Different founders, different venture outcomes: A comparative analysis of academic and non-academic startups ☆

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ABSTRACT

What role do differences in founders' occupational backgrounds play in new venture performance? Analyzing a novel dataset of 2998 founders creating 1723 innovative startups in biomedicine, we find that the likelihood and hazard of achieving a liquidity event are lower for academic than for non-academic startups. However, academic startups produce as many patents and receive as much funding as non-academic startups, suggesting that the observed differences in achieving a liquidity event are not driven by differential invention performance. Exploiting heterogeneity among academic startups, we also find that differences between professor and student startups do not explain academic startups' comparatively low performance on the exit market vis-à-vis non-academic startups. Yet, startups founded by superstar professors perform similarly to non-academic startups on the exit market for new ventures, and better than startups founded by highly productive professors but without external certification.

1. Introduction

How do differences in founders' occupational backgrounds relate to new venture performance? Prior studies have shown that the characteristics of the occupations individuals choose can have an important and enduring effect on individuals capabilities and any resulting comparative advantages (Bercovitz and Feldman, 2007). This imprinting effect persists over time, including when individuals transition into entrepreneurship (Colombo and Piva, 2012).

Extant literature has related new venture performance outcomes to founders' employment histories within specific institutional contexts (e.g., Campbell et al., 2012; Chatterji, 2009; Elfenbein et al., 2010; Fuller and Rothaermel, 2012; Gregorio and Shane, 2003; Zucker et al., 2002). However, our knowledge about how differences in founders' occupational backgrounds spanning multiple institutional contexts - such as academia and industry - impact new venture performance remains limited. This is an important gap given that differences in institutional environments may lead entrepreneurs to systematically pursue distinct technologies and commercialization strategies. These fundamentally different approaches (Powell and Colyvas, 2008; Thornton and Ocasio, 1999) could then result in heterogeneity across innovative startups in terms of their subsequent performance. Evidence of heterogeneity across innovative startups, in turn, has policy implications as our understanding grows that one-size-fits-all policies appear to be suboptimal, and more nuanced approaches in attempting to induce entrepreneurship and innovation may be warranted (Colombelli et al., 2016).

To advance our understanding of the relationship between heterogeneity in founders' occupational backgrounds spanning distinct institutional settings and new venture performance, we examine founders and their startups operating in two innovative sectors: biotechnology and medical devices ("biomedicine"). These sectors are R&D- and

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innovation-intensive, and thus provide important contributions to developed economies' employment and economic growth (Antonipillai and Lee, 2016). Moreover, the role of occupational imprinting in biomedicine appears especially relevant given that the creation and commercialization of new technologies often require a bundle of tacit knowledge, complex skills, and expertise that founders acquire over years spent in their occupational training (Colombo and Grilli, 2010).

In the classical Schumpeterian sense, we propose that academic founders have a comparative *invention* advantage while industry founders have a comparative *innovation* advantage.[1] As such, we set out to assess how academic and non-academic founders' comparative advantages translate into new venture performance. Our *ex-ante* conjecture is that academic founders have a comparative advantage in the production of new knowledge and technologies. In contrast, we submit that founders with an industry background are more likely to have a comparative advantage along the commercialization dimension (i.e., transforming new technologies into viable products and services).

To evaluate the proposed comparative advantages held by different types of ventures along the knowledge conversion process from invention to innovation, we develop our empirical analysis in two parts. We begin by distinguishing between academic and non-academic startups. Successively, we exploit fine-grained heterogeneity within the category of academic startups to explore possible mechanisms behind the observed performance differentials between academic and non-academic startups. We thereby attempt to unpack the black box of academic startups to gain a deeper understanding about how academic startups, in general, and how different types of academic ventures, in particular, perform in comparison to non-academic startups.

For our empirical analysis we build on Conti and Roche (forthcoming) and examine a sample of 2998 founders from different occupational backgrounds who created 1723 startups between 2005 and 2012. We draw the sample of startups from Crunchbase, which contains detailed information regarding the startups' sectors of operation, founding dates, founder biographies, financing rounds, and exit events. We complement these initial data with several other sources, such as VentureXpert, the US Patent and Trademark Office (USPTO), Scopus, Web of Science (WoS), LinkedIn, as well as the companies' websites, generating a unique and rich dataset of startups, their founding teams, and new venture performance outcomes.

Our results reveal several interesting patterns. We show that academic startups produce as many patents and receive as much funding as non-academic startups. However, the likelihood and hazard of achieving a liquidity event (i.e., an initial public offering (IPO) or acquisition) are lower for academic than for non-academic startups. Together, these results suggest that academic and non-academic startups do not differ along the invention dimension. However, it appears that startups founded by academics take longer to exit than those created by non-academic startups suggesting differences along the innovation dimension.

We next examine heterogeneity within the category of academic startups to assess whether professor startups hold a comparative invention advantage relative to student startups, and, if so, whether this translates into differential performance outcomes. The results indicate that although students start ventures with fewer patents than professors, student startups are as likely and as quick to experience a liquidity event as professor startups. These results suggest that although professor and student startups' may differ in terms of the types of projects they pursue, their innovation outcomes are similar.

Finally, we explore heterogeneity within the category of startups founded by professors to assess which factors may help academic startups close the observed commercialization gap with non-academic startups. Specifically, we assess whether certification by an external,

renowned institution such as the Nobel Prize Committee might counterbalance the comparative innovation disadvantage of academic founders. We compare the performance outcomes of startups initiated by professors with external certification to startups founded by similarly productive professors but without such external certification. Our results show that startups founded by highly productive professors with external certification - that is, academic superstars, perform as well as non-academic startups on the exit market (i.e., IPO or acquisition). This suggests that startups created with the involvement of a superstar professor can close the commercialization gap we detect for academic startups relative to non-academic startups.

2. Conceptual framework

The occupations individuals pursue shape their mental models, capabilities, skills, and expertise in a way that reflects the characteristics of each unique work environment (Burton and Beckman, 2007). This effect has been suggested to be a result of imprinting (Stinchcombe, 1965), which persists over time and affects subsequent decisions and behavior. Prior research focusing on Silicon Valley high-tech startups has documented how the mental models and initial decisions of founders during the genesis of new ventures persist over time and thus influence subsequent organizational performance (Baron et al., 1999). More recent work has provided evidence that this imprinting effect persists even when individuals transition to new occupations, including when they start new ventures (Colombo and Piva, 2012).

Generally, individuals choose occupations from which they derive the highest expected utility (Roach and Sauermann, 2010; Stern, 2004). The characteristics of the occupations individuals pursue have an enduring influence on their accumulated tacit knowledge, capabilities, and beliefs (Minola et al., 2013). These differences in cognition shape individuals' comparative advantages (Bercovitz and Feldman, 2007; Simsek et al., 2015). Moreover, the observed differences in cognition tend to persist even when individuals switch jobs, including when making the transition into entrepreneurship (Colombo and Piva, 2012; McEvily et al., 2012). As such, occupational imprinting has been documented to shape founders' behaviors (Powell and Sandholtz, 2012) as well as their capabilities and resources (Colombo and Piva, 2012). Further research theorizes that these behaviors, resources, and capabilities find their expression in the development of distinct organizational structures, routines, and processes in founders' new ventures (Bryant, 2014). Such research also provides empirical evidence showing that organizational practices are, indeed, transferred from parent companies to spawns via their founders (Feldman et al., 2019). Despite these contributions, however, little is known about how occupational imprinting of founders influences the early stage performance of startups (Hahn et al., 2018).

Extant literature, moreover, has examined how different career backgrounds of founders relate to startups' performance outcomes within specific institutional contexts (e.g., Chatterji, 2009; Gregorio and Shane, 2003; Zucker et al., 2002). This literature distinguishes, for example, between characteristics such as the size of firms spawning new ventures (Elfenbein et al., 2010), industry affiliation of previous employers (Chatterji, 2009), the relative quality of employees within the source firm (Campbell et al., 2012), and the prominence of founders (Fuller and Rothaermel, 2012). The focus of this line of research, however, has largely been confined to a single institutional setting when examining the influence of founders' occupational backgrounds on subsequent new venture performance. As a consequence, our knowledge regarding how startups initiated by founders hailing from occupations with distinct institutional backgrounds fare in comparison to each other, or regarding the capabilities and resources that may matter for explaining any resulting performance differentials is still limited (Agarwal and Shah, 2014; Wennberg et al., 2011).

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[1] We follow the definition of innovation as commercialized invention as put forward by Schumpeter (1934).

2.1. Academic versus non-academic founders

The main distinction we make in this paper is between academic and non-academic founders. Since the Bayh-Dole Act of 1980, the number of academic startups has increased rapidly in the US (Audretsch, 2014; Rothaermel et al., 2007), thereby, representing a fundamental engine for innovation, especially in knowledge-intensive areas (Acs and Audretsch, 1990; AUTM, 2016). Notwithstanding, academic founders differ from non-academic founders with respect to the type of knowledge they possess, their capabilities, and resulting behaviors. One reason for these differences is that academic founders undergo extensive technical training relative to non-academic entrepreneurs (Fini et al., 2017), and as such, specialize in scientific problem solving (Schilling and Green, 2011). In comparison to venture founders with an industry background, academic founders tend to exhibit a relatively larger stock of scientific knowledge, have generally better access to specialized equipment and instruments, as well as exposure to the latest ideas and research findings, all else being equal. Academic founders typically create and develop the technologies underlying their new ventures within their own laboratories (Colombo and Piva, 2012). The insights academic founders obtain from their experiments allow them to gain intimate and often tacit knowledge about when and why a technology may succeed or fail (Fuller and Rothaermel, 2012). Combining these arguments, *ceteris paribus*, academic founders should exhibit higher levels of expertise as well as greater experience pertaining to basic research and novel technologies relative to non-academic founders. Having received extensive training in the basic sciences and research in academic laboratories over many years (Stephan, 2012), academic founders, therefore, should possess a comparative advantage in producing new knowledge and technologies relative to non-academic founders.

A further reason why academic and non-academic founders differ is that academic founders spend the bulk of their careers within the university setting or comparable research institutions. The university research setting and commercial setting are fundamentally different along many dimensions, which find their expression in different organizational structures and reward systems as well as in different organizational cultures. For instance, academic founders might pursue projects that are more early-stage than those of non-academic founders, thus, prolonging the time to exit (Aghion et al., 2008). Furthermore, academic founders may have lower levels of experience with regulatory (Roberts, 1991), commercial (Colombo and Piva, 2012) and managerial functions (Brüderl et al., 1992; Rothaermel and Thursby, 2005), as well as exhibit less expertise in connecting their inventions with complementary assets often required for successful innovation (Rothaermel, 2001; Teece, 1986). In contrast, given their occupational background in industry, non-academic founders will likely possess relevant market knowledge (Agarwal and Shah, 2014; Hahn et al., 2018), which could expedite the commercialization process.

Given these arguments, we conjecture that academic founders exhibit a comparative advantage vis-à-vis non-academic founders in producing new knowledge and technologies (invention), while non-academic founders have a comparative advantage vis-à-vis academic founders in terms of bringing new technologies to the market (innovation). We suggest that the differences in occupational imprinting between academic and non-academic founders may result in distinct comparative advantages, which in turn motivate the guiding question of this paper: How do distinct comparative advantages of academic versus non-academic founders translate into startup characteristics and early venture performance?

2.2. Heterogeneity among academic founders

To gain further insights into how founders' occupational backgrounds and any resulting comparative advantages may affect startup outcomes, we examine heterogeneity among founders beyond the distinction between academic and non-academic entrepreneurs. In particular, we focus on academic startups given that the extant literature has highlighted important nuances in the way distinct actors within academia produce and disseminate new knowledge (Sauermann and Stephan, 2013). Therefore, we ask: How do differences among founders of academic startups influence their comparative advantage and subsequent new venture performance relative to non-academic startups?

2.3. Professor versus PhD student founders

The first distinction we make among academic founders is between professors and PhD students. Previous literature attributes a critical, often complementary role in entrepreneurship to both professors and students (Boh and Strom, 2016; Roberts, 1991). Professors and students, however, differ from each other in terms of their knowledge, capabilities, and projects they pursue. For instance, professors and students have distinct stocks of knowledge and expertise (Murray 2004; Stephan, 2012). Based on cumulative experience, professors, on average, possess deeper scientific expertise than students (Müller, 2010). As such, professors may leverage their accumulated knowledge capital to develop more promising technologies and to attract investors (Fuller and Rothaermel, 2012).

It is also important to stress that professor and student founders are likely to engage in different types of startups (Gans and Stern, 2017). Studies have highlighted that students are faced with relatively lower opportunity costs of entrepreneurial entry than professors given differences in the characteristics of their occupations (Ching et al., 2018). Unlike professors, students do not hold well-paid, tenured faculty positions and are, therefore, more sensitive to business cycles. As such, students have lower opportunity costs for transitioning into entrepreneurship, which may also lower the quality threshold of turning their ideas into new ventures (Conti and Roche, forthcoming).

2.4. Heterogeneity among professor founders

The second distinction we make within academia is between academic superstars and other types of academic founders. Prior literature suggests that academic superstars may have a comparative commercialization advantage vis-à-vis other founders (e.g., Fuller and Rothaermel, 2012; Higgins et al., 2011). As put forward by Rosen (1981) in his seminal work on the economics of superstars, one reason for this advantage could be that superstars are endowed with (unobservable) inherent superior talent or quality, which can be applied to a range of activities such as making fundamental breakthroughs in basic sciences, but also to starting businesses (Feldman et al., 2019; Stuart and Ding, 2006).

An alternative reason could be that, all else equal, the external certification academic superstar founders receive by winning prestigious prizes or by becoming members of an elite group, may help them overcome information asymmetries related to their technologies (Megginson and Weiss, 1991). Especially given the inherent opaqueness about startups' underlying quality (Conti et al., 2013a; 2013b), the certification these academic superstar founders receive may be an important channel that allows potential investors to assess the quality of a given startup. Given that academic founders lack commercialization experience (Jensen and Thursby, 2001; Rothaermel and Thursby, 2005) and tend to pursue early-stage technologies (Aghion et al., 2008), quality signals such as conveyed by stardom may play an important role in closing the commercialization gap between academic and non-academic startups (Spence, 1973).

3. Data

3.1. Data sources and construction

We assembled the data for the empirical analyses by drawing from various sources, which enabled us to create not only a novel dataset, but also to tailor it for our analyses. We constructed the main dataset from the population of US startups listed on Crunchbase, an online directory of startups, their employees and investors (used in recent prior work, see for example, Wu (2016) and Conti and Roche (forthcoming). Crunchbase records extensive information on the founding members, startups' sectors and technologies, founding date, financing rounds, and employee biographies. A substantial component of the data is collected by Crunchbase staff, while the remaining portion is crowdsourced and subsequently reviewed. An important advantage of Crunchbase is that the database provides a larger coverage of technology startups than traditional databases such as VentureXpert and VentureSource, both of which focus on venture capital-funded startups only (Block and Sandner, 2009). In addition, Crunchbase is synchronized with AngelList, thus providing a more comprehensive coverage of startup financing. Moreover, in contrast to the more traditional databases, Crunchbase provides information regarding startups seeking capital, but that have not necessarily succeeded in raising any funds. This feature is an important advantage for our study as it limits potential selection and survivor bias.

From the list of Crunchbase startups established in the United States, we retained those operating in biomedicine (that is, biotechnology and medical devices). Biomedicine is a particularly innovative and knowledge intensive area (Kenney, 1986; Zucker et al., 1998; Stephan, 2012) and, as such, provides important contributions to developed countries' employment and economic growth (Antonipillai and Lee, 2016). Moreover, biotechnology and medical devices are especially relevant because both the production and the commercialization of new technologies require a set of complex skills and expertise that founders can acquire through their prior occupations (Colombo and Grilli, 2010). Indeed, given the tacit nature of the knowledge needed for the invention and commercialization of new technologies, it is only through years of 'on-the-job training' that such skills can be acquired. Since Crunchbase's coverage of startups has been validated to be accurate in more recent years (Wu, 2016), we only retained startups founded after 2004. Furthermore, we excluded those startups founded after 2012 to provide sufficient time to evaluate startups' performance outcomes.

As any other dataset of startups, Crunchbase has incomplete coverage of founders. To verify and increase the set of founder identities, we conducted additional searches in a comprehensive fashion. Using information available primarily from each startup's website, LinkedIn, and Bloomberg, we were able to identify the founding team for 1790 of the 2064 companies (87%). The average number of founders per startup is approximately two, which is in line with other studies examining early-stage startups (Ewens and Marx, 2018; Kaplan et al., 2009). We excluded 116 founders who resided outside of the US at the time their company was established and their respective startups to ensure comparability across startups avoiding the introduction of biases that may stem from country-specific characteristics. We further dropped 30 startups created by founders that we could not classify as purely academic or non-academic. These 'other founders' are university administrative staff who work in the institutional environment of academia, but whose job is regulated by different norms, requires other training, and follows distinct career trajectories than those of professors and PhD students.

The final sample is composed of 1723 companies and 2998 founders. All the individuals in our dataset are the original founders of their respective startups, but hail from different occupational backgrounds. For each of these founders, we collected detailed information regarding their occupation, education, and gender prior to establishing a given startup using the same secondary sources listed above. We further complemented the data available from Crunchbase with startup patent information retrieved from Thomson Innovation (now Clarivate Analytics). We additionally collected fine-grained information for academic founders from Scopus, Web of Science (WoS), university websites, and other sources. These data consist of information on university affiliation(s), the individual's academic position (PhD student, postdoc, (untenured) assistant professor, and (tenured) professor), their publication output, as well as whether the individual founder is a Nobel Prize Laureate (Nobel), a member of the National Academy of Sciences (NAS), or a Highly Cited Researcher (HCR).[2]

3.2. Descriptive statistics

Fig. 1 presents the distribution of employment categories among the founders in our sample: 9.8% are students,[3] 22.5% are university professors, three percent are university administrative staff, and the remaining 64.7% are firm employees.[4] Turning to descriptive statistics for the 1723 startups founded by the entrepreneurs in our sample (Table 1), we note that 1231 (71%) operated in biotechnology, while 492 (29%) were active in the medical device sector.

We define an academic startup as a new venture that was founded by at least one professor or at least one student affiliated with a university at the time of founding. Approximately 39% of the new ventures created in biomedicine are academic startups (highlighting the role academic startups play in these innovation-intensive sectors), while 61% of the new ventures in biomedicine were non-academic startups. Nine percent of the new ventures in our sample are startups founded by at least one student, but no professors, and 30% were founded by at least one professor.

Startups created by superstar professors account for five percent of the new ventures in our sample. This category of superstar professors includes Nobel Prize Laureates, members of the National Academy of Sciences, and WoS' Highly Cited Researchers.[5] Of the startups in our sample, six percent were founded by professors who are in the 75th percentile in terms of their publication output, but who were not externally endorsed by any of the above-mentioned institutions.

The average amount of funds a startup raised within five years of their inception is $12.66 million. Not surprisingly, the amount of funding startups raise is skewed as the median of $0.26 million indicates. Within the sample of startups, 35% received VC funding, within five years of their inception. The average number of US granted patents that startups applied for within three years of inception is 1.68. We find that 14% achieved a liquidity event by May 2016.[6] Nine percent of the startups have at least one female founder, and 26% have at least one founder who graduated from a top-tier university.[7]

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[2] The list of HCR is available at *clarivate.com/hcr/researchers-list/archived-lists/* (accessed March, 2018).

[3] The student category consists of predominately PhD students and postdocs. Only 15 (0.8% of the initial sample) of the founders are individuals who had just obtained their undergraduate university degree.

[4] Thirty percent were previously employed in firms with more than 10 employees, 10% previously worked at firms with 10 employees or less, and 24% had previously worked as either a founder or a CXO of a startup. In this paper we will not further exploit heterogeneity of firm employees given the focus of the research question.

[5] For descriptive statistics by founder type, please refer to the Appendix, Table A1.

[6] The average time to achieving a liquidity event lies at approximately 5.5 years.

[7] We determine top-tier universities following the 2016 Academic Ranking of World Universities ("Shanghai Ranking", accessible at *shanghairanking.com*).

Fig. 1. Founders' occupational background.
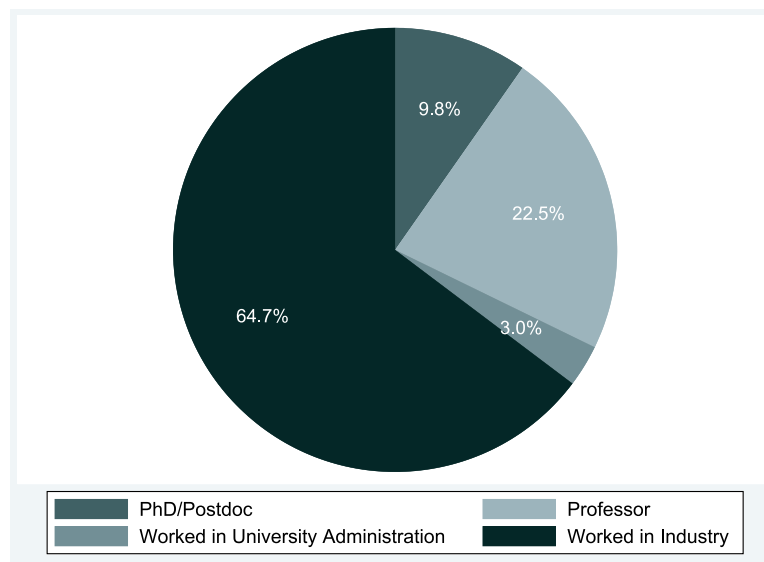
Table 1
Summary statistics.

	Min	Mean	p50	max
Academic startup	0.00	0.39	0.00	1.00
- Student/no professor	0.00	0.09	0.00	1.00
- At least one professor	0.00	0.30	0.00	1.00
- Professor - Nobel/NAS/HCR	0.00	0.05	0.00	1.00
- Professor - Top 75th pct.	0.00	0.06	0.00	1.00
Number patents	0.00	1.68	0.00	145.00
Amount of funds raised ($million)	0.00	12.66	0.26	507.00
VC (= 0/1)	0.00	0.35	0.00	1.00
IPO a/o acquired	0.00	0.14	0.00	1.00
Team size	1.00	1.74	2.00	7.00
At least one female founder	0.00	0.09	0.00	1.00
At least one top-tier university	0.00	0.26	0.00	1.00
Biotechnology sector	0.00	0.71	1.00	1.00
State unemployment rate	2.61	7.23	6.87	13.78
Startup age in 2015	3.00	6.52	7.00	10.00
Observations	1723			

4. Regression results

We now turn to the empirical analysis to understand how startups initiated by founders with different occupational backgrounds fare in comparison to each other. Moreover, we attempt to shed some light on which types of capabilities and resources as passed on through institutional imprinting may matter along the invention and innovation process for explaining early stage performance differentials in new technology ventures. We do this to answer our research questions of how founders' occupational background relates to new venture performance, and what potential factors drive possible differences.

4.1. Academic versus non-academic founders

In Table 2, we report the results from estimating the relationship between a founders' occupational background and a set of venture outcomes. The regression equation we estimate is:

$$Y_i = \alpha ACADEMIC_i + \beta X_i + f_{State} + f_{Founding\ year} + f_{Sector} + \epsilon_i \quad (1)$$

Each observation corresponds to a given startup i. The dependent variable Y_i refers to the outcomes for startup i. To identify suitable startup outcome measures we follow the existing literature that distinguishes between innovative and financial outcomes (e.g., Hochberg et al., 2007; Nanda and Rhodes-Kropf, 2013; Conti et al., 2019; Conti

and Graham, 2020; Townsend, 2015).[8]

The first outcome we examine, *Patents*, is the aggregate number of US granted patents a startup applied for within three years of inception. Following prior literature (Acs and Audretsch, 1989), we view the number of patents as a proxy for a startup's knowledge and technology stock, and therefore, inventive output. This is especially appropriate in industries with strong science-technology linkages such as in biomedicine. By using patent application dates, we are measuring the timing of an invention as close as possible. Moreover, by counting only those patents that were granted from such applications, we condition on valuable technologies (Conti and Graham, 2020). Given the highly skewed distribution of the startups' number of patents, we log transform this variable.

The second outcome is the amount of funding in US dollars a startup raised (*Funds*). This variable is measured within five years of a startup's inception. Given the highly skewed distribution of the amount of funding startups raise, we also log transform this variable. The third outcome, *VC*, is an indicator that equals one if the focal startup received VC funding within five years of its inception and zero otherwise.

We distinguish these three intermediary performance outcomes from the final outcome, which is an indicator for whether a focal startup experiences a *Liquidity Event*. This dependent variable is frequently used to assess new venture performance (e.g., Eesley et al., 2014; Nanda and Rhodes-Kropf, 2013; Townsend, 2015), and equals one if the startup either went public via an initial public offering (IPO) or was acquired. In further robustness checks, we recode this last performance indicator including only those acquisitions made by the top five percent of acquirers as measured by their relative acquisition intensity (*p95*).

The variable $ACADEMIC_i$ is our main variable of interest in Eq. (1). This is an indicator that takes on a value of one if the startup was founded by at least one professor and/or one student (enrolled in academia at the time they became founders) and zero if the startup was created by non-academic founders. The $ACADEMIC_i$ coefficient thus captures the relative difference in any of the outcomes in Eq. (1) that can be ascribed to the occupational background of the founders, all else equal.

The vector X_i encompasses the set of controls included in each of the models. Time-varying controls are measured in the period preceding Y_i.

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[8] Whenever we log transform a variable we add one - ln(x + 1) - to take zero outcomes into account.

Table 2
Performance outcomes for academic versus non-academic startups.

				Models			
				Liquidity event			
	(I) Patents (log)	(II) Funds (log)	(III) VC (= 0/1)	(IV) Reduced	(V) Full	(VI) Reduced p95	(VII) Full p95
ACADEMIC	−0.0534	−0.415	−0.0411*	−0.0818***	−0.0732***	−0.0648***	−0.0568***
	(0.0390)	(0.384)	(0.0205)	(0.0170)	(0.0186)	(0.0101)	(0.0106)
Number patents (log)		0.501**	0.107***		0.0373***		0.0337***
		(0.194)	(0.0142)		(0.0106)		(0.00949)
Funds (log)	0.000968		0.0139***		0.000794		0.00116
	(0.00186)		(0.00126)		(0.00145)		(0.000968)
VC (= 0/1)	0.297***				0.103***		0.0930***
	(0.0359)				(0.0202)		(0.0234)
Team size (log)	0.00218	1.529***	0.0901***	0.0542***	0.0396**	0.0411**	0.0273*
	(0.0613)	(0.397)	(0.0210)	(0.0193)	(0.0161)	(0.0168)	(0.0150)
At least one top-tier university	−0.0450	0.524	0.00268	0.0163	0.0170	0.0116	0.0120
	(0.0309)	(0.437)	(0.0222)	(0.0140)	(0.0125)	(0.0115)	(0.0108)
At least one female founder	−0.00272	0.981*	−0.0568	−0.0664***	−0.0619***	−0.0496***	−0.0460***
	(0.0446)	(0.493)	(0.0350)	(0.0243)	(0.0230)	(0.0139)	(0.0138)
State unemployment rate	−0.0423**	−0.204	−0.00439	−0.0170	−0.0138	−0.00819	−0.00521
	(0.0194)	(0.181)	(0.0170)	(0.0105)	(0.0101)	(0.00789)	(0.00710)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1723	1723	1723	1723	1723	1723	1723
R-sq.	0.121	0.150	0.181	0.0931	0.122	0.0766	0.108

Notes: All models are estimated using Ordinary Least Squares (OLS). Each observation corresponds to a given startup *i*. In column (I), the outcome *Patents*, is the aggregate number of U.S. granted patents a startup applied for within three years of inception (expressed in natural logarithm). In column II, the outcome variable we examine is the amount of funds a startup raised (expressed in natural logarithm). The outcome in column III, *VC*, is an indicator that equals one if the focal startup received VC funding within five years of its inception and zero otherwise. The outcome in columns IV and V is an indicator that equals one if the startup either went public via an IPO or was acquired by May 2016. In columns IV and VII, we recode this liquidity event indicator only including those acquisitions made by the top five percent acquirers as measured by their relative acquisition intensity (*p95*). We cluster standard errors at the state level. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

First, we include the number of founders a startup had at inception (*Team size*), intended as a proxy for the size of a venture at founding. We include the natural log transformation of this variable because the number of founding members is highly skewed across startups.[9] Next, we use an indicator, *At least one top-tier university*, that equals one if at least one founder had obtained their highest university degree at a top-tier university and zero otherwise. A university is considered to be top-tier if it ranks among the top-20 world universities, according to the 2016 Academic Ranking of World Universities. The variable *At least one female founder* equals one if at least one founder is female. Additionally, *State unemployment rate* is the unemployment rate measured during the year a startup was founded in the US state in which the startup was registered. This variable captures linear trends at the state and founding-year level.

In this regression model, we control for state and founding-year fixed effects (f_{State} and $f_{Founding\,year}$) to capture trends that may be specific to the state in which founders are located and the year in which they choose to start their company.[10] The sector fixed effects (f_{Sector}) consist of an indicator that equals one for startups operating in biotechnology, and zero for startups operating in medical devices. We include this indicator variable to control for field-specific trends. In each regression model, we cluster standard errors at the state level to account for intra-group correlation.

Table 2 displays the results from estimating Eq. (1) for each of the outcomes Y_i mentioned above. Column I reports the estimation results for the number of patents (*Patents*). Academic and non-academic startups do not statistically differ in terms of the number of patents they apply for within three years of inception (*p*-value: 0.179). VC funding is a strong positive predictor of the number of patents, and the state unemployment rate negatively predicts the stock of patents a startup has.

Column II presents the results for the amount of funding a startup raised within five years of its inception. As shown, the amount of funding academic startups received does not differ significantly from the amount of funding non-academic startups raised, all else equal (*p*-value: 0.286). The log number of patents, team size, and having at least one female founder instead positively and significantly predict the amount of funds a startup raised. Finally, having a founding team member who graduated from a top-tier university and the state unemployment rate at founding do not have a statistically significant effect on the amount of funds raised.

Column III displays the results for the likelihood that a startup received VC funding. Here, academic startups are significantly less likely to receive VC funding than non-academic startups. The magnitude of the coefficient suggests that being an academic startup reduces the likelihood of receiving VC funding by four percentage points, which equates to a 11.4 percent decline relative to the mean. The controls *Funds, Number of patents*, and *Team size* each positively predict the likelihood that a startup receives VC funding, while all other controls in the model are not statistically significant.

Column IV and V display the estimation results for the dependent variable *Liquidity Event*. In column IV, we exclude the intermediary startup outcomes we discussed earlier i.e., patents, the amount of funds raised, and VC funding. In column V, we include these intermediary startup outcomes as controls. The results displayed in column IV show

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[9] The results are not sensitive, however, to using different functional forms.

[10] Founding-year fixed effects are stronger controls for age-related trends than the age of a startup. In fact, these fixed effects do not constrain the relationship between startup age and performance outcomes to a linear functional form.

that academic startups are significantly less likely to experience a liquidity event than non-academic startups. The magnitude of the effect suggests that academic startups are 8.2 percentage points less likely to exit via an IPO or an acquisition than non-academic startups. This represents a 58.6% decrease from the mean. This effect remains statistically significant once we control for intermediary startup outcomes in column V. As expected, these controls are positive predictors of a startup's likelihood of achieving a liquidity event. Notably, the magnitude of the *ACADEMIC* coefficient declines only slightly to 7.3 percentage points relative to column IV. These results are robust to using a more refined set of outcomes (columns VI and VII): IPOs and acquisitions made by the top 95th percentile of acquirers only (*p95*). These results are also robust to substituting the indicator *ACADEMIC* with the share of academics as reported in Table A2 of the Appendix.

Besides the differences we have highlighted, academic and non-academic startups may also differ in the timing to achieve certain milestones. Recent work in the entrepreneurship literature emphasizes the importance of considering life-cycle contingencies when assessing entrepreneurial performance (Clough et al., 2019; Maurer and Ebers, 2006). In response to this call, we additionally report the results from estimating a Cox proportional hazard model for: i) the time (in years) to a first financing round, and ii) the time to achieving a liquidity event (in years) for each startup. The general model we estimate takes on the following functional form:

$$\lambda(t|Z_i) = \lambda_0(t)exp(\alpha ACADEMIC_i + \beta Z_i) \qquad (2)$$

where $\lambda(t)$ is the hazard function, which is determined by the baseline hazard $\lambda_0(t)$, our variable of interest $ACADEMIC_i$, and a set of time-variant and time-invariant controls contained in Z_i. The time-variant covariates are the accumulated number of patents (*Accum. number of patents*) and the accumulated amount of funding (*Accum. amount of funds*) as of time t, whether a startup has received VC funding (*VC*) as of time t, and the *State unemployment rate* in time t. The time-invariant variables we control for are *Team size*, an indicator equal to one if the startup had at least one female founder, and an indicator equal to one if one of the founders graduated from a top-tier university. As in Eq. (1), we also control for state, founding-year, and sector fixed effects. We cluster standard errors at the startup level to account for intra-group correlation, and report hazard ratios. Hazard ratios greater (smaller) than one indicate a positive (negative) relationship with the risk of achieving i) a first round of financing, and ii) a liquidity event.

The results from estimating Eq. (2) are presented in Table 3. Column I of Table 3 reports the hazard of achieving a first round of financing. In line with our earlier results, the coefficient on the indicator for the occupational background of the founders, *ACADEMIC*, is not statistically significant on conventional levels (*p*-value: 0.609). This result suggests that academic and non-academic startups do not differ in their time to first funding. Column II and III present the results for estimating time to liquidity, excluding the intermediary startup outcomes (column II) and controlling for them (column III). Regardless of the model specification, academic startups have a lower risk of experiencing a liquidity event at each time t. Consistent with our findings in Table 2, the magnitude of the coefficient declines only slightly with the full set of controls. Excluding the amount of funding a startup raised, whether it received VC funding, and the number of patents it filed, the risk that academic startups achieve a liquidity event is 44% lower than for non-academic startups (column II). In the fully-specified model (column III), the difference between academic and non-academic startups is 41%.[11]

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[11] In Figure A1 of the Appendix, we report Nelson-Aalen Cumulative Hazard curves for the time to first round of financing and the time to achieving a liquidity event. The descriptive evidence presented confirms our findings that: i) academic startups do not significantly differ from non-academic startups in terms of their hazard of raising their first financing round and ii) the hazard of exiting via an IPO or an acquisition is higher for non-academic than for

Table 3

Performance outcomes for academic versus non-academic startups: hazard of raising first round of funds and experiencing a liquidity event.

	Models		
	(I) Time to first round	(II) Time to liquidity	(III)
		Reduced	Full
	Hazard Ratios		
ACADEMIC	0.969	0.556***	0.586***
	(0.0593)	(0.104)	(0.109)
Accum. number of patents (log)	1.021		1.204***
	(0.0182)		(0.0567)
Accum. amount of funds (log)			1.067***
			(0.0138)
VC (= 0/1)			1.762***
			(0.330)
Teamsize (log)	1.160**	1.624***	1.438**
	(0.0774)	(0.281)	(0.238)
At least one top-tier university	1.106	1.035	1.029
	(0.0701)	(0.186)	(0.182)
At least one female founder	1.079	0.637	0.629
	(0.112)	(0.210)	(0.215)
State unemployment rate	1.027	0.990	0.983
	(0.0220)	(0.0690)	(0.0681)
State FE	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Observations	6444	9231	9231
LogLikelihood	−7382.7	−1030.9	−990.8

Notes: We report the results from estimating a Cox proportional hazard model for: i) the time in years to a first financing round (column (I)), and ii) the time in years to achieving a liquidity event (columns II and III). We report hazard ratios. Hazard ratios greater (smaller) than one indicate a positive (negative) relationship with the risk of achieving i) a first round of financing, and ii) a liquidity event. We cluster standard errors at the startup level. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Collectively, these results suggest that although academic founders produce as many patents and raise as funding as non-academic founders, it takes them longer to clear the exit market. Building on the suggestive evidence presented, we consider which factors could help academic startups close the commercialization gap with non-academic startups in the next subsection.

4.2. Professor versus PhD student founders

To gain deeper insights into the mechanisms driving startup exit performance differentials, we distinguish between different types of founders within academia by creating two mutually exclusive categories of academic ventures. These categories are: i) startups founded by students without the participation of any faculty members, and ii) startups founded by at least one professor. As discussed in Section 2, this distinction is relevant for at least two reasons. First, it is possible that students may produce technologies of relatively lower quality given they have less accumulated experience than professors. Second, it is possible that students pursue projects with different quality thresholds than professors given their distinct outside options. An invention advantage could help academics reduce the commercialization gap with non-academic startups, and in that case we should observe smaller exit performance differences between professor and non-academic startups than between student startups and non-academic startups. To examine

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(*footnote continued*)
academic startups.

Table 4
Performance outcomes for startups founded by professors versus students.

	Models				
				Liquidity event	
	(I) Patents (log)	(II) Funds (log)	(III) VC (= 0/1)	(IV) Reduced	(V) Full
PROF (at least one professor)	−0.00381	0.0337	−0.0266	−0.0767***	−0.0734***
	(0.0405)	(0.359)	(0.0239)	(0.0175)	(0.0195)
STUD (student/no professor)	−0.202***	−1.753***	−0.0846**	−0.0971***	−0.0725***
	(0.0400)	(0.586)	(0.0320)	(0.0222)	(0.0205)
Number patents (log)		0.453**	0.105***		0.0374***
		(0.189)	(0.0139)		(0.0107)
Funds (log)	0.000589		0.0137***		0.000796
	(0.00185)		(0.00125)		(0.00145)
VC (= 0/1)	0.292***				0.103***
	(0.0363)				(0.0202)
Team size (log)	−0.00728	1.435***	0.0872***	0.0531***	0.0396**
	(0.0629)	(0.398)	(0.0198)	(0.0191)	(0.0161)
At least one top-tier university	−0.0364	0.598	0.00515	0.0172	0.0170
	(0.0310)	(0.464)	(0.0226)	(0.0145)	(0.0129)
At least one female founder	0.0167	1.154**	−0.0510	−0.0644**	−0.0620**
	(0.0437)	(0.497)	(0.0332)	(0.0243)	(0.0232)
State unemployment rate	−0.0383**	−0.169	−0.00327	−0.0166	−0.0138
	(0.0185)	(0.183)	(0.0172)	(0.0106)	(0.0102)
State FE	Yes	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Observations	1723	1723	1723	1723	1723
R-sq.	0.126	0.153	0.182	0.0933	0.122

Notes: We examine the same startup performance outcomes as those described in Table 2. *PROF* is an indicator that equals one if startup i was initiated by at least one professor and zero otherwise, while *STUD* is an indicator for whether the startup was founded by at least one graduate student without the involvement of a professor. The reference category is represented by startups without academic founders. We cluster standard errors at the state level. Significance noted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

this conjecture, we modify Eq. (1) as follows:

$$Y_i = \alpha PROF_i + \gamma STUD_i + \beta X_i + f_{State} + f_{Founding\ year} + f_{Sector} + \epsilon_i \qquad (3)$$

As before, Y_i corresponds to any of the following outcomes: the number of US granted patents applied for within three years of inception, the amount of funding raised with five years of a startup's inception, the likelihood of receiving VC funding during the same period, and the likelihood of experiencing a liquidity event as of 2016. $PROF_i$ is an indicator that equals one if startup i was initiated by at least one professor and zero otherwise, while $STUD_i$ is an indicator for whether the startup was founded by at least one PhD student without the involvement of a professor. The reference category consists of startups initiated by non-academic founders only. The vectors X_i, f_{State}, $f_{Founding\ year}$, and f_{Sector} contain the same controls and fixed effects as those listed in Eq. (1). Again, we cluster standard errors at the state level.

We present results from estimating Eq. (3) in Table 4. As reported in column I, student startups apply for 20% fewer patents relative to professor and non-academic startups. Not only do student startups have less patents, but they also significantly raise less funds (column II). In fact, the coefficient indicates that being a student venture reduces the amount of funding raised by 175%. In contrast, professor startups do not differ from non-academic startups in the amount of funding raised. Similarly, results reported in column III show that student startups are less likely to attract VC funding than both professor startups and non-academic startups, whereas the latter two categories do not differ from each other.

The estimates in column IV show that while both student startups and professor startups are less likely to achieve a liquidity event relative to non-academic startups, there is no significant difference within academic startups relative to their likelihood of experiencing either an IPO or an acquisition (*p*-value for test of equality of coefficients: 0.246).

In column V, we add as controls the intermediary startup performance outcomes (i.e., patents, the amount of funds raised, and VC funding). The magnitude of the coefficient related to student startups declines from 0.097 to 0.073 suggesting that students pursue different projects than professors.

Taken together, while these results provide some indication that startups founded by students without professor involvement are less resource- and patent-intensive, these companies perform similarly on the exit market to those startups founded by professors. This suggests that although professors and students may pursue different types of ventures (in terms of formal IP), they do not differ in achieving a liquidity event. These findings are in line with Conti and Roche (forthcoming) who suggest that tight labor market conditions push students to pursue projects of lower quality, on average, than those pursued by professors. The fact that professors and students exhibit no difference with respect to the exit market might be the result of students initiating startups of lower quality and professors creating new ventures that rely relatively more on basic technologies that require more time to clear the exit market.[12]

4.3. Heterogeneity among professor founders

Herein, we submit that observed differences between academic and

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[12] In Table A3 of the Appendix we present the results from estimating Eq. (2) distinguishing between professor and student startups. The results indicate that student startups take significantly longer to raise their first round of funding, whereas professor startups do not differ from non-academic startups. However, student and professor startups both have an equally lower risk of achieving a liquidity event in each period t relative to non-academic startups.

non-academic startups might be explained, in part, by heterogeneity within startups created by professors. To examine this possibility, we distinguish between academic superstar professors and other professor founders. For one, it is possible that superstar academics may be able to close the commercialization gap with non-academic founders given their skills and abilities. For another, it is possible that external certification could aid superstar academics in reducing the commercialization gap. In an attempt to disentangle these explanations, we generate three categories of professor startups: *i)* startups founded by academic superstars defined as highly productive researchers whose scholarly quality has been certified by a prestigious external institution (i.e., Nobel Prize Laureates, National Academy of Sciences Members, and WoS' Highly Cited Researchers), *ii)* similarly productive professors without external quality certification, and *iii)* startups founded by all other professors.

We modify Eq. (3) as follows:

$$Y_i = \alpha SuperstarPROF_i + \mu HighlyProdPROF_i + \delta OtherPROF_i + \gamma STUD_i$$
$$+ \beta X_i + f_{State} + f_{Founding\ year} + f_{Sector} + \epsilon_i \tag{4}$$

The outcomes Y_i are the same as those employed in Eq. (1). We apply different cut-offs with regard to the professors' publication output to identify highly productive professors without endorsement (category ii) above). We use the number of scientific articles a professor published five years before creating a focal startup and identify those professors who lie in the upper 75th, 80th, and 90th percentiles within their respective disciplines, but are not Nobel Prize Laureates, National Academy of Sciences members, or Highly Cited Researchers.[13] The 80th and 90th percentile cutoffs serve primarily as robustness for our 75th cutoff findings. The vectors X_i, f_{State}, $f_{Founding\ year}$, and f_{Sector} contain the same controls and fixed effects as those used in Eq. (1). Standard errors are clustered at the state level.

We report the results from estimating Eq. (4) in Table 5. As shown in column I of Table 5, we find no significant differences in terms of the number of patents a startup applied for within three years of its inception. All different types of professor startups perform similarly to non-academic startups in this regard. We find a similar pattern when we examine the amount of funding raised (column II). However, the results in column III show that superstar professors are significantly more likely to receive VC funding than all other types of startups - academic and non-academic alike. Finally, we find that startups founded by superstar professors are as likely as non-academic startups to achieve a liquidity event, while startups founded by professors who are similarly productive but who lack external certification perform no better than all the other categories of academic startups (column IV).

As a robustness check, we find that these results are largely confirmed when we use the 80th and 90th percentile of publication output to define the category of highly productive professors without external certification (see columns V-XII of Table 5). We note that while we observe a difference in the likelihood of achieving a liquidity event between startups founded by superstar professors and other non-certified but similarly productive professors, this difference is no longer statistically significant. This is largely due to the fact that there are very few observations of startups founded by professors in the 80th ($N = 85$) and 90th ($N = 38$) percentile that are not also externally certified.[14]

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[13] There are not enough observations to estimate the regression equations using a 95th percentile cutoff.

[14] In Table A4 of the Appendix, we report the results from estimating a hazard model, which considers the same sub-categories of academic startups as in columns I - IV of Table 5. For sake of brevity, we only report results using the 75th percentile cutoff for defining highly productive but non-certified professors. While we find in Table 5 that these professors significantly differ from certified professors in terms of their likelihood of experiencing a liquidity event, they do not significantly differ in their relative risk of achieving such event in each period t compared to non-academic startups (column II).

Taken together, these findings suggest that there are differences within academia in terms of clearing the exit market. In particular, the observed performance differentials between academic founders relative to non-academic founders do not hold for all types of founders in academia. Startups founded with a superstar academic appear to have an advantage at securing VC funding and in achieving a liquidity event.

5. Discussion and conclusion

Herein, we examine how differences between academic and non-academic occupational backgrounds of founders may result in entrepreneurial performance differentials. In the high-technology context, academia and industry are particularly relevant given that these institutions represent the two major environments involved in entrepreneurship (Fini and Lacetera, 2010; Murray, 2010). Moreover, both - academia and industry - are considered essential drivers of innovation and economic growth (Cohen et al., 2002; Grimaldi et al., 2011; Roach and Sauermann, 2015; Thursby et al., 2001). As such, we pursue an important, yet under-researched question for advancing our understanding of heterogeneity across innovative startups: How do founders' occupational backgrounds relate to new venture performance?

We develop conjectures for the intermediary output and early-stage commercialization success of startups based on the occupational backgrounds of the respective founders. Given differences in mental models and preferences, passed on through experience and on-the-job training, our *ex-ante* conjecture is that academic founders have a comparative *invention* advantage while industry founders have a comparative *innovation* advantage. To assess this proposition, we examine a sample of 2998 founders from academic and non-academic backgrounds who created 1723 startups between 2005 and 2012.

In line with our baseline hypothesis, we find suggestive evidence that academic startups may be comparatively disadvantaged in bringing new technologies to the market. In particular, the likelihood and hazard of achieving a liquidity event are lower for academic than for non-academic startups. However, academic startups produce as many patents and receive as much funding as non-academic startups. This result provides some evidence that while academic and non-academic ventures do not differ in terms of their ability to generate IP-protected technologies, they differ substantially in their time to clearing the exit market.

In a next step, we exploit heterogeneity within the category of academic founders based on our fine-grained data. Assessing the relative performance of academic startups is a thorny yet important issue on its own, provided the fundamental role universities play in the production of new knowledge in high-tech industries (Mowery et al., 2001). In particular, we more closely examine professor and student ventures. In analyzing heterogeneity within academic startups (while using non-academic startups as a reference category), we distinguish between startups founded by professors and those initiated by PhD students without professor involvement. We find suggestive evidence that although PhD students produce fewer patents than professors, student-founded companies are as likely and as quick to experience a liquidity event as professor-founded ventures. These results are in line with Conti and Roche (forthcoming) who find that tight labor market conditions push students to pursue projects of lower quality, on average, than those pursued by professors. The fact that professors and students exhibit no difference with respect to the exit market might be the result of students initiating startups of lower quality and professors creating new ventures that rely relatively more on basic technologies that require more time to clear the exit market Conti and Roche (forthcoming).

Delving deeper into our analysis of heterogeneity within academia, we provide suggestive evidence that there are differences in comparative commercialization advantages among academic professor founders. In particular, we find that startups initiated by highly productive

Table 5
Performance outcomes for startups founded by endorsed professors versus others.

	75th Pct.				80th Pct.				90th Pct.			
	(I) Patents (log)	(II) Funds (log)	(III) VC	(IV) Liquidity	(V) Patents (log)	(VI) Funds (log)	(VII) VC	(VIII) Liquidity	(IX) Patents (log)	(X) Funds (log)	(XI) VC	(XII) Liquidity
SuperstarPROF	0.0758 (0.0701)	0.483 (1.107)	0.165*** (0.0327)	0.112 (0.0473)	0.0758 (0.0698)	0.487 (1.106)	0.165*** (0.0329)	0.0118 (0.0474)	0.0757 (0.0696)	0.483 (1.116)	0.164*** (0.0329)	0.0118 (0.0475)
HighlyProdPROF (75th pct.)	0.0115 (0.0879)	−0.325 (1.030)	−0.0311 (0.0441)	−0.0768* (0.0397)								
OtherPROF (75th pct.)	−0.0249 (0.0599)	0.0515 (0.390)	−0.0644** (0.0243)	−0.0899*** (0.0163)								
HighlyProdPROF (80th pct.)					0.00935 (0.0952)	−0.127 (1.098)	−0.00812 (0.0568)	−0.0567 (0.0400)				
OtherPROF (80th pct.)					−0.0219 (0.0579)	−0.0181 (0.423)	−0.0671*** (0.0226)	−0.0934*** (0.0160)				
HighlyProdPROF (90th pct.)									0.0512 (0.136)	−0.748 (0.915)	−0.0655 (0.0863)	0.00801 (0.0871)
OtherPROF (90th pct.)									−0.0221 (0.0527)	0.0233 (0.506)	−0.0557** (0.0234)	−0.0949*** (0.0142)
STUD	−0.200*** (0.0397)	−1.748*** (0.576)	−0.0809** (0.0313)	−0.0712*** (0.0206)	−0.200*** (0.0395)	−1.746*** (0.577)	−0.0804** (0.0313)	−0.0709*** (0.0206)	−0.200*** (0.0395)	−1.748*** (0.574)	−0.0812** (0.0314)	−0.0708*** (0.0207)
Number patents (log)		0.449** (0.196)	0.102*** (0.0139)	0.0367*** (0.0106)		0.448** (0.197)	0.102*** (0.0139)	0.0366*** (0.0105)		0.449** (0.196)	0.103*** (0.0137)	0.0365*** (0.0103)
Funds (log)	0.000625 (0.00187)		0.0137*** (0.00124)	0.000824 (0.00152)	0.000617 (0.00187)		0.0137*** (0.00124)	0.000827 (0.00151)	0.000628 (0.00187)		0.0137*** (0.00123)	0.000844 (0.00151)
VC (= 0/1)	0.287*** (0.0363)			0.0990*** (0.0200)	0.287*** (0.0365)			0.0987*** (0.0199)	0.288*** (0.0358)			0.0992*** (0.0204)
Team size (log)	−0.0135 (0.0608)	1.413*** (0.393)	0.0729*** (0.0186)	0.0337** (0.0147)	−0.0135 (0.0600)	1.406*** (0.388)	0.0719*** (0.0187)	0.0329** (0.0146)	−0.0134 (0.0611)	1.413*** (0.395)	0.0740*** (0.0187)	0.0327** (0.0149)
At least one top-tier university	−0.0381 (0.0315)	0.589 (0.462)	0.00112 (0.0228)	0.0152 (0.0130)	−0.0384 (0.0321)	0.590 (0.458)	0.000354 (0.0228)	0.0147 (0.0134)	−0.0385 (0.0314)	0.593 (0.459)	0.00128 (0.0229)	0.0146 (0.0130)
At least one female founder	0.0175 (0.0440)	1.156** (0.497)	−0.0488 (0.0326)	−0.0613** (0.0234)	0.0176 (0.0439)	1.158** (0.499)	−0.0483 (0.0325)	−0.0610** (0.0234)	0.0169 (0.0443)	1.163** (0.498)	−0.0489 (0.0328)	−0.0619** (0.0226)
State unemployment rate	−0.0386** (0.0184)	−0.172 (0.182)	−0.00404 (0.0172)	−0.0142 (0.0104)	−0.0386** (0.0184)	−0.171 (0.182)	−0.00395 (0.0172)	−0.0141 (0.0104)	−0.0384** (0.0185)	−0.174 (0.182)	−0.00416 (0.0171)	−0.0138 (0.0105)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1723	1723	1723	1723	1723	1723	1723	1723	1723	1723	1723	1723
R-sq.	0.126	0.153	0.190	0.125	0.126	0.153	0.190	0.126	0.126	0.153	0.190	0.127

Notes: We examine the same startup performance outcomes as those described in Table 2. We consider three categories of professor startups. These are: i) startups founded by highly successful researchers whose scholarly quality has been certified by a renowned institution (i.e., Nobel Prize Laureates, National Academy of Sciences Members, and Highly Cited Researchers), ii) similarly productive professors without external certification, and iii) startups founded by all other professors. The reference category is represented by startups without academic founders. We cluster standard errors at the state level. Significance noted as: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

professors who are either Nobel Prize Laureates, members of the National Academy of Sciences, or Highly-Cited Researchers - that is, academic superstars - perform as well as non-academic startups on the exit market. Conversely, startups established by highly productive professors but without external certification perform worse on the exit market than non-academic startups. These results could be the outcome of superstar professors assuming a certification role or pursuing projects with more commercial promise. These findings resonate with earlier work such as by Higgins et al. (2011), who document that new life science ventures with a Nobel Prize Laureate on their scientific advisory board tend to perform better. Moreover, Fuller and Rothaermel (2012) provide evidence that star faculty founders are able to overcome the liability from not being located in a geographic cluster in which VCs are active.

Our finding that it takes startups created by academic founders relatively longer than startups initiated by non-academic founders to clear the exit market, moreover, draws attention to important economic implications regarding the return on investment(s). For those investing in academic startups, any potential return on investment will likely take longer to be realized and may, as a result, entail higher costs (and possibly higher risks) than investments into non-academic startups. Therefore, it becomes important to assess early on, and to the extent possible, whether new technologies could be developed and commercialized by non-academic founders in a relatively shorter time span to reduce these inherent liabilities (Aghion et al., 2008).

Summa summarum, we attempt to make several contributions to the extant literature. First, we compare and contrast venture characteristics and outcomes among startups founded by entrepreneurs with distinctly different occupational backgrounds, which span two important institutional environments (that is, academia and industry). In doing so, we move beyond prior studies that have examined the role of founders' occupational backgrounds within one specific institutional environment (Burton and Beckman, 2007; Campbell et al., 2012; Chatterji, 2009; Elfenbein et al., 2010; Fuller and Rothaermel, 2012; Di Gregorio and Shane, 2003; Zucker et al., 2002). In line with these prior studies we provide suggestive evidence that occupational imprinting conferred by different institutional environments may produce marked effects on venture performance outcomes.

Second, by comparing and contrasting academic to non-academic startups, we add to the literature that has examined academic startups' survival and success (e.g., Nerkar and Shane, 2003; Rothaermel et al., 2007; Rothaermel and Thursby, 2005; Shane and Stuart, 2002). This literature has seldom compared academic to non-academic startups (Wennberg et al., 2011), neglecting the distinct role the academic institutional environment plays in shaping the ventures it spawns. Third, we explore heterogeneity within academic startups along underexplored dimensions: professor founders versus student founders, on the one hand, and superstar founders versus other professor founders, on the other. Extant studies have focused on the technological characteristics that correlate with academic startups' success (e.g., Nerkar and Shane, 2003; Rothaermel and Thursby, 2005; Shane and Stuart, 2002) and the role of incubators and TTOs (Bercovitz and Feldman, 2007; Wright et al., 2008), but have generally overlooked heterogeneity in academic founders' characteristics. Finally, recognizing that there exists significant heterogeneity among startups (Colombelli et al., 2016), we shed light on possible mechanisms governing the specific subsample of innovative startups, which provide significant potential for economic benefits.

This study, moreover, has several policy implications. Our findings highlight the importance of deepening our knowledge about the root of performance differences of innovative startups across distinct institutional environments. As such, our research findings may aid in designing more nuanced policy interventions for fostering entrepreneurship and innovation. In light of our result that academic startups generally underperform relative to non-academic startups, on the innovation dimension, governments as well as universities could focus on

providing academics with complementary resources for commercializing technologies developed in their laboratories. This is in line with prior work, which has documented that students' entrepreneurial commitment is enhanced by comprehensive university initiatives (Minola et al., 2016). Similarly, Lyons and Zhang (2018) document that complementary services such as university entrepreneurial training programs are especially valuable for individuals who lack the resources and capabilities needed for success in entrepreneurship.

Lastly, university TTOs and incubators could help non-superstar professors overcome the observed commercialization disadvantages. By showcasing and promoting these academics' technologies to external investors, TTOs and incubators could assume the role of certifying bodies as well as of match-makers between academic ventures and investors. Gaining a deeper and more nuanced understanding of innovative startups enables decision makers to move beyond a 'one-size-fits-all' policy, and to enact fine-grained interventions that would be more effective in fostering entrepreneurial innovation, employment, and economic growth (Colombelli et al., 2016).

As with any research, our study is not without limitations, which at the same time provide opportunities for future research. One possible limitation could be that we define an academic startup as a venture that was founded by at least one professor or one student affiliated with a given university at the time the startup was launched. Building on current work highlighting the important role of founding teams for startup performance (for an in-depth review, see Nikiforou et al. (2018)), an interesting avenue for future research could be to examine the composition of founding teams in more depth. The composition of teams consisting of academic and non-academic founders may have important implications for the comparative invention and innovation advantage of startups because of complementarities in skills and abilities held by different team members (Franco-Leal et al., 2016; Visintin and Pittino, 2014).

A natural extension of our baseline hypothesis that academic founders possess a comparative invention advantage while non-academic founders possess a comparative innovation advantage could be taking a closer look at founding teams that consist of both academic and non-academic founders. Although we provide some preliminary evidence that our results are robust to using the share of academic founders in the new venture team as our main independent variable (see Table A2), deeper theoretical and empirical work is clearly warranted. Future research may help us better understand notions such as optimal ratios of different founder backgrounds when assessing early stage venture performance.

Although we take great care in untangling the heterogeneity among different types of academic founders, a closer look at heterogeneity within the category of non-academic founders is also a promising avenue for future work, yet beyond the scope of this paper. Such an extension of our current work seems particularly fruitful because the majority of the venture founders in our sample do not have an academic founder. Thus, a possible future research question may be whether founders who worked for small firms are more similar to academic founders than founders who worked previously at large firms. This question seems particularly promising given the conflicting results provided by the few studies attempting to address this issue. For instance, some work looks at individuals with a science and/or engineering degree and shows that small firms spawn more startups (Elfenbein et al., 2010). Other studies have documented that biotechnology entrepreneurs often hail from larger firms because working for larger firms is considered an important first step prior to 'taking the plunge' into entrepreneurship (Hess and Rothaermel, 2012).

We must also stress the need for follow-on research to establish causality claims in order to inform both the academic literature as well as policy decision makers alike. In this paper, we suggest a number of potential mechanisms driving our results. As an extension, however, future research could pursue approaches such as experimental and quasi-experimental estimation strategies that could help deal with

obvious identification challenges.

We close by highlighting our contribution that non-academic startups appear to fare better than academic startups on the exit market. Moreover, we find no systematic differences with regard to patents and the amount of funds raised by academic startups in comparison to non-academic startups. Our additional heterogeneity analyses using fine-grained data suggest that the observed commercialization disadvantage of academic startups do not hold for all types of founders in academia.

Declaration of Competing Interest

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.respol.2020.104062

References

Acs, Z., Audretsch, D., 1989. Patents as a measure of innovative activity. Kyklos 42 (2), 171–180.
Acs, Z., Audretsch, D., 1990. Innovation and Small Firms. MIT Press, Boston.
Agarwal, R., Shah, S.K., 2014. Knowledge sources of entrepreneurship: firm formation by academic, user and employee innovators. Res. Policy 43, 1109–1133.
Aghion, P., Dewatripont, M., Stein, J.C., 2008. Academic freedom, private-sector focus, and the process of innovation. RAND J. Econ. 39, 617–635.
Antonipillai, J., Lee, M.K., 2016. Intellectual property and the US economy: 2016 update. Economics & Statistics Administration and US Patent and Trademark Office, Washington, DC.
Association of University Technology Managers, 2016 AUTM. AUTM US Licensing Activity Survey: FY2016. https://www.autm.net/AUTMMain/media/SurveyReportsPDF/AUTM_FY2016_US_Highlights_no_Appendix_WEB.pdf.
Audretsch, D., 2014. From the entrepreneurial university to the university for the entrepreneurial society. J. Technol. Transf. 39, 313321.
Baron, J.N., Burton, M.D., Hannan, M.T., 1999. Engineering bureaucracy: the genesis of formal policies, positions, and structures in high-technology firms. J. Law Econ. Organ. 15 (1), 141.
Bercovitz, J.E., Feldman, M.P., 2007. Fishing upstream: firm innovation strategy and university research alliances. Res. Policy 36, 930–948.
Block, J., Sandner, P., 2009. What is the Effect of the Financial Crisis on Venture Capital Financing? Empirical Evidence From US Internet Start-ups. 11. Venture Capital, pp. 29530.
Boh, W.F., De-Haan, U., Strom, R., 2016. University technology transfer through entrepreneurship: faculty and students in spinoffs. J. Technol. Transf. 41, 661–669.
Brüderl, J., Preisendrfer, P., Ziegler, R., 1992. Survival chances of newly founded business organizations. Am. Sociol. Rev. 227–242.
Bryant, P.T., 2014. Imprinting by design: The microfoundations of entrepreneurial adaptation. Entrep. Theory Pract. 38, 1081–1102.
Burton, M.D., Beckman, C.M., 2007. Leaving a legacy: position imprints and successor turnover in young firms. (2): 239266. Am. Sociol. Rev. 72.
Campbell, B.A., Ganco, M., Franco, A.M., Agarwal, R., 2012. Who leaves, where to, and why worry? employee mobility, entrepreneurship and effects on source firm performance. Strateg. Manag. J. 33, 65–87.
Chatterji, A.K., 2009. Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. Strateg. Manag. J. 30, 185–206.
Ching, K., Gans, J., Stern, S., 2018. Control versus execution: endogenous appropriability and entrepreneurial strategy. Ind. Corp. Change 120.
Clough, D.R., Fang, T.P., Vissa, B., Wu, A., 2019. Turning lead into gold: How do entrepreneurs mobilize resources to exploit opportunities? Acad. Manag. Proc.
Cohen, W.M., Nelson, R.R., Walsh, J.P., 2002. Links and impacts: the influence of public research on industrial R&D. Manag. Sci. 48, 1–23.
Colombelli, A., Krafft, J., Vivarelli, M., 2016. To be born is not enough: the key role of innovative start-ups. Small Bus. Econ. 47, 277–291.
Colombo, M.G., Grilli, L., 2010. On growth drivers of high-tech start-ups: exploring the role of founders' human capital and venture capital. J. Bus. Vent. 25, 610–626.
Colombo, M.G., Piva, E., 2012. Firms genetic characteristics and competence-enlarging strategies: a comparison between academic and non-academic high-tech start-ups. Res. Policy 41, 79–92.
Conti, A., Dass, N., DiLorenzo, F., Graham, S.J., 2019. Venture capital investment strategies under financing constraints: evidence from the 2008 financial crisis. Res. Policy 48, 799–812.
Conti, A., Graham, S.J.H., 2020. Valuable choices: prominent venture capitalists influence on startup CEO replacement and performance. Manag. Sci. 66 (23), 1325–1350.
Conti, A., Roche, M. P., Forthcoming. Lowering the bar? external conditions, opportunity costs, and high-tech startup outcomes. Organization Science, 1–42.
Conti, A., Thursby, J., Thursby, M., 2013a. Patents as signals for startup financing. J. Ind. Econ. 61, 592–622.
Conti, A., Thursby, M., Rothaermel, F.T., 2013b. Show me the right stuff: Signals for high-tech startups. J. Econ. Manag. Strateg. 22, 341–364.
Eesley, C.E., Hsu, D.H., Roberts, E.B., 2014. The contingent effects of top management teams on venture performance: aligning founding team composition with innovation strategy and commercialization. Strateg. Manag. J. 35 (12), 1798.
Elfenbein, D.W., Hamilton, B.H., Zenger, T.R., 2010. The small firm effect and the entrepreneurial spawning of scientists and engineers. Manag. Sci. 56, 659–681.
Ewens, M., Marx, M., 2018. Founder replacement and startup performance. Rev. Financ. Stud. 31 (4), 1532–1565.
Feldman, M.P., Ozcan, S., Reichstein, T., 2019. Falling not far from the tree: entrepreneurs and organizational heritage. Organ. Sci. Articles in Advance
Fini, R., Fu, K., Mathisen, M.T., Rasmussen, E., Wright, M., 2017. Institutional determinants of university spin-off quantity and quality: a longitudinal, multilevel, cross-country study. Small Bus. Econ. 48, 361–391.
Fini, R., Lacetera, N., 2010. Different yokes for different folks: individual preferences, institutional logics, and the commercialization of academic research. In: Libecap, D., Thursby, M., Hoskinson, S. (Eds.), spanning Boundaries and Disciplines: University Technology Commercialization in the Idea AgeEmerald group publishing limited, Bingley, pp. 1–25.
Fuller, A.W., Rothaermel, F.T., 2012. When stars shine: the effects of faculty founders on new technology ventures. Strateg. Entrep. J. 6, 220–235.
Gans, J.S., Stern, S., 2017. Endogenous appropriability. Am. Econ. Rev. 107, 317–321.
DiGregorio, D., Shane, S., 2003. Why do some universities generate more start-ups than others? Res. Policy 32, 209–227.
Grimaldi, R., Kenney, M., Siegel, D.S., Wright, M., 2011. 30 years after bayhdole: reassessing academic entrepreneurship. Res. Policy 40, 1045–1057.
Hahn, D., Minola, T., Eddleston, K.A., 2018. How do scientists contribute to the performance of innovative start-ups? An imprinting perspective on open innovation. J. Manag. Stud.
Hess, A., Rothaermel, F.T., 2012. Intellectual human capital and the emergence of biotechnology: trends and patterns, 1974-2006. IEEE Trans. Eng. Manag. 59, 65–76. 65–76.
Higgins, M., Stephan, P., Thursby, J., 2011. Conveying quality and value in emerging industries: star scientists and the role of signals in biotechnology. Res. Policy 40, 605–617.
Hochberg, Y.V., Ljungqvist, A., Lu, Y., 2007. Whom you know matters: venture capital networks and investment performance. J. Financ. 62, 251–301.
Jensen, R., Thursby, M., 2001. Proofs and prototypes for sale: the licensing of university inventions. Am. Econ. Rev. 91, 240–259.
Kaplan, S.N., Sensoy, B.A., Strömberg, P., 2009. Should investors bet on the jockey or the horse? Evidence from the evolution of firms from early business plans to public companies. J. Financ. 64, 75–115.
Kenney, M., 1986. Biotechnology. The University Industrial Complex. Yale University Press, New Haven.
Franco-Leal, N., Soetanto, D., Camelo-Ordaz, C., 2016. Do they matter? the role of non-academics in the internationalization of academic spin-offs. J. Int. Entrep. 14, 410–440.
Lyons, E., Zhang, L., 2018. Who does (not) benefit from entrepreneurship programs? Strateg. Manag. J. 39, 85–112.
Maurer, I., Ebers, M., 2006. Dynamics of social capital and their performance implications: lessons from biotechnology start-ups. Admin. Sci. Q. 51, 262–292.
McEvily, B., Jaffee, J., Tortoriello, M., 2012. Not all bridging ties are equal: Network imprinting and firm growth in the nashville legal industry. Organ. Sci. 23, 547–563. 1933 Mc,.1978.
Megginson, W.L., Weiss, K.A., 1991. Venture capitalist certification in initial public offerings. J. Financ. 46, 879–903.
Minola, T., Donina, D., Meoli, M., 2016. Students climbing the entrepreneurial ladder: does university internationalization pay off? Small Bus. Econ. 47, 565–587.
Minola, T., Migliorini, P., Serarols-Tarrés, C., 2013. To have and have not: founders human capital and university start-up survival. J. Technol. Transf. 39 (4), 567–593.
Mowery, D.C., Nelson, R.R., Sampat, B.N., Ziedonis, A.A., 2001. The growth of patenting and licensing by U.S. universities: an assessment of the effects of the Bayh-Dole act of 1980. Res. Policy 30, 99–119.
Müller, K., 2010. Academic spin-offs transfer speed analyzing the time from leaving university to venture. Res. Policy 39, 189–199.
Murray, F., 2004. The role of academic inventors in entrepreneurial firms: sharing the laboratory lif. Res. Policy 33 (4), 643–659.
Murray, F., 2010. The oncomouse that roared: hybrid exchange strategies as a source of distinction at the boundary of overlapping institutions. Am. J. Sociol. 116, 341–388.
Nanda, R., Rhodes-Kropf, M., 2013. Investment cycles and startup innovation. J. Financ. Econ. 110, 403–418.
Nerkar, A., Shane, S., 2003. When do start-ups that exploit patented academic knowledge survive? Int. J. Ind. Organ. 21 (9), 1391–1410.
Nikiforou, A., Zabara, T., Clarysse, B., Gruber, M., 2018. The role of teams in academic spin-offs. Acad. Manag. Perspect. 32, 78–103.
Powell, W.W., Colyvas, J.A., 2008. Microfoundations of institutional theory. In: Greenwood, R., Oliver, C., Suddaby, R., Sahlin, K. (Eds.), The SAGE handbook of organizational institutionalismSAGE, London, pp. 276–298.
Powell, W.W., Sandholtz, K.W., 2012. Amphibious entrepreneurs and the emergence of organizational forms. Strateg. Entrep. J. 6, 94–115.
Roach, M., Sauermann, H., 2010. A taste for science? Phd scientists academic orientation and self-selection into research careers in industry. Res. Policy 39, 422–434.
Roach, M., Sauermann, H., 2015. Founder or joiner? The role of preferences and context in shaping different entrepreneurial interests. Manag. Sci. 61, 2160–2184.
Roberts, E.B., 1991. Entrepreneurs in High Technology: Lessons From MIT and Beyond. Oxford University Press, Oxford.

Rosen, S., 1981. The economics of superstars. Am. Econ. Rev. 71, 845–858.

Rothaermel, F.T., 2001. Complementary assets, strategic alliances, and the incumbents advantage: an empirical study of industry and firm effects in the biopharmaceutical industry. Res. Policy 30 (8), 1235–1251.

Rothaermel, F.T., Agung, S.D., Jiang, L., 2007. University entrepreneurship: a taxonomy of the literature. Ind. Corp. Change 16, 691–791.

Rothaermel, F.T., Thursby, M., 2005. Incubator firm failure or graduation?: The role of university linkages. Res. Policy 34, 1076–1090.

Sauermann, H., Stephan, P., 2013. Conflicting logics? A multidimensional view of industrial and academic science. Organ. Sci. 24, 889–909.

Schilling, M.A., Green, E., 2011. Recombinant search and breakthrough idea generation: an analysis of high impact papers in the social sciences. Res. Policy 40, 1321–1331.

Schumpeter, J.A., 1934. Theory of Economic Development. London, Oxford University Press.

Shane, S., Stuart, T., 2002. Organizational endowments and the performance of university start-ups. Manag. Sci. 48, 154–170.

Simsek, Z., Fox, B.C., Heavey, C., 2015. Whats past is prologue a framework, review, and future directions for organizational research on imprinting. J. Manag. 41, 288–317.

Spence, M., 1973. Job market signaling. Q. J. Econ. 87 (3), 355–374.

Stephan, P.E., 2012. How Economics Shapes Science. Harvard University Press, Cambridge.

Stern, S., 2004. Do scientists pay to be scientists? Manag. Sci. 50, 835–853.

Stinchcombe, A.L., 1965. Organizations and Social Structure. Routledge, New York.

Stuart, T.E, Ding, W.W., 2006. When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. Am. J. Sociology 112 (1), 97–144.

Teece, D.J., 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Res. Policy 15 (6), 285305.

Thornton, P.H., Ocasio, W., 1999. Institutional logics and the historical contingency of power in organizations: executive succession in the higher education publishing industry 1958–1990. Am. J. Sociol. 105, 801–843.

Thursby, J.G., Jensen, R., Thursby, M.C., 2001. Objectives, characteristics and outcomes of university licensing: a survey of major US universities. J. Technol. Transf. 26, 59–72.

Townsend, R.R., 2015. Propagation of financial shocks: the case of venture capital. Manag. Sci. 61, 2782–2802.

Visintin, F., Pittino, D., 2014. Founding team composition and early performance of university based spin-off companies. Technovation 34, 31–43.

Wennberg, K., Wiklund, J., Wright, M., 2011. The effectiveness of university knowledge spillovers: performance differences between university spinoffs and corporate spin-offs. Res. Policy 40, 1128–1143.

Wright, M., Clarysse, B., Lockett, A., Knockaert, M., 2008. Mid-range universities' linkages with industry: knowledge types and the role of intermediaries. Res. Policy 37, 1205–1223.

Wu, A., 2016. Organizational decision-making and information: angel investments by venture capital partners. Acad. Manag. Best Pap. Proc. 189–194.

Zucker, L.G., Darby, M.R., Armstrong, J.S., 2002. Commercializing knowledge: university science, knowledge capture, and firm performance in biotechnology. Manag. Sci. 48, 138–153.

Zucker, L.G., Darby, M.R., Brewer, M.B., 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. Am. Econ. Rev. 88, 290–306.