD. Note that the figure reports the ratio of earnings of founders with years after PhD at or below the median of 13 years, to earnings of founders with 14 or more years after PhD among PhDs in science and engineering. Lighter shaded bars correspond to imputed salaries for the 2006 and 2008 surveys. See Appendix B.

absolute terms. The average inflation-adjusted earnings of founders with below the median post-PhD experience were $72,616 in 1997, whereas 20 years later their earnings were $57,517, a decline of more than 20% (Table A7).

When viewed together, these two findings do not seem to be consistent with the simple "aging" hypothesis of the potential startup population. If, for example, the increase in the post-PhD experience of startup founders was mainly driven by the dwindling supply of less experienced potential founders, there would be no reason for the earnings of such founders that do appear in the data to go down relative to the earnings of more experienced founders, let alone for an absolute decline in such earnings. Instead, the evidence is consistent with the presence of factors operating on the "demand" side, namely, those coming from increasing knowledge complexity demands. As noted by Jones (2009), more work experience is akin to prolonging the training in preparation for shouldering the burden of knowledge (see also Braguinsky et al., 2012). Increasing work experience among science-based founders over time would be exactly what we would expect to see in the data if the burden of knowledge were a major factor driving the decision to found a startup. Moreover, in this case, it is also easy to understand why experienced founders would develop an increasing earnings advantage over less experienced founders over time.

The SDR data offer a unique opportunity to probe the hypothesis further by looking at trends in the nature of work. Specifically, we examine the number of different tasks performed, especially R&D tasks that founders have to deal with.

Figure 3A illustrates the dynamics of the number of tasks reported by founders. The total number (with a maximum of 14) is measured on the left-hand scale whereas the numbers of management and R&D tasks, whose maxima are five and four, respectively, are measured on the right-hand scale. The average number of all tasks for founders increased by about 15% from the beginning to the end of our sample, a statistically significant difference using a double-sided *t*-test. Furthermore, although the number of both R&D and management tasks increased, the increase is more pronounced in R&D, for which it rose by more than 50% from 1997 to 2017. The increase in R&D tasks was equally pronounced at all experience levels (Column 1 in Table 2 below). As a result, R&D tasks that comprised about 25% of all tasks conducted by founders in 1997 increased to 34% of all tasks in 2017. This was not accompanied by any decline in management tasks, so the founders had to shoulder the burden of doing more R&D tasks while also performing the same or more management tasks.

Panel B of Figure 3 contrasts the above findings with the trends for workers at established firms. The number of R&D tasks increases by about 12% from 1997 to 2017. The number of management tasks handled by workers, however, remained relatively flat. Also, workers had to deal with significantly fewer management tasks than founders in terms of levels: about 25% fewer at the beginning of the study period, with the gap increasing toward the end of it.

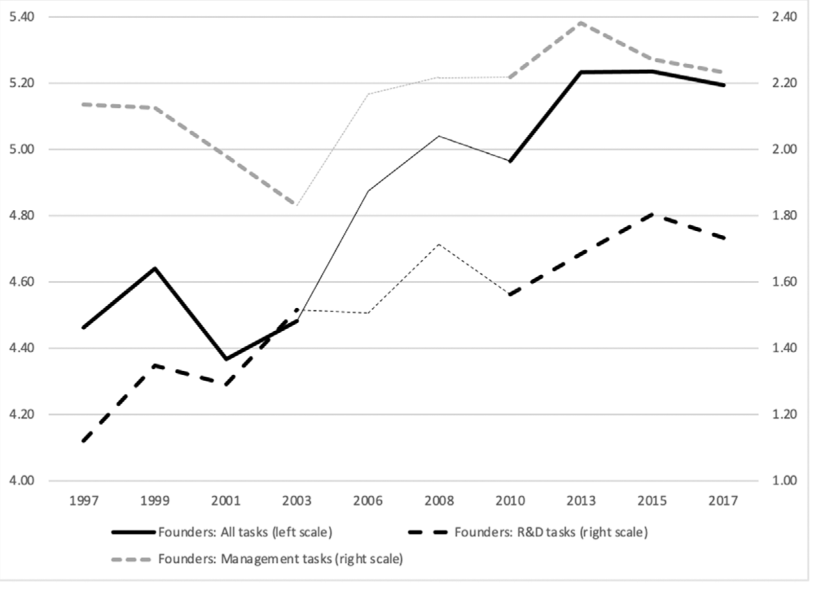
Compared with an established firm, managing a startup is likely to constrain founders' ability to organize the knowledge hierarchy efficiently at least until it has grown well beyond its initial size and financial constraints have been reduced. Lacking an efficient allocation of skills in the hierarchy, this constraint implies that founders would take on more work tasks themselves when the complexity of innovation increases, and this is consistent with the evidence in Figure 3.

5.2 | More formal analyses

The evidence so far suggests that science-based startups, especially those founded by less experienced PhDs may have struggled to effectively manage the increasing complexity of innovation. To examine this more rigorously, while accounting for various other differences between founders and workers, we turn to regression analysis. The estimation equation is:

$$y_{it} = \alpha + \beta_1 t + \beta_2 \exp_{it} + \gamma \cdot X_{it} + \varepsilon_{it}, \tag{1}$$

Panel A. The number of all, R&D, and management work activities among founders



Panel B.
The number of all, R&D, and management work activities among workers at established firms

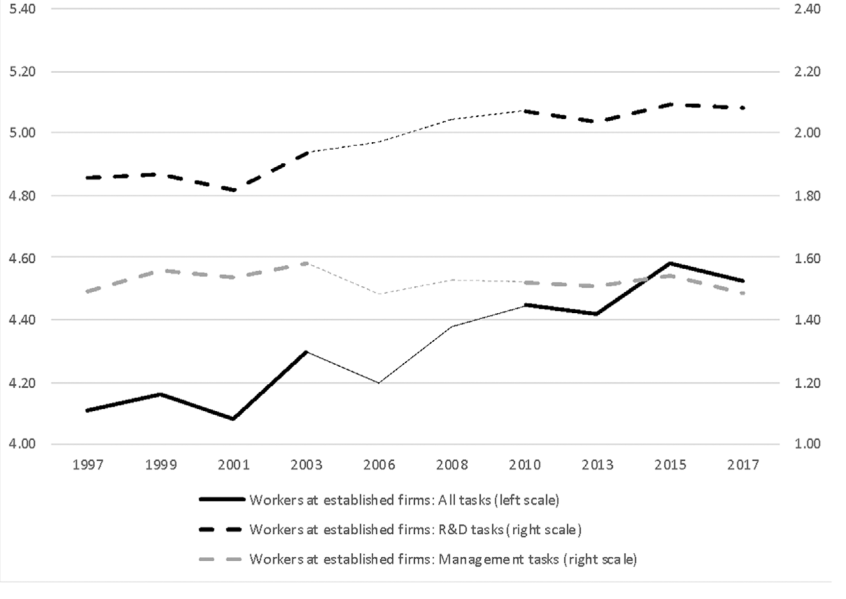


FIGURE 3 (A) The number of all, R&D, and management work activities among founders (B) The number of all, R&D, and management work activities among workers at established firms. Note that the R&D activities consist of "basic research," "applied research," "development," and "design." Management activities consist of "accounting, finance, contracts," "human resources," "managing or supervising people or projects," "sales, purchasing, marketing, customer service, public relations," and "quality or productivity management." The total number of work activities includes, in addition to the above, computer programming, employee relations, production, operations and maintenance, teaching as well as other work activities. See Table A2. Thinner lines connect imputed data for the 2006 and 2008 surveys. See Appendix B.

TABLE 2 R&D tasks and the span of control: founders and workers at established firms.

Panel A. Factors that affect the number of R&D tasks		
	DV: IHS-transformed number of R&D tasks	
	Founders (1)	Workers at established firms (2)
Time trend	0.0109 (0.002)	0.0075 (0.000)
Experience (years after PhD)	−0.0021 (0.002)	−0.0052 (0.000)
Constant	0.905 (0.196)	0.953 (0.048)
Other controls: gender, ethnicity, occupation, and US state of employment	Included	Included
Observations	2101	65,485
R^2	0.345	0.274

Panel B. Factors that affect the span of control and depth of the hierarchy				
	DV: span of control (IHS-transformed no. of individuals directly supervised)		DV: depth of hierarchy (IHS-transformed no. of individuals indirectly supervised)	
	Founders (3)	Workers at established firms (4)	Founders (5)	Workers at established firms (6)
Time trend	0.0001 (0.004)	−0.0046 (0.001)	−0.0027 (0.004)	0.0032 (0.001)
Experience (years after PhD)	−0.0010 (0.002)	0.0064 (0.001)	0.0051 (0.003)	0.0101 (0.001)
Constant	1.058 (0.405)	0.686 (0.081)	0.717 (0.413)	−0.054 (0.099)
Other controls: gender, ethnicity, occupation, and US state of employment	Included	Included	Included	Included
Observations	2101	65,485	2101	65,485
R^2	0.208	0.218	0.264	0.470

Note: Estimation method—OLS using National Science Foundation weights. Robust standard errors in parentheses. Observations with zeroes included using inverse hyperbolic sine (IHS) transformations, defined as $y = \ln\left(x + \sqrt{x^2+1}\right)$.

where y_{it} denotes outcome variables for individual i at time t, which are (a) the number of R&D tasks, (b) the span of control, and (c) the depth of the hierarchy; t is the time trend; $\exp_{it}$ denotes experience (years after PhD) of individual i at time t; X_{it} is a vector of controls, consisting of demographic, occupational, and geographic location dummies; and ε_{it} is the error term.[7] We employ pooled cross-section ordinary least squares (OLS) because startups are new businesses that are "redrawn" in each survey, and we estimate Equation (1) separately on the samples of founders and workers at established firms.[8] Estimation results are presented in Table 2.

The coefficients on the time trend variable in Columns (1) and (2) in Panel A confirm that the number of R&D tasks for both founders and workers at established firms is trending up, while trending stronger for founders (the coefficients for founders and workers are highly statistically significantly different). Thus, one might conclude that the increasing burden of knowledge to some extent affects all science-based workers; both founders and employees at established firms. However, coefficients on work experience show that workers at established firms, but not founders, tend to perform fewer R&D tasks as their experience grows (the difference is highly statistically significant). Thus, established firms but not startups appear to employ a greater division of labor in innovation by assigning more experienced workers to team leadership roles. In Panel B, we dig deeper into this by looking at the span of control and the depth of the hierarchy. Neither of these changes over time for founders. Most startups are small, so opportunities to restructure to counter the increasing complexity in innovation must be inherently limited.

In contrast, both the span of control and the depth of the hierarchy, and especially the latter, strongly increase with experience for workers with science backgrounds at established firms, in line with such workers performing fewer R&D tasks as they age. Significantly, the negative coefficient on the time trend for the span of control in column (4) indicates that the span of control *decreases* over time for workers at established firms, on average by about 0.46% per year (statistically highly significant). In contrast, the coefficient on the time trend for the depth of the hierarchy in column (6) is positive and statistically also highly significant, indicating that hierarchies *deepen* over time for workers at established firms on average by about 0.32% per year. Together, the results suggest that established firms cope with the increasing complexity of innovation by introducing additional layers of hierarchy and by narrowing their science-based workers' scope of work.[9]

We probe this line of reasoning further by looking at large firms. If the increasing complexity of innovation is indeed a culprit but can be mitigated by introducing additional layers of management, large firms should have greater opportunities to implement these organizational changes because they can more easily absorb the additional fixed cost of additional management layers (Caliendo & Rossi-Hansberg, 2012). Hence, we re-estimate Equation (1) for workers at large firms, which are those with 5000 or more employees. In Table 3, Columns (1), (3), and (5), we present estimation results from eight surveys in which the question about employer age was asked, so the sample is limited to employees at large firms that we know are not startups. In Columns (2), (4), and (6), we employ data from all 11 available surveys under the assumption that firms with 5000 or more employees are highly unlikely to be startups. Results from all surveys and from the eight surveys where we know firm age are very similar.

Comparing the estimation results in Table 3 to those in Table 2, we notice that the coefficient on the time trend variable in the number of R&D tasks is smaller among workers at large firms compared with all workers and is about half the magnitude of the corresponding coefficient for founders in Column (1) of Table 2 (all difference mentioned are highly statistically significant). Thus, workers at large firms faced an increase in the burden of knowledge at about half the pace of founders. Perhaps even more interestingly, the coefficient on the time trend variable in the regression where the dependent variable is the depth of the hierarchy is twice the magnitude of the coefficient in the same regression for the sample of all workers at established firms in Table 2. Thus, to offset the increasing burden of knowledge, large firms create deeper hierarchies at twice the rate compared with all firms.[10]

As larger firms find better ways to cope with the burden of knowledge, PhD degree holders should naturally start choosing to be employed by such firms more. The flip side of this would be a decrease in the share of PhD degree holders employed by small firms. Elfenbein et al. (2010) find that experience working at small firms is closely related to the propensity of subsequently founding startups; therefore, decreasing share of employment in such firms could indirectly contribute to decreasing science-based startup rates.

To see how important this factor may be quantitatively, in Figure 4, we present the dynamics of the shares of employment of PhDs in science and engineering at large (5000 or more employees) and small (<25 employees) for-profit firms, using all available surveys. The share of PhDs employed at small firms has dropped by about a quarter (from around 12% to around 9%) since the late 1990s. The share employed in the smallest firms (<10 employees, not shown) has seen similar declines. The trend for PhDs to choose employment in large firms as opposed to small firms may therefore be contributing to lower startup rates not just directly but also indirectly by narrowing opportunities to "learn" entrepreneurship through small-firm employment.

We also confirmed the evidence on founders' earnings in regression analysis which includes various controls. In Table 4, the estimation equation is similar to Equation (1) except that the outcome variable is the (logged) salary of individual *i* at time *t*, while the explanatory variables of interest include the (inverse hyperbolic sine-transformed)

TABLE 3 R&D tasks and the span of control: workers at large established firms.

Panel A. Factors affecting the number of R&D tasks for employees at large firms		
	DV: IHS-transformed number of R&D tasks	
	(1) Workers at large established firms	(2) Workers at all large firms
Time trend	0.0057 (0.001)	0.0045 (0.000)
Experience (years after PhD)	−0.0048 (0.000)	−0.0051 (0.000)
Constant	1.0095 (0.073)	1.0372 (0.063)
Other controls: gender, ethnicity, occupation, and US state of employment	Included	Included
Observations	36,115	47,987
R^2	0.226	0.222

Panel B. Factors affecting the span of control and depth of the hierarchy				
	DV: span of control (IHS-transformed no. of individuals directly supervised)		DV: depth of hierarchy (IHS-transformed no. of individuals indirectly supervised)	
	(3) Workers at large established firms	(4) Workers at all large firms	(5) Workers at large established firms	(6) Workers at all large firms
Time trend	−0.0036 (0.001)	−0.0028 (0.001)	0.0065 (0.001)	0.0065 (0.001)
Experience (years after PhD)	0.0077 (0.001)	0.0063 (0.001)	0.0117 (0.001)	0.0099 (0.001)
Constant	0.6277 (0.130)	0.6230 (0.113)	−0.1227 (0.158)	−0.0877 (0.131)
Other controls: gender, ethnicity, occupation, and US state of employment	Included	Included	Included	Included
Observations	36,115	47,987	36,115	47,987
R^2	0.210	0.222	0.489	0.502

Note: Estimation method—pooled OLS using weighted National Science Foundation data. Robust standard errors in parentheses. Since there are observations with zero number of R&D-related work activities as well as zero span of control and depth of hierarchy, we use the inverse hyperbolic sine (IHS) transformations, defined as $y = \ln\left(x + \sqrt{x^2+1}\right)$.

number of R&D tasks, the span of control, and the depth of the hierarchy, and there is an interaction term between the time trend and experience.

Founders' earnings decline on average by about 1.6% per year (Column 1, Row 1, statistically highly significant). However, as we already saw, this is offset by an opposite trend in returns to experience. The mean number of years after PhD in the sample of founders is 15.9 years; hence, the coefficient on the interaction term between experience and time trend implies that the negative baseline time trend is offset at the mean work experience. In contrast, workers' real earnings grow over time regardless of experience (Column 2, Row 1, statistically highly significant).

Workers at established firms are also rewarded for taking on more tasks. Doubling the number of R&D tasks increases earnings for workers at established firms by 4.4%. The point estimate for founders is similar, but the standard errors are high so the most we can say in this case is that, controlling for all other factors, there is large variance in outcomes.

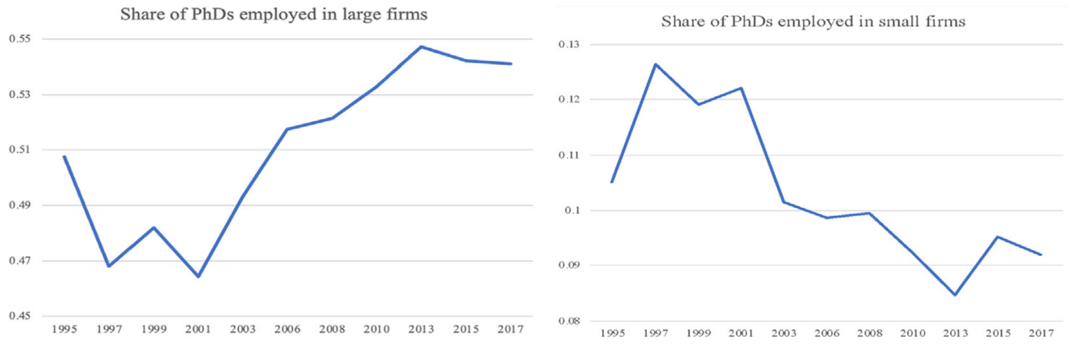


FIGURE 4 Share of PhDs employed in large and small for-profit firms in total. "Small" firms are those with <25 employees, as in Elfenbein et al. (2010). *Source*: Author calculations using weighted National Science Foundation data. "Large" firms are those with 5000 or more employees.

TABLE 4 Earnings of founders and workers at established firms.

DV: Log (real earnings)	Founders (1)	Workers at established firms (2)
Time trend	−0.0163 (0.006)	0.0039 (0.001)
Experience (years after PhD)	0.0121 (0.009)	0.0277 (0.001)
Experience squared	−0.0005 (0.000)	−0.0005 (0.000)
Experience × time trend	0.0011 (0.000)	0.0001 (0.000)
IHS-transformed number of R&D tasks	0.0488 (0.046)	0.0437 (0.005)
Span of control (IHS-transformed no. of individuals directly supervised)	0.0498 (0.029)	0.0466 (0.002)
Depth of hierarchy (IHS-transformed no. of individuals indirectly supervised)	0.0820 (0.024)	0.0461 (0.003)
Constant	10.0238 (0.455)	10.5638 (0.042)
Other controls: gender, ethnicity, occupation, and US state of employment	Included	Included
Observations	2101	65,485
R^2	0.138	0.221

Note: Estimation method—OLS using National Science Foundation weights. Robust standard errors in parentheses. Observations with zeroes included using inverse hyperbolic sine (IHS) transformations.

5.3 | Evidence from R&D-focused founders

If increasing complexity of innovation is indeed a major factor behind the decline in science-based startups, we would expect the patterns documented above to be magnified among founders whose startups are the most R&D-intensive. We use this logic to evaluate our hypothesis further using some additional data from the SDR surveys.

To begin with, Table 5 presents the dynamics of the share of R&D-focused founders, R&D-focused owners of established incorporated businesses, and R&D-focused workers at established firms in the total number of individuals in each category, as well as the share of R&D-focused workers at all large firms using all available surveys (regardless of business age).[11] The share of R&D-focused founders among all founders in Column (1) increases over time—from 26% in 1997 to 32% in 2017, an increase of 21%. However, the share of R&D-focused business owners among owners of established businesses in column (2) rises even faster, from about 12% in 1997 to over 30% in

2017, suggesting that the burden of knowledge is widespread. Thus, when we split the data between startups and established own businesses as before, we see that the rate of R&D-focused startups steeply declines, and this decline, from 54% in 1997 to 20% in 2017, is larger in magnitude than the decline in the overall startup rate shown in Figure 1.

Note that an R&D-focused founder and a startup engaged in R&D might not be the same thing. A business might be primarily engaged in R&D whereas the owner primarily manages a team of researchers. An increasing burden of knowledge, leading to an increasing number of task execution exceptions brought to the attention of the owner might shift her primary work activity from management to R&D. In fact, this is the interpretation that appears to us to be most consistent with the large increase in the share of R&D-focused owners among established incorporated own businesses. That is, we think that the fact that owners of so many established businesses tend to report R&D as their main work activity later in the sample could be driven by an increasing number of exceptions brought to the attention of the owner rather than a reprofiling of the business itself. Note also that, as can be seen in Columns (3) and (4) of Table 5, the share of R&D-focused workers at established firms remains stable and even appears to decline slightly in the sample of workers at large firms. This further favors interpreting the increase in the fraction of R&D-focused business owners as evidence of the need for them to deal with an increasing number of exceptions because of the rising complexity of innovation and lack of recourse to taller hierarchies.

If the increasing burden of knowledge is indeed an important driver of these trends, it should also be reflected in a steeper earnings decline for especially less experienced R&D-focused founders compared with other founders. In Table 6, we present the estimation results from the same regression for which results were in Table 4, but with the sample limited to R&D-focused founders. The negative earnings time trend is indeed much more pronounced in Table 6 than it is in Table 4—the decline at the baseline is more than 4.4% per year and statistically highly significant. Notably, comparing the coefficients on the interaction term between experience and time trend in Tables 4 and 6, the returns to experience are increasing over time for R&D-focused founders at twice the rate of all founders while the point estimates of the returns to the span of control also indicate that R&D-focused founders can increase their earnings by much more than other founders if they can lead larger teams. Thus, more experienced R&D-focused founders as well as those who manage to quickly overcome the initial founding team size constraint appear to be in a good position to compensate for the increasing burden of knowledge that haunts their less experienced and smaller-sized peers. We will come back to this issue in the next section where we examine the trends in the quality of human capital of science-based startups.

TABLE 5 The dynamics of shares of R&D-focused founders and workers in total.

Year	(1) Founders	(2) Owners of established incorporated businesses	(3) Workers at established firms	(4) Workers at all large firms
1995				0.600
1997	0.261	0.118	0.509	0.586
1999	0.288	0.150	0.520	0.598
2001	0.316	0.157	0.508	0.578
2003	0.359	0.297	0.512	0.555
2006				0.545
2008				0.566
2010	0.309	0.279	0.524	0.561
2013	0.308	0.285	0.503	0.531
2015	0.373	0.287	0.512	0.553
2017	0.316	0.328	0.517	0.547

Source: Author calculations using weighted National Science Foundation data.

TABLE 6 Earnings of R&D-focused founders and workers at established firms.

DV: Log (real earnings)	(1) Founders	(2) Workers at established firms
Time trend	−0.0445 (0.012)	0.0027 (0.001)
Experience (years after PhD)	−0.0161 (0.013)	0.0293 (0.001)
Experience squared	−0.0003 (0.000)	−0.0005 (0.000)
Experience × time trend	0.0026 (0.001)	0.0001 (0.000)
IHS-transformed number of R&D tasks	−0.1521 (0.123)	0.0326 (0.009)
Span of control (IHS-transformed no. of individuals directly supervised)	0.1109 (0.054)	0.0372 (0.003)
Depth of hierarchy (IHS-transformed no. of individuals indirectly supervised)	0.0549 (0.044)	0.0364 (0.004)
Constant	11.9358 (0.477)	10.7582 (0.048)
Other controls: gender, ethnicity, occupation, and US state of employment	Included	Included
Observations	690	33,710
R^2	0.234	0.179

Note: Estimation method—OLS using weighted National Science Foundation data. Robust standard errors in parentheses. Since there are observations with zero numbers of R&D-related work activities as well as zero span of control and depth of hierarchy, we use the inverse hyperbolic sine (IHS) transformations, defined as $y = \ln\left(x + \sqrt{x^2 + 1}\right)$.

In summary, we find that while R&D-focused owners are becoming more plentiful among both science-based startup founders and established business owners, this is likely to be driven by such science-based business owners having to shoulder more R&D tasks on their own due to the relative lack of opportunity to delegate R&D tasks in startups. This explanation appears to be most consistent with the fact that both the startup rates and earnings' declines are even more pronounced among R&D-focused founders than among all founders.

6 | WHO CHOOSES STARTUPS?

6.1 | The human capital of founders and startups' quality

Some research has found a declining trend in cognitive skills among new entrants (Ayyagari & Maksimovic, 2017). Our previous analysis suggesting increasing burden of knowledge as a reason for the decline in science-based startup ratios appears to lead us to a different conclusion—if knowledge-related demands on founders are growing, the human capital of those who still choose to found them should be going up, not down. We already saw this to be true in the previous section in terms of prefounding work experience. Here, we probe this issue further by examining the changes in the human capital of founders over the time span of our analysis.

SDR surveys have a (partial) longitudinal aspect, as each new survey between 1995 and 2013 returned to previous survey respondents, while new PhD recipients were added to every survey. The attrition rate between adjacent surveys is about 10%–15%. In 2015, however, the survey was sent to an almost entirely new sample of respondents (the attrition rate from 2013 to the 2015 survey is about 90%). Hence, we use two waves of panel data available for founders: the 1997–2013 wave and the 2015–2017 wave.

To estimate changes in the human capital of founders we use the longitudinal aspect of the data and look at all those employed at a private-for-profit business in a survey. We create a dummy that equals one if the individual is reported to be a startup founder in the next survey and zero if he or she remained employed at a private-sector for-profit business in the next survey as well. We then use a standard approach (Azoulay et al., 2020; Choi et al., 2019) with prior ("prechoice") salaries as a measure of the human capital of future founders to obtain an estimate of the human capital differential between future founders and those who remained in paid work for other firms, based on how much they earned while both types of individuals were previously employed for pay. Because the demographics are different across future founders and those who remained in paid work for other firms (in particular, the former tend to have more experience than the latter), we employ predicted logged prechoice salaries from an earnings regression estimated separately on the data from each relevant prechoice survey (1995, 1997, 1999, 2001, 2008, 2010, and 2015), in which the dependent variable is the prechoice logged salary, and the explanatory variables are work experience and its squared term, tenure on the current (prechoice) job, gender and ethnicity dummies, as well as 75 occupation dummies, US state of employment (e.g., Massachusetts) dummies, and eight employer size-category dummies. Figure 5 plots these predicted logged prechoice salaries and the 95% confidence intervals.

As seen in Figure 5, the average predicted earnings of those who become founders in the next survey are lower than the average predicted earnings of those who remain at private sector for-profit businesses in the 1990s. However, the predicted earnings converge in 2001 and then the average predicted earnings of those who become founders exceeded those of workers who continue to work for other firms in 2008–2010. Because of the small sample size of founders in these longitudinal data, the 95% confidence intervals for the most part overlap. The only time when there is a statistically significant difference at the 5% level between predicted prechoice salaries of these two categories of individuals, in 2010, the prechoice predicted salaries of future founders are actually higher than those who continue to work for other firms. This suggests that PhDs who left paid employment to start their own incorporated businesses between 2010 and 2013, that is, right after the Great Recession, had significantly higher human capital than those who remained in paid work.

In Figure 6, we look at an alternative measure of human capital—the share of individuals who graduated from top-ranked PhD programs. SDR data contain Integrated Postsecondary Education codes for the institutions from which the respondents graduated and their field of specialization in the graduate program. We matched these codes with the National Research Council (NRC) PhD program rankings published in 1993 and constructed a dummy that equals one if the individual graduated from a PhD-granting institution in the top 15 in the NRC rankings and zero otherwise. We also added to these top-ranked programs graduates whose specific PhD area was among the top 15 in the NRC's area rankings (the areas were mathematics and physics, engineering, social sciences, and biological sciences). Figure 6 is consistent with Figure 5 in showing that founders lag behind in terms of the share graduating from top-ranked programs in the 1990s but catch up to a large degree after 2003. Notably, the catchup trend is even more pronounced among founders with below the median years after PhD, despite the evidence presented that they suffer an increasing earnings penalty over time.

Our findings indicating increasing human capital of founders over time is consistent with a "selection effect" due to higher barriers to entry that, according to our story, stem from the increasing burden of knowledge. Note that this selection effect does not have to lead to an increase in average earnings of the remaining founders, because the increasing burden of knowledge reduces earnings at all levels of human capital.

The increase in human capital of founders in recent years should translate into better startup growth. As mentioned, most startups start small. Despite higher human capital of founders in more recent years, there is not much of a trend toward higher initial startup size—the fraction of businesses with fewer than 10 employees among all startups was 85% in 1997 while that fraction declined to 82% in 2017, with some fluctuations in-between. However, those that survive tend to grow faster in more recent years.

To examine growth of surviving startups we construct panel data of startup founders. Specifically, we track founders, retaining those who manage their own incorporated businesses between two surveys. Figure 7 shows changes in the average size category of startups from one survey year to the next.[12] Figure 7 displays that surviving startups are larger in the period 2003–2015 than they are in the period 1997–2001. Moreover, growth rates accelerate over time: growth is between 3% and 5% for startups first observed between 1997 and 2001 but then increase and reach 10% for startups first observed in 2015. The increase in growth rates for surviving startups is confirmed in a regression using repeated observations on founders across two adjacent surveys. The coefficient on time trend

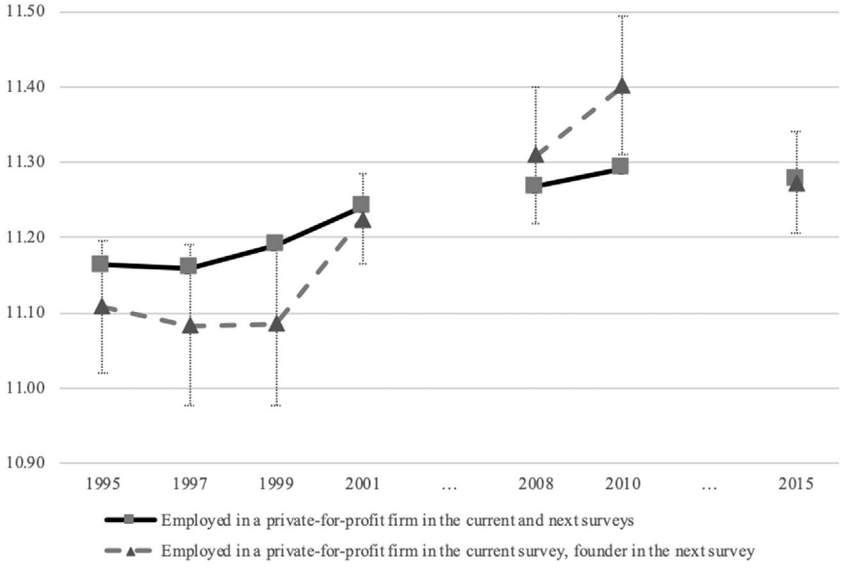


FIGURE 5 Predicted logged prechoice salaries for those becoming startup founders in the next survey and those remaining as wage workers. The bars represent 95% confidence intervals. *Source*: Author estimates based on National Science Foundation data.

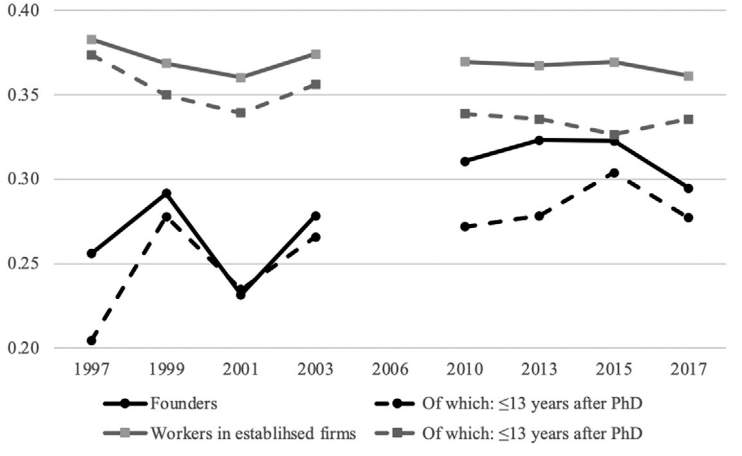


FIGURE 6 Share of graduates from top-ranked programs. *Source*: Author calculations using weighted National Science Foundation data.

implies that growth rates are increasing by about 1.6% per year, after controlling for the initial startup size and individual fixed effects, statistically significant at the 5% level (Table 7). Thus, there might be a silver lining: while increasing complexity of innovation is associated with a reduction in the number of startups, those that do form are started by individuals with higher human capital, they tend to be larger in size initially, and they also tend to grow faster over time.

6.2 | Changes in job motivation and job satisfaction

Figure 8 shows a key insight on changes of job motivation among startup founders versus paid workers over time.[13] Not surprisingly perhaps, the degree of independence is listed as very important relative to salary at much higher rates among startup founders than among workers (Hamilton, 2000; Roach & Sauermann, 2015). More interesting is the dynamics of these numbers. For workers at established firms, the relative importance of the salary factor steadily grows over time relative to the degree of independence and it exceeds the importance of the degree of independence after 2013 for all workers and already after 2010 for young workers (below the median age of 45).[14] Significantly, less experienced workers list salary as a relatively more important factor compared with independence than do all workers.

The trends among startup founders are even more interesting. For all startup founders there is either no trend or perhaps a slight trend toward increasing relative importance of the salary factor, similarly to workers in established firms. Among young startup founders, however, we see an opposite trend where the relative importance of the degree of independence becomes stronger compared with the salary factor over time. The difference between

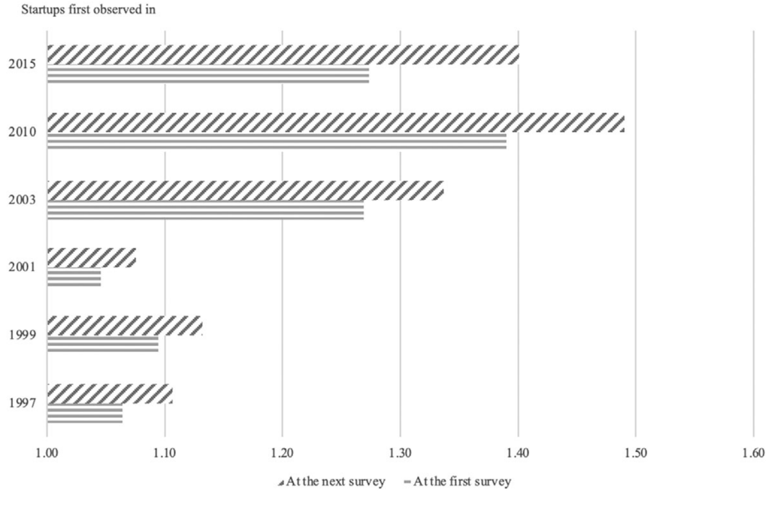


FIGURE 7 Average size of startups in panel data: years of first and next survey. *Source*: Author calculations using weighted National Science Foundation data.

TABLE 7 Growth rates of startup sizes in panel data.

DV:	Logged size category in the next survey, minus logged size category in the first observed survey
Time trend	0.016 (0.008)
Logged size category in the first observed survey	−0.917 (0.043)
Constant	0.789 (0.114)
Individual fixed effects	Included
Observations	542
Within R^2	0.180

Note: Estimation method—panel estimation with individual fixed effects, using weighted National Science Foundation data (weights for each individual averaged across two surveys). Robust standard errors in parentheses.

the fraction of those who listed independence as very important and those who listed salary as very important increases on average by ~50% from the start to the end of our sample.

Another interesting insight can be obtained from job satisfaction with respect to salary and degree of independence among startup founders and paid workers. There is a steep decline in the fraction of those satisfied with their salary on the principal job among young startup founders (Table A9). This is consistent with the trend in their real earnings and provides a cross-validation of both findings (Table A7). However, the satisfaction with the degree of independence is relatively stable at a high level, and even after a steep decline in the 2010s, the degree of satisfaction among young startup founders with their salary on the principal job is not that much below the degree of satisfaction among young paid workers with their salary in established firms.

In sum, we may conclude that new demands presented by the burden of knowledge have raised the requirements for founders' human capital and that market selection increasingly "chooses" PhD degree holders who place especially high value on independence to launch science-based startups. In contrast, those who choose to work for established firms display an increasing preference for salary.

6.3 | Robustness and alternative explanations

We wanted to gain insights about the dynamics of startups most likely to contribute to innovation and growth in the economy. For that purpose, we studied founders with a PhD in science and engineering who started an incorporated business. Founders of non-registered businesses or sole proprietors were thus excluded. In this section, we briefly examine what happens if we perturb that measure and also consider some more potential alternative interpretations of our findings. Note that in previous sections we already showed that our findings hold across all demographics, PhD fields, and location choices as well as that they are robust to excluding computer and IT-related fields and occupations, which represent a small minority of PhDs in science and engineering anyway.

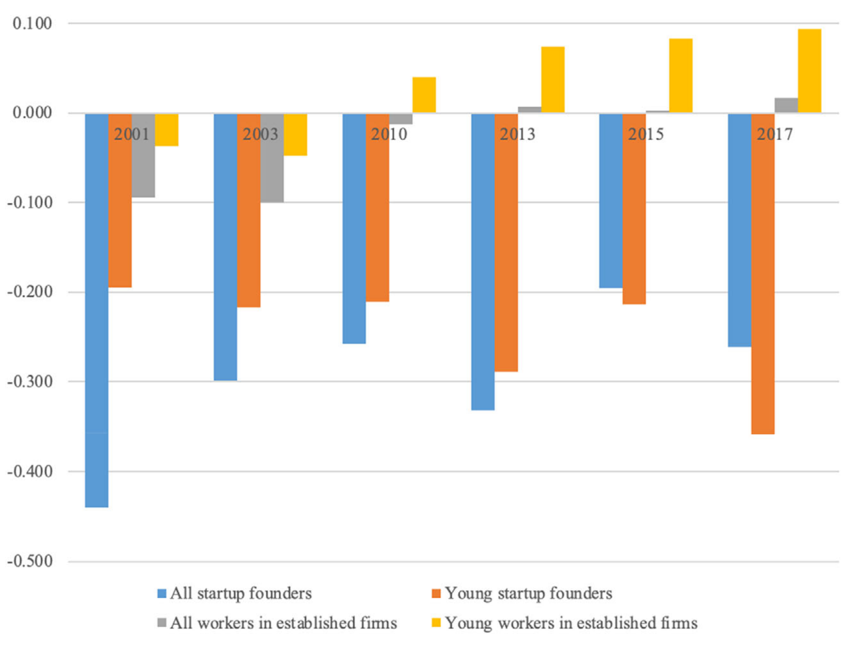


FIGURE 8 Differences in fractions for whom salary is very important and for whom independence is very important.

6.3.1 | Type of entrepreneurial opportunity

Following a series of articles showing that incorporated businesses pursue the highest opportunities, we chose to analyze founders of incorporated startups. Past research (Braguinsky et al., 2012; Ohyama, 2015) has employed the relation between the job and the highest degree as an alternative proxy for Schumpeterian entrepreneurs in these data. SDR surveys contain answers to the question about this relationship, with possible answers being "closely related," "somewhat related," and "not related at all." Following Braguinsky et al. (2012), we constructed a dummy that equals one if the answer was "closely related" and zero otherwise, and we call such business owners/self-employed in new businesses "education-job related (EJR)" founders, regardless of whether their businesses were incorporated. About half the self-employed and business owners and also founders in the sample fall into this category.

In Table 8, we repeated the estimations of Equation (1) above on the sample of EJR founders. The number of R&D tasks exhibits a positive time trend very similar in magnitude to the sample of incorporated startup founders in Table 2. EJR founders have to cope with a number of R&D tasks that are, once again, increasing over time at twice the rate experienced by workers at large, established firms. However, we see that in this case, the time trend is offset by experience (years after PhD), meaning that more experienced EJR founders tend to perform fewer R&D tasks over time. As in the main sample, EJR founders on average do not have recourse to deeper hierarchies, and while the coefficient on time trend in the regression with the span of control as the outcome variable is estimated to be positive, it is only marginally statistically significant. We also examined the time trend in earnings of EJR founders and found the results similar to those presented for incorporated founders in Table 4. The details are in Appendix H.

6.3.2 | Declining supply of PhDs?

Could the decline in the creation of science-based startups somehow be driven by a decline in the number of PhDs? It appears not. The overall supply of recent science and engineering PhD recipients is actually going up, as the number of PhDs awarded in science and engineering fields increased from 28,486 in 1997 to 41,294 in 2017 (National Science Foundation, National Center for Science and Engineering Statistics, 2019).

6.3.3 | Aging of the population?

Over the past few decades, the US population has been aging. Since young people tend to disproportionately found or join new businesses (Ouimet & Zarutskie, 2014), the aging of those receiving PhDs could explain the decline in Figure 1 (Hopenhayn et al., 2018; Karahan et al., 2019). However, if we define "young" as those below the median age of 45 (or any other reasonable cutoff, for that matter), the share of such young founders in the total number of all founders was stable throughout the period studied. Furthermore, while the age at which individuals received their PhDs in science and engineering had increased steadily until about 1993—the average recipient was 28.7 years old in 1971 and 31.3 years old in 1995—this trend was halted and even reversed after that—the average recipient in 2015 was 30.3 years old (Figure A13). Apparently, the age of founders is not strongly associated with the decline in science-based startups.[15]

6.3.4 | Declining venture capital?

A simple explanation for the decline in science-based startups would be if the amount of venture capital for startups has declined. However, the supply of venture funding has instead substantially increased since the dot com crash.

TABLE 8 The number of R&D tasks, the span of control, and the depth of the hierarchy for EJR founders.

DV:	IHS-transformed number of R&D tasks	IHS-transformed span of control	IHS-transformed depth of hierarchy
Time	0.0103 (0.002)	0.0061 (0.003)	−0.0015 (0.003)
Experience (years after PhD)	−0.0050 (0.002)	−0.0046 (0.002)	0.0012 (0.003)
Constant	1.108 (0.216)	0.794 (0.446)	0.639 (0.393)
Other controls: gender, ethnicity, occupation, and US state of employment	Included	Included	Included
Observations	2093	2093	2093
R^2	0.478	0.257	0.317

Note: Estimation method: OLS using weighted National Science Foundation data. Robust standard errors in parentheses. EJR refers to respondents whose answer to the question about the relationship between their job and the highest degree earned was that the two were "closely related."
Abbreviations: EJR, education-job related; IHS, inverse hyperbolic sine.

For example, the amount of global venture capital investments increased 10-fold, from $25 billion in 2004 to $254 billion in 2018 (National Venture Capital Association, 2019). More than 8380 venture-backed companies received $131 billion in funding in 2018, surpassing the $100 billion mark set at the height of the dot-com boom in 2000. For more detail on how venture capital has shifted over the years, see Lerner and Nanda (2020). Nevertheless, the recent decline in VC disbursements may potentially accelerate the trends observed.

7 | DISCUSSION

Human capital is argued to be a key source of firm competitive advantage (Castanias & Helfat, 1991, 2001). But, the same attributes that make employees strategic assets also create strategic dilemmas (Coff, 1997). We show in this article that startups face increasing pressure to motivate PhD-educated founders and their workers to create, join, and stay in startups. Startups appear to have been in a losing battle. To this effect, we first establish a new fact. Between 1997 and 2017, the share of startup founders with PhD degrees in science and engineering among all independent incorporated businesses owned by individuals with PhD degrees in science and engineering in the United States declined by around 38%, not limited to any particular founder demographic, ethnic group, region, occupation, or field of science. The declines are even larger among foreign born and minority founders. The employment share at startups has followed the same path of decline.[16] The trends appear despite a massive increase in venture capital funding and an impressive absolute growth in the number of PhDs. There are similar trends in startups in the high-tech sector and among inventor-founders (Goldschlag & Akcigit, 2022; Goldschlag & Miranda, 2020). The decline is large enough to contemplate if there is a need for managerial or public policy action. To do so one first needs an answer to the question "Why is this happening?"

To address this question, we set out on a journey of abductive reasoning (Pillai et al., 2021; Shani et al., 2020; Tohmé & Crespo, 2013), to produce exploratory hypotheses and yield plausible explanations about these puzzling phenomena. Using individual-level work data we show that founders in science-based startups have had to perform an increasing number of R&D tasks over time while also increasing the number of management tasks that they must perform. Nevertheless, their earnings generally have not reflected the added workload, as average earnings have been declining, although more experienced founders have seen an increase in earnings.

We also documented that their outside option to go and work for established firms has instead considerably improved along the same dimensions that have deteriorated in startups. Established firms, and especially larger ones, have had more room to adjust their innovative human capital management practices, in particular by introducing more layers in their hierarchies, reducing knowledge workers' span of control, and allocating more experienced workers to positions with greater managerial responsibility. Hence, they attract recent PhDs in greater numbers and therefore, fewer of these tend to create and join startups.

The totality of the evidence uncovered in this article points to an increasing complexity of innovation as a plausible explanation for the decline in science-based startups. The natural limits imposed by running a small firm with little opportunity to delegate R&D work and an already high and increasing degree of multitasking by the founder have made it more difficult to manage innovation in science-based startups over time. More experienced founders are therefore sought, and the few that are available fare better in terms of earnings.

Why should one care that innovative work has gotten, relatively, more comfortable in large firms? While a secular decline of new firms in mature industries might be a normal function of industry evolution (Klepper, 1996; Agarwal et al., 2020), such a decline in new, high-tech industries is a relatively recent phenomenon (Haltiwanger et al., 2014). This can have profound implications for innovation. After all, it is new firms from which many new technologies and business opportunities typically originate (Schumpeter, 1942) so that "[a] country cannot be great over a sustained period without a steady flow of great new firms" (Klepper, 2016, p. 62).

Our findings do suggest that there might be a silver lining: science-based startups that are still being founded appear to be larger and grow faster, and their founders tend to have not just more experience but also relatively higher human capital over time. The data also suggest that the recent declines in PhD founders are jointly driven by changes in pecuniary compensations and changing job tasks. It is plausible that the decline in the fraction of PhD founders and employees may flatten out as there are strong intrinsic motivations both to becoming a scientist and for a scientist to become a founder (or joiner) of a startup (Roach & Sauermann, 2015; Stern, 2004). Recall that we also find not just a trend toward higher human capital of the remaining founders, but also a tendency to be relatively more motivated by nonpecuniary motivations in more recent years. Those motivations may continue to fuel the creation of startups in the future.

That said, if the noted increase in pay difference remains, there could still be a permanently lower supply of willing founders in the future. If the goal is to restore business dynamism in the high-tech sector, alleviating the negative impacts of the increasing complexity of innovation should perhaps be front and center in the strategy to attain it. Practitioners and policy makers may need to find ways to make the job of the founder more attractive to keep the flow of commercialization of new ideas coming. For founders, that may mean more training in multitasking and use of advanced management practices and technical management tools. Another alternative is more, and better lubrication of the market for good and experienced "natural" founders, and we see some indications in the data that this is happening. The findings in this article point to the importance of secularly increasing value of complementary assets in work practices, especially for founders and employees that are high value generators. An alternative view is that the increasing dominance of a few very large tech firms that the increasing burden of knowledge is fueling is just fine, and that startups need not play an important role for economic development.

The data we employ in this study is individual- and work-based. In particular, we have very little firm-level data, which limits our ability to test alternative hypotheses. Note, however, that the level of detail about work activities available in the SDR surveys is not available in the Census (LEHD or even ACS) data and there is no known bridge between SDR surveys and Census data. Thus, as it is, we suggest that our conclusions from individual-level work data at the very least present an important and novel explanation to consider for the declining dynamism in science-based startups. Future research might be able to overcome current data limitations and bring together firm-level and individual-level analyses for an even more comprehensive picture of what is going on in the most technologically important parts among US businesses.

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ENDNOTES

[1] We use the terms "science-based startup founders," "startup founders," and "founders" interchangeably throughout this article.

[2] Most research examining the decline in business dynamics has focused on an economy-wide, "macro" perspective, with potential explanations centering around increased market concentration and the dominance of "superstar" firms (De Loecker et al., 2020; Autor, Dorn, Katz, Patterson & Van Reenen, 2020), changing demographics (aging) of the US population (Hopenhayn et al., 2018; Karahan, Pugsley & Sahin., 2019), and so forth. See Akcigit and Ates (2021), for a recent review of this literature.

[3] While long recognized as one of the three basic forms of human reasoning (Pierce, 1997), abductive reasoning is recently being rediscovered in the strategy, organization as well as economic literature (Heckman & Singer, 2017; Pillai et al., 2021; Shani et al., 2020; Tohmé & Crespo, 2013). Abductive reasoning "produces exploratory hypotheses" and "yields plausible explanations about puzzling phenomena … following a question, such as 'What is going on?'" (Shani et al., 2020, pp. 64–65).

[4] The choice of joining academia is not analyzed in this article. Others have noted a secular decline in this choice among PhD graduates in Science and Engineering. See, for example, Nature (2022).

[5] The other factors asked include benefits, job security, job location, opportunities for advancement, intellectual challenge, level of responsibility, and contribution to society. The questions were asked in the 2001, 2003, 2010, 2013, 2015, and 2017 surveys. See Appendix G for details.

[6] Computer-related occupations include computer and information scientists, system analysts, database and network administrators, computer software and hardware engineers, computer programmers, and so forth. More details can be found in Appendix D.

[7] While we included only basic demographic, labor experience, occupation, and geographical location controls in the main regression specifications here and below, the SDR data present a rich set of other potential controls (see Appendix B where we use a rich set of controls to estimate business age). We re-estimated all the regressions below while adding those other controls (dummies for: schools the individuals graduated from the relationship between job and education, marital and citizenship status, children in the household, whether the spouse works full-time or part time, as well as tenure on the current job and its square term). The results were very similar, if anything, the magnitude of the coefficients on the variables of interest was for the most part larger and statistical significance remained strong. Details are available upon request.

[8] In recognition of inherent difficulties with cross-sample comparisons of entrepreneurs and workers, especially in survey data (see, e.g., Hamilton, 2000), all the analyses here and below are based on comparing time trends *within* each sample of founders and workers, respectively.

[9] Suppose that a firm with 2 R&D teams with 10 members each added a second layer made up of a single manager, promoted from a supervisory position on one of the teams. The newly promoted manager had nine direct reports before the change but now has 0 direct and 19 indirect reports. Her replacement will have eight, not nine, direct reports. More generally, reorganizing a firm by adding layers of hierarchy while holding the firm size constant can be seen as accompanied by a decrease in the number of direct reports and an increase in the number of indirect reports.

[10] Recall that our analysis concerns workers with PhDs, and so primarily these results refer to changes in the hierarchy for those working on scientific tasks.

[11] See Table 1 for the definition of R&D-focused respondents.

[12] Since we need repeated observations from two surveys, we had to drop 2017 which is the last year in the data.

[13] We use responses to questions about the importance of various factors when thinking about a job. In this figure, we focus on the fraction of those who responded that salary was very important versus the fraction of those who responded that the degree of independence was very important and compare them across startup founders and workers in established firms, and across time. See Table A8 for absolute numbers in each category.

[14] We use age rather than experience here because we are dealing with differences in preferences which are more likely to be different among younger and older rather than more or less experienced individuals. That said, the findings are very similar if we use the median years after PhD as a cutoff instead, as in the rest of this article.

[15] In contrast, as mentioned, accumulated work experience (years after PhD) prior to founding a startup did tend to increase over time. See the discussion in Appendix E.

[16] We follow common practice (e.g., Decker et al., 2014; Haltiwanger et al., 2014) and define startup rates (and employment in them) as the share of new incorporated businesses with PhD founders in all incorporated businesses with PhD owners (and employment in them). The point is to examine the trend in where PhDs decide to apply their skills; startups or

established firms. We do not study the share of self-employment among all workers, and we do not study the absolute number of startups.

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