Research Policy 50 (2021) 104347

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Spin doctors vs the spawn of capitalism: Who founds university and corporate startups?

Alex Coad [a], Ulrich Kaiser [b,*], Johan Kuhn [c]

[a] Waseda Business School, Japan
[b] University of Zurich, Switzerland; Copenhagen Business School; Centre for European Economic Research and IZA-Institute of Labor Economics
[c] Economic Policy, Analysis and Consulting, Denmark

A R T I C L E I N F O

JEL classification:
L26
I23
O31
O32

Keywords:
University startups
Corporate startups
Founder characteristics
Employee retention
Human capital

A B S T R A C T

We compare individuals presently employed either at a university, or at a firm from an R&D-intensive sector, and analyze which of their personal-specific and employer-specific characteristics are related to their choice to leave their present employer for an own startup. Our data set combines the population of Danish employees with their present employers. We focus on persons who at least hold a Bachelor's degree in engineering, sciences and health and track them over 2001-2012. We show that (i) there are overall few differences between the characteristics of university and corporate startup entrepreneurs, (ii) common factors associated with startup activity of both university and corporate employees are education, top management team membership, previous job mobility and being male, (iii) it is primarily human capital-related characteristics that are related to startup choice of university employees while (iv) the characteristics of the present workplace are the foremost factors of entrepreneurial activity by corporate employees.

1. Introduction

There is substantial corporate and university startup activity across the world (Feldman et al., 2002; Gubitta et al., 2016). These two types of startups contribute significantly to technological progress (Franco and Filson, 2006; Shane, 2004; Zahra et al., 2007) and play crucial roles in national innovation systems as conduits of knowledge spillovers (Audretsch and Keilbach, 2008, Hvide and Jones, 2018). Although much research has focused on the determinants of firm foundation in general, nevertheless *differences* in founders' personal characteristics between these two groups, corporate and university startup entrepreneurs (CSEs and USEs), are hitherto largely unexplored. This seems important, since the characteristics of USE and CSE founders may be rooted in differences in motives and incentives (Åstebro and Thompson, 2011; Sauermann, 2017) and in turn may feed into subsequent performance differentials (Klepper and Sleeper, 2005; Sauermann, 2017).

To accurately describe the factors that push STEMM graduates, i.e. holders of at least a Bachelor's degree in science, engineering or health (i.e. STEMM fields)[1], from alternative types of dependent employment into entrepreneurship, we use register data that tracks the entire population of Danish residents between 2001 and 2012. We differentiate between (i) USEs, defined as individuals who found a firm after a spell in university employment and (ii) CSEs, individuals who found out of an employment spell at a firm in R&D-intensive industries. Like Wennberg et al. (2011), who use Swedish register data akin to ours to compare university and corporate spinoffs, our focus is on R&D-intensive industries in order to make corporate startup activity similar to university startup activity. While existing work had to focus on fairly restrictive sets of control variables, and even Wennberg et al. (2011) exclusively rely on human capital variables, the richness of our data allows us to include accurate and detailed measures of not only human capital but also of income and wealth, family background and characteristics of the present workplace. The set of variables we consider closely resembles the type of information contained in CVs that are at the disposal of human resource departments as well as non-governmental and governmental entrepreneurship promotion agencies.

We make three contributions. First, going beyond the literature on the antecedents of transitions into spells of entrepreneurship (Nanda and Sørensen, 2010; Stuart and Ding, 2006) and the literature on startup founders' characteristics (Ouimet and Zarutskie, 2014; Sauermann,

* Corresponding author at: University of Zurich, Department of Business Administration, Chair for Entrepreneurship, Plattenstr. 14, Zürich 8032, Switzerland.
E-mail addresses: alex.coad@waseda.jp (A. Coad), ulrich.kaiser@business.uzh.ch (U. Kaiser).

[1] STEMM denotes Science, Technology, Engineering, Mathematics, and Medicine (e.g. Fini et al., 2020).

https://doi.org/10.1016/j.respol.2021.104347
Received 4 March 2019; Received in revised form 9 August 2021; Accepted 10 August 2021
Available online 10 September 2021

2017), we focus specifically on comparing USEs and CSEs, by linking detailed individual-specific and present employer-specific information to entrepreneurial choice. Other studies, like Clarysse et al. (2011a), Ensley and Hmieleski (2005) as well as Wennberg et al. (2011) also compare university and corporate startups but exclusively deal with performance and use data on more mature firms.[2] Second, we compare founders from universities to founders from R&D-intensive industries, while existing research (usually at the firm-level rather than the individual-level) has to date mainly focused on university startups to the exclusion of corporate startups (Wennberg et al., 2011). If USEs and CSEs indeed differed from one another in terms of their observed personal characteristics, this may partly explain the observed differences between the post entry behavior of firms that originated in the public research domain and other high-tech startups (Clarysse and Moray, 2004; Colombo and Piva, 2012; Ensley and Hmieleski, 2005; Klepper and Sleeper, 2005). If their personal characteristics are similar, performance differences are likely to be driven by "inheritance effects" — tacit and codified knowledge passed on to the entrepreneur by her previous employer (Agrawal et al., 2016; Clarysse et al., 2011b; Wennberg et al., 2011) — or by unobserved (to us) personality traits. Third, we add to the literature by providing descriptive evidence from regressions on comprehensive data. The entrepreneurship literature and in particular its strand that deals with university startups has long been plagued by data problems, most importantly biased samples, a focus on specific industries, data provided by technology transfer offices and lack of meaningful comparison groups (Elfenbein et al., 2010; Rothaermel et al., 2007). Unlike survey evidence from selected samples, population data clearly shows that startup activity by both USEs and CSEs is rare, as only 0.36 percent of university employees and only 0.64 percent of high-tech sector employees found a startup in any given year.

We find that only few factors have a significant effect on startup activity by USEs and CSEs, and these few differences between movers and stayers are similar between USEs and CSEs. This is despite having a large and comprehensive set of explanatory variables regarding demographic and human capital characteristics (although we have no direct indicators of knowledge flows or technology transfer). Factors that are significantly positively associated with both university and corporate entrepreneurship are being male and previous job mobility. Having a "manager" role is also positively associated with entrepreneurship, although we acknowledge that the meaning of a managerial role differs between university and industry.

In contrast, the main differences between USEs and CSEs are the field and the length of education, self-employment experience and the number of own patents. A Master's degree in engineering, self-employment experience from secondary employment, the number of patents an individual holds and family wealth constitute additional significant variables for university employees. For CSEs we furthermore find a positive relation between self-employment choice and a high relative position in the own employers' income distribution as well as father self-employment. Own employer size and own employer patent stock are negatively related to self-employment for corporate STEMM graduates.

In extensive robustness checks we show that focusing on more selected subsamples of individuals – as the existing literature does – generates even less evidence for differences between university or corporate stayers and leavers and between USEs and CSEs. This could be due to a reduced number of observations, and may also be related to a substantial increase in the homogeneity of individuals once we e.g. focus on specific startups only. For our key robustness check, the sample of high-tech entrepreneurs, we do, however, find that family income is a determinant of CSE activity.

Our paper proceeds as follows: Section 2 provides our theoretical background. Section 3 discusses our database. Section 4 provides descriptive statistics and estimation results for entrepreneurial choice. Section 5 concludes.

2. Background

2.1. Types of spinoff: definitions

2.1.1. University startup entrepreneurs (USEs)

Academic engagement can take many forms, such as collaborative research, consulting, sponsored research, contract research, patenting, and academic entrepreneurship (Perkmann et al., 2013, their Table 3). In this paper, we focus on academic entrepreneurship, i.e. new firm formation by individuals coming from universities.

We begin with the USO definition put forward by Agarwal and Shah (2014, p1114, emphasis in original): "Academic entrepreneurship (also referred to as university spinoffs or academic spinouts) is defined as new venture formation by faculty, staff or students who innovate in an academic or non-profit research context, and subsequently found a firm that directly exploits this knowledge (Shane, 2004)." While the definition of Agarwal and Shah refers to those who innovate in a research context, others require that the founders (or at least one member of the founder team) must have studied or worked at a university (Dorner et al., 2017, p2).

We define university startup entrepreneurs as persons who are employed at a university in year t and work in a new firm in year $t+1$. Our mobility-based definition aligns with existing studies (Druilhe and Garnsey, 2003; Fini et al., 2011; Rappert et al., 1999; Steffenson et al., 1999; Visintin and Pittino, 2014). It is, however, broader than Shane (2004) or much existing literature that requires both a mobility event to occur and the formal transfer of IP from the university to the startups (Clarysse and Moray, 2004; Colombo et al., 2010; Nicolaou and Birley, 2003a, b; Rothaermel et al., 2007; Zahra et al., 2007). This is also why we use the term "startup" instead of "spinoff", hence preferring the broader acronym USE (University Startup Entrepreneur) to the more restrictive acronym USO (University Spin Off), where the latter can be considered to be a subset of the former. A key advantage of our broader definition is that it avoids problems with the definition and transfer of knowledge and IP that was developed by the founder during his/her time at the university, and that it does not focus on high-technology industries like software or semiconductors (Braun and Macdonald, 1982), disk drives (Christensen, 1993; Franco and Filson, 2006) or, more generally, IP-based startups only.

Another benefit is that we do not exclude startups that do not involve IP-transfers but which still may be regarded as "relevant" on a broader scale like AirBnb, Groupon, Starbucks, TaskRabbit, Tinder, Uber etc. (or, in a Danish context, Donkey Republic, Jysk, pleo, Momondo or Tiger).

The prototypical USE in the minds of the broader public probably involves a university professor starting a successful high-tech venture. However, this stereotype need not represent all USEs. USEs could also correspond to junior faculty or staff (Agarwal and Shah, 2014), and also to graduate students (Dorner et al., 2017; Hayter et al., 2017; Wright et al., 2017) or university administrators (Roche et al., 2020) and may even include alumni startups (Müller 2010; Siegel and Wright, 2015, their Table 1).

USEs could hypothetically correspond to firms started by administrative staff such as secretaries, according to the definitions above. The sample of USEs and CSEs in Roche et al. (2020) contains 3% university administrators. However, according to the Agarwal and Shah (2014) definition, the administrative staff would have to exploit knowledge developed at the university, which could refer to either the transfer of specific research results, or the transfer of specific skills and competencies acquired (Dorner et al., 2017, p2). In our analysis, we only

[2] Ensley and Hmielski (2005) even use data selected on the performance variable by comparing fast growing corporate spinoffs to university startups to find that university spinoffs grow faster than corporate spinoffs.

Table 1
Overview of previous comparisons of USOs and CSOs.

Source	Data	# observations	Dependent variables	Explanatory variables	Findings
Zahra et al., 2007	Mail survey in 5 states, USA	78 USOs, 91 CSOs	Productivity, profitability, revenue growth	Knowledge conversion capability (KCC) indicator, firm-specific controls	3 KCC components influence USOs and CSOs differently
Clarysse et al., 2011a	Flanders, Belgium 1991-2002	48 CSOs, 73 USOs	Growth of sales and employment	Technology-specific (scope, newness, tacitness, relatedness), age, size, startup capital	CSOs' growth benefits from narrow-focused technologies, while USOs' growth benefits from broad technologies
Wennberg et al., 2011	Private incorporated companies in Sweden in knowledge-intensive sectors, 1994-2001	528 USOs, 8663 CSOs	Survival, employment growth, sales growth	Parent organization variables, Team human capital variables	CSOs perform better than USOs in both survival and growth. Industry experience matters more than education for CSO & USO performance. The nature of the parent organization matters more for CSOs than USOs.
Hvide and Jones (2018)	All incorporated entrants in Norway, 2000-2007.	128 USEs, 452 CSEs, where USEs/CSEs refer to startups by PhD holders	Number of USEs & CSEs, and their survival, sales, employees and profits after the first 5 years	Age, education, marital status, income, and wealth are controlled for but not reported.	Shifting ownership rights from faculty to universities (i.e. abolishing the 'professor's privilege') led to a reduction in number and quality of USEs
Roche et al. (2020)	Crunchbase merged with data on patents, publications, and research recognition	1723 innovative startups in biomedicine, created by 2998 founders	Exit via IPO or acquisition. Also: patents granted, funding raised, receipt of venture capital funding	Patents, funds raised, venture capital funding, team size, gender, state unemployment rate, sector, year	USEs less likely to achieve a liquidity event. However, USEs produce as many patents and receive as much funding as non-academic startups.
This paper	Danish census data, 2001-2012	443 USEs, 1083 CSEs, and hundreds of thousands of 'stayers'	New firm formation	Rich set of variables on human capital, income and wealth, family background, other personal characteristics, and present employer characteristics	Overall low predictive power: CSEs resemble USEs, few variables are significant. Relatively important role of current employer characteristics.

consider individuals with at least a Bachelor's degree,[3] to ensure that only those individuals with a minimum university education (and hence with a minimum probability to have actually acquired relevant knowledge) are included in the USE (and CSE) category. Furthermore, our data cannot detect whether the USE actually draws on knowledge developed at the university.[4] For example, a researcher from a cancer research institute who started a flower shop would be treated as a university start-up entrepreneur in our analysis. However, we consider that, even in the case of new venture creation based on entirely unrelated technical knowledge, nevertheless the culture and practices at the spawning organization must have had at least some influence on the emerging new venture. Therefore, we focus instead on individuals with at least a Bachelor's degree who were previously employed in a university and who leave to start their own business. In addition, we run a large number of robustness checks where we re-run our regressions on specific subsamples, e.g. to consider only patent-holders or to condition on individuals who found in high-tech industries.

2.1.2. *Corporate startup entrepreneurs (CSEs)*

CSEs appear under many different labels, such as "intra-industry spin-offs" (Klepper, 2002), "spinouts" (Agarwal et al., 2004), and "employee entrepreneurship" (Agarwal and Shah, 2014), and are defined as "new venture creation when employees of existing firms found a firm in the same industry" (Agarwal and Shah, 2014, p1111).

The prototypical CSE as observed by the broader public is probably founded by a patent-holding manager of a high-tech manufacturing firm. While some empirical studies have only collected observations on CSEs if the CSE entrepreneurs have patents (e.g. Ganco, 2013), nevertheless this does not necessarily mean that firms can only qualify as CSEs if the CSE founders have patented. Relatedly, some authors argue that CSEs are valuable because of the managerial experience they may have gained at their previous employer (e.g. Agarwal and Shah, 2014). However, our definition of CSEs does not require that CSEs be managers; CSEs could also include secretaries and administrative staff. Dahl and Sorenson (2014) used Danish register data like ours and observed that spinoff entrepreneurs had less managerial experience than non-spinoff entrepreneurs (i.e. those entering industries in which they did not have experience). In our empirical analysis, we disaggregate by subsamples (e.g. by age, patentholder status, academic degree) to approach subsamples of individuals that are more likely to have management experience.

We define CSEs as individuals who are employed in a high-tech firm in year t and who found a new firm in $t+1$. We hence again apply a broad startup definition that does not take into account the formal transfer of ownership rights as considered by some studies on corporate startups (Lindholm, 1997; Parhankangas and Arenius, 2003). Since we do not observe the transfer of technology or IP from the initial corporate context to the new venture, we prefer the term CSE to CSO.

CSEs benefit from various types of useful knowledge, such as entrepreneurial capabilities, industry-specific knowledge, operational knowledge, and technical and market know-how to enable product innovation (Agarwal and Shah, 2014).

One of the valuable assets of CSEs is their social capital that was accumulated during their time at the firm (Byun et al., 2019). This can be a source of industry knowledge and networking capital. Dahl and Sorenson (2014) observe that corporate spinoff entrepreneurs with prior industry experience as employees are able to hire higher-quality employees than those without such experience.

2.2. *Contrasting USEs and CSEs*

While the CSE definition refers to startups in the same industry, this makes less sense for USEs, instead USEs are expected to directly exploit the knowledge developed at the university. This latter notion is vaguely defined, however, and open to different interpretations. Dorner et al. (2017) distinguish between USEs that transfer research results and new scientific methods or techniques ("transfer spinoffs") and USEs that transfer specific skills acquired by founders during their university work ("competence spinoffs"). This latter type of spinoff is hard to measure, and can arguably include all conceivable instances of entrepreneurship by university employees, because skills and practices learnt at one workplace will somehow be transferable to new contexts, even those

[3] Hvide and Jones (2018) focus instead on PhDs.

[4] This remains a difficult challenge for spinoff research. To our knowledge, detailed knowledge on the technologies transferred through spinoffs is not available in any census dataset.

that appear to be unrelated at first glance. To take into account the different role of knowledge transfer in entrepreneurial motivations, we repeat our analysis on various subsamples (e.g. on subsamples of patent holders).

The empirical literature comparing USEs and CSEs has traditionally focused on comparing university spinoffs and corporate spinoffs (Zahra et al., 2007; Clarysse et al., 2011a; Wennberg et al., 2011), although some scholars have compared USEs with a comparison group of “new technology-based firms” (Ensley and Hmieleski, 2005; Mathisen and Rasmussen, 2019) or high-tech startups (Dorner et al., 2017). Here we prefer to compare USEs with CSEs, to better capture the notion of transfers of knowledge from the parent organization (universities or parent firms) into a new venture.

Table 1 summarizes the previous empirical literature to which we contribute. A first observation is that most previous studies have focused on small samples (Clarysse et al., 2011a). Hvide and Jones (2018) present large sample evidence, but their focus is on national institutional reform and their results for USEs vs CSEs are not presented in detail. Also, there is a gap in the literature regarding the role of human capital, income and wealth, and family background characteristics. Furthermore, previous studies have generally considered firm performance variables (in particular, sales growth) but not the actual startup decision. A consequence of this is that some studies investigate USEs and CSEs at the firm-level (e.g. Wennberg et al, 2011) whereas our analysis of USE and CSE founding is at the entrepreneur-level. We therefore contribute to this strand of literature by providing large-sample representative evidence to investigate the factors associated with USEs and CSEs.

2.3. Motivations for starting USEs vs CSEs

Table 2 contrasts USEs and CSEs in terms of motivations for founding, according to some salient dimensions often found in the literature. Half of the differences in Table 2 between USEs and CSEs relate to non-pecuniary motivations. While not all of the variables in Table 2 are measured in our data, nevertheless connecting our discussion to the broader theoretical literature can help identify some concrete differences between USEs and CSEs in their founding motivations, and awareness of these differences enables predictions for our variables.

The literature on new firm formation distinguishes between ‘opportunity entrepreneurship’ and ‘necessity entrepreneurship’ (Reynolds, 2005). The former corresponds to the exploitation of promising business opportunities where there are considerable prospects for innovation, growth and profits, while the latter corresponds to starting an imitative, low-growth business for lack of better employment opportunities, often corresponding to an escape from unemployment. ‘Necessity entrepreneurship’ seems less relevant in our comparison of USEs and CSEs, because it is assumed that individuals always have the option to continue their present employment. A third category of startup motivations corresponds to a phenomenon known as “lifestyle entrepreneurship” (Ateljevic and Doorne, 2000; Walker and Brown, 2004; Nightingale and Coad, 2016), where individuals may leave their current employment to start a new venture (perhaps a low-potential venture offering lower pay) for non-pecuniary reasons such as autonomy, the psychological freedom of being one’s own boss, job satisfaction, pride in the job, a flexible lifestyle, the ability to choose working hours and to balance work and family responsibilities, pursuing one’s own interests, encountering new challenges, and so on (Ateljevic and Doorne, 2000; Walker and Brown, 2004; Benz and Frey, 2008; Nightingale and Coad, 2016).

2.3.1. Opportunity entrepreneurship

Both USEs and CSEs can correspond to cases of high-impact ‘opportunity entrepreneurship.’ USEs can draw on scientific and technological expertise to develop new business processes and products, while CSEs can draw on a deeper knowledge of commercialization opportunities and familiarity with contemporary businesses processes and marketable products.USEs differ considerably from CSEs in terms of support from the parent organization. CSEs may have to battle against their parent organizations to leave the firm, to set up a rival firm in the same industry, and to take the patents and IPR (or perhaps to poach the employees) from the parent organization (Ganco et al., 2015; Shah et al., 2019). In contrast, USEs are generally treated favourably by the parent organization (Fini et al., 2020). Stimulating entrepreneurship in university contexts has connotations of a public good, with institutional interventions favouring academic entrepreneurship coming from universities themselves or public policy (Fini et al., 2020). Universities often have specialised entrepreneurship support personnel who organize entrepreneurship support classes, to help post-docs, PhD students,[5] and even faculty to overcome their skill gaps and to learn about the process of launching their startup, perhaps even attending these classes during regular working hours (Hayter and Parker, 2019). University-level enthusiasm for supporting its employee startups is moderated by support at the department level (Rasmussen et al., 2014). While some department heads may be relatively hostile to the startups (in the sense of resisting university policy to allocate resources to support the startup), other department heads may be generous and provide “tangible resources such as research time, laboratory space, equipment, consumables, and research support” (Rasmussen et al., 2014, p102), as well as support in applying for research funding, and even proof-of-concept funding to build a prototype to show to industry (Rasmussen et al., 2014). This seems to have no counterpart in the corporate sector: CSEs would be blocked by top management and department heads rather than willingly subsidized. Universities may also facilitate USEs by reducing uncertainty surrounding future employment in the case of USE failure. Universities often allow USE founders to keep an affiliation at the university (the case of “academic stasis” in Nicolaou and Souitaris, 2016) and may accept returning employees who were unsuccessful with their USE. We are not aware of such phenomena in the corporate context, where employee entrepreneurship has adverse effects on the parent firm (Agarwal et al., 2016), and firms instead focus on discouraging employees leaving to found CSEs. In addition to USE support from universities, macro-level public policy initiatives could provide support targeted at university employees with the goal of encouraging them to start their own businesses (Hayter and Parker, 2019; Fini et al., 2020).[6] Considering that USEs may be formed with the blessing (and resources) of their former employer, while CSEs may have to battle against their former employer as an additional obstacle to CSE founding, this suggests that CSEs require more resources at startup (e.g. founder income, social capital associated to managerial roles) to help them overcome their additional hurdles.

With regards to patents and IPR, public policy initiatives in many countries have been set up to allow university researchers to have some control rights over the patents and intellectual property developed at the university research lab (Geuna and Rossi, 2011; Hvide and Jones, 2018), with the explicit policy goal to facilitate the formation of USEs. For CSEs, however, it is more common for the parent organization to discourage employees from founding CSEs using the parent organization’s technology, for example by aggressively enforcing patents (Ganco et al., 2015).

2.3.2. Non-pecuniary motivations for entrepreneurship

2.3.2.1. Non-pecuniary motivations for USEs. A defining characteristic of

[5] PhD students are paid university employees in some European countries.

[6] For example, former US President Barack Obama signed into law the America COMPETES (Creating Opportunities to Meaningfully Promote Excellence in Technology, Education, and Science) Reauthorization Act of 2010 (P.L. 111–358), which includes specific language acknowledging and promoting non-academic career development opportunities among masters and PhD students (Hayter and Parker, 2019).

Table 2
Effects of various factors on the opportunity and non-pecuniary motivations for entrepreneurial firm formation.

	USE Relative effect on startup probability	Reason	CSE Relative effect on startup probability	Reason
OPPORTUNITY ENTREPRENEURSHIP				
Support from the parent organization	POSITIVE	University initiatives to support USEs: TTOs, entrepreneurial training, provision of resources Macro-level Public Policy initiatives (Fini et al., 2020)	NEGATIVE	CSEs are seen as detrimental to parent firms (Agarwal et al., 2016) Mobility hindered by CNCs: covenants not to compete (Starr et al., 2018)
Patent and IPR enforcement	POSITIVE	Policy initiatives in many countries to encourage faculty to keep some or all of the IPR of their university research (Hvide and Jones, 2018)	NEGATIVE	Firms can aggressively enforce patents to deter employees from leaving (Ganco et al., 2015)
Employment risk	POSITIVE	USE founders can maintain an affiliation at the university ('academic stasis'), and perhaps return to a job if their USE fails (Nicolaou and Souitaris, 2016)	NEGATIVE	No such 'stasis' effect for CSE founders. Probably they cannot return to their previous employer
NON-PECUNIARY MOTIVATIONS FOR ENTREPRENEURSHIP				
The need for autonomy and 'being one's own boss'	NEGATIVE	University jobs already have fairly high autonomy	POSITIVE	Need for autonomy
Escaping a 'bad boss'	NEGATIVE	Employees have autonomy and monitoring is less intense	POSITIVE	Employees are closely monitored by their boss
Options for employment elsewhere	NEGATIVE	Employees are free to move elsewhere, and can accurately signal their current productivity (e.g. on their employer's website) on a global scale Employees may even carry their research grant with them to the new employer	POSITIVE	Employees may be prohibited from working for a rival. Employees may not be able to transparently signal their current productivity

NOTES: necessity entrepreneurship is not considered here, because it is assumed that individuals have the option to continue with their present employer.

universities is their culture of having a "taste for science" and prioritizing science over the pursuit of profit. University employees may adopt a "scientific" mindset, which could mean that they try to step backwards and infer laws and abstract theories from observations of reality, instead of taking the opposite "engineering" approach of reconfiguring resources on a trial-and-error basis ("messy tinkering") to address speculative future market needs (Nightingale, 2014). Furthermore, the relative remoteness of university employees from market forces and contact with clients means that they have less management and marketing knowledge. Academics are often criticized for their lack of understanding of the commercial world (Boehm and Hogan, 2014). Academic entrepreneurs may therefore lack the leadership experience and management experience that can be found in private sector employment (Colombo and Piva, 2012). Hayter and Parker (2019) report that Principal Investigators (PIs) of research projects are sometimes perceived as lacking "soft skills" such as "management skills", even though they are managing large research projects.

Given the degree of specialization and expertise of faculty, close supervision and monitoring is difficult, and instead faculty is given considerable autonomy to carry out its tasks. Such a culture of autonomy and "being one's own boss" is one of the hallmarks of entrepreneurship (Benz and Frey, 2008). Another "entrepreneurial" characteristic of academics is that they have been described as "jacks-of-all-trades" (Staniforth and Hariand, 1999; Lazear 2005), due to their various roles in managing research projects and acquiring resources, on top of their traditional roles of teaching, supervision, maintaining scientific awareness, and evaluating opportunities for scientific research (Boehm and Hogan, 2014).

We therefore suspect that few USEs occur because of the motivation of "being one's own boss". Given that universities confer considerable autonomy to faculty, we conjecture that the proverb *"people don't quit a job, they quit a boss"* (Shaw, 2019) is less relevant for university employees than for corporate employees. Furthermore, because of the autonomy enjoyed by university employees, and their personal responsibility in choosing their tasks (especially for research staff), they would not leave a job for the oft-heard reason that they felt their skills and strengths were not being used, or because they lacked opportunities for career advancement within the organization (Kacperczyk and Marx, 2016). For these reasons, we expect that present employer characteristics could have a more prominent role for CSEs than for USEs. For example, the "small firm effect" (Elfenbein et al., 2010; Kacperczyk and Marx, 2016) which has been observed to push individuals from small firms towards founding their own firms, could be expected to be more relevant for CSEs than for USEs.

Academics are highly motivated by science, and the profit motive is less intense (Stern, 2004). Academics may be reluctant to pursue opportunities if there is no scientific component to the work task: "Particularly when collaborating with the best academic researchers, firms need to take into account that these academics will under most circumstances only work with them if there is also some academic benefit to be derived" (Perkmann et al., 2013, p433). We expect that few university employees will spin out of a university to start their own firm if there is no knowledge component, because the organizational norms of autonomy reduce the need for autonomy that constitutes a non-pecuniary benefit of entrepreneurship (Benz and Frey, 2008). Furthermore, university jobs may be more stable than jobs elsewhere – at least once tenure is granted – because the culture is often sheltered from the threats of market competition that prevail in profit-seeking sectors of the economy (hence, also reducing the "necessity" motivation for entrepreneurship as an alternative to unemployment). A fortiori, core university faculty with secure, reasonably well-paid employment would not leave their jobs for a high-risk venture unless the expected gain was very high. In robustness checks, we test for any differences that formal education and academic rank may make to the decision to leave academe for a startup.

2.3.2.2. Non-pecuniary motivations are more relevant for CSEs. The non-pecuniary motivation for firm formation therefore seems more relevant for CSEs than for USEs, for various reasons.

First, many new ventures are founded because of an individual's desire for self-realization, autonomy, and to 'be one's own boss' (Walker and Brown, 2004; Benz and Frey, 2008; Müller, 2010). However, as discussed above, the nature of university working conditions is such that many individuals (faculty and graduate students, although not necessarily post-docs, Hayter and Parker (2019)) are not closely monitored and have relatively high levels of task autonomy. Employees in firms, however, are monitored more closely and are probably in more frequent contact with their supervisors. Monitoring costs in firms can be considered to be lower than monitoring costs in universities, because academic activities are complex and open-ended (Bodas Freitas et al., 2013).

Second, and relatedly, frictions with a 'bad boss' lead to job mobility (Shaw, 2019), and spinoff formation (Klepper and Thompson, 2010; Shah et al., 2019). Individuals may spin out because of disagreements concerning the previous employer's management practices or concerning the commercial value of business opportunities (Dahl and Sorenson, 2014, p672; Garvin, 1983; Klepper and Sleeper, 2005; Klepper and Thompson, 2010). However, the motivation to quit an employer to escape a bad boss seems less relevant for USEs compared to CSEs. University faculty and graduate students have considerable task autonomy, as discussed above, although post-docs might be in closer contact with their project PIs (principal investigators) (Hayter and Parker, 2019). Corporate sector employees, however, may maintain closer contact with their bosses, have lower task autonomy, and be more dependent on their bosses regarding their performance evaluations and promotion possibilities.

Third, with regards to employee retention, various institutional features suggest that mobility is easier from universities than from firms. Employee mobility from high-tech firms is often framed as an 'expropriation problem' (Ganco et al., 2015). Firms often use 'covenants not to compete' (CNCs) to discourage employees from working in rival firms in the same sector (Starr et al., 2018), although we are not aware of CNCs for university faculty, employees or graduate students.[7] Mobility of university faculty is common and is even facilitated by various institutional features. University employees can more transparently attach their name to their work outputs to signal their productivity on the labour market. For some tasks (such as authoring of books and articles, and even for anonymous peer-reviewing thanks to Publons.com), academics can attach their name to their scientific outputs.[8] Faculty usually have their own websites, set up by their employing universities, to transparently signal their achievements (publications, teaching outputs, and more). This presumably makes academics less beholden to their bosses, and easier for outsiders to evaluate their work outputs. Companies do no such thing to make their employees' individual contributions and productivity so clearly visible.

Overall, therefore, the preceding discussion suggests some differences in the determinants of USE vs CSE formation, in particular tilting the motivations of startup formation towards encouraging 'opportunity' USEs while discouraging USEs founded for non-pecuniary motivations. The next subsection draws on Table 2 to derive predictions for the variables in our dataset. Regarding total numbers of USEs and CSEs, the evidence is mixed, since some institutional factors would encourage USEs, while others would encourage CSEs.

2.4. Research questions

Research into USEs and CSEs has a tradition of being empirical and phenomenological rather than theoretical. Perkmann et al. (2013, p425) write that "research on academic engagement has produced predominantly phenomenon-focused studies." Our paper complements this stream of literature, by presenting an exploratory quantitative analysis of a nationally-representative dataset that contains both a range of variables already tested in the literature and a large number of relatively novel variables relating to human capital, income and wealth, family background, and other personal characteristics. As a consequence, developing a large number of hypotheses would be inappropriate (Helfat, 2007). Nevertheless, we propose some broad research questions, to orient our analysis and the interpretation of the results.

A first theme is that individuals may found a new business for reasons that are not objectively linked to the business opportunity itself, but for non-pecuniary motivations. Table 2 suggests that the non-pecuniary motivation will be stronger for CSEs than for USEs. Such non-pecuniary motivations for entrepreneurship could be related to an individual's self-employment experience – presumably those with entrepreneurial experience are more alert to business opportunities and less hesitant to exploiting these opportunities through entrepreneurial entry. Relatedly, the self-employment history of the parents may stimulate preferences for entrepreneurial entry, through channels such as exposure to a role model (Laspita et al., 2012). Furthermore, work experience at a larger number of workplaces can be positively associated with self-employment, because highly mobile individuals may have a "taste for variety" or discomfort in standard employment contexts that pushes them into entrepreneurship (Frederiksen et al., 2016), corresponding to non-pecuniary motivations for entrepreneurship rather than opportunity entrepreneurship. Therefore, we suspect that these variables (years of self-employment experience, self-employment experience of the parents or spouse, and number of different workplaces) will affect USE or CSE formation. Furthermore, we expect that these variables have a stronger role for stimulating CSEs than USEs, because non-pecuniary motivations for entrepreneurship are expected to be more relevant for CSEs than USEs (Table 2). The flipside of considering that CSEs are more affected by non-pecuniary motivations, would be to consider that USEs are more strongly affected by the quality of the business opportunity (for example, that patents are more relevant for USEs than CSEs).

A second theme is resources required for startup. On the one hand, USEs may lack the resources, social capital, and complementary assets required for taking a novel idea or a scientific invention all the way to market (Teece, 1986). USEs may lack knowledge of operations, manufacturing processes, and marketing and customer characteristics. Therefore, we could expect that USEs whose founders have higher personal income, and higher personal and household wealth, as well as higher social capital and business networks (as proxied by having a managerial role, with the caveat that being a manager may have different meanings when comparing universities and industry) are more likely to overcome these resource constraints and form a credible USE business. On the other hand, however, CSEs may have to overcome hurdles of breaking away from their former employer that are less relevant for USEs (as discussed above). Therefore, the role of resources (personal income, manager status, etc) and the founding of USEs or CSEs is an empirical question.

A third theme is education fields, which vary considerably in terms of characteristics of the knowledge base (complexity, knowledge cumulativeness, technological opportunity, etc) as well as complementary assets and appropriability instruments (Agarwal and Shah, 2014). Ganco (2013) shows that knowledge complexity has an influence on the different options faced by potential CSE founders in terms of staying with their employer, switching to a rival firm, or starting a CSE alone or with a team of co-inventors. In some disciplines, it is easier to transfer a scientific discovery into a commercial product. In some disciplines, existing mechanisms for IP protection can deter entry by small-scale ventures (Hall et al., 2021). In some disciplines, practical experience and availability of complementary assets may be easily available due to institutional factors, e.g. if medical researchers are frequently exposed to medical practice in the context of university hospitals. We therefore test how our results vary across educational fields – natural sciences, engineering, and health – in our robustness analyses.

[7] There might be a case for CNCs affecting post-docs, although we are not aware of any evidence on this matter. Any such agreement might take the form of a project-specific confidentiality agreement instead.

[8] This is not always the case, in some countries (e.g. some institutes in Korea and France) PhD students must work on their supervisors project and are not allowed to work on or publish their own side-projects or to publish any research work without getting their supervisor's approval, and this sometimes means adding their supervisor as a co-author while at other times it means the supervisor can veto and kill the student's project. Perhaps variations in institutional features of academia could affect the meaning of USEs in different countries. These institutional differences could be an interesting topic for further work into USEs.

3. Data and definitions

3.1. Data

The backbone of our database is the “Integrated Database for Labour Market Research” (IDA). IDA is a matched employer-employee register dataset which covers all employers and employees in Denmark from 1980 onwards on an annual basis. IDA was developed in the 1990s on the basis of mandatory state pension scheme contributions introduced in 1964. The database has since been extended, and now includes many dimensions of economic activity and also individual background characteristics added via Danish individual-specific identifiers used by the public sector, e.g., for tax collection, house ownership, healthcare or education.

The firm-level data was initially based on administrative units that identified single employers, but after the introduction of new firm identifiers in 1999, the organizations defined by these identifiers became the standard mainstay of analyses of Danish firms. Firm register data is mostly collected by the Danish Business Authority and the Danish Tax Authority. These sources feed into the firm data for this analysis, which is supplied by Statistics Denmark, and which is the only provider of firm data that can be matched with detailed person data.

Statistics Denmark data is standard for Danish entrepreneurship research (e.g. Dahl and Sorenson, 2012; Nanda and Sørensen, 2010), and allows the analysis of two generations of comparable raw data: the Statistics Denmark employer-employee data, and more recently, the Statistics Denmark Entrepreneurship Database.[9]

Unlike older studies which defined startups based on several data sources (e.g. Malchow-Møller et al., 2011), more recent work benefits from a coherent dataset that allows the identification of startups, the Danish Entrepreneurship Database provided by Statistics Denmark which was established in 2005. It has become the standard database for entrepreneurship research on Danish firm register data (e.g. Dahl and Sorenson, 2012). The Entrepreneurship database presently spans the years 2001-2012.

The Danish Entrepreneurship Database is partly based on Statistics Denmark’s data that is inaccessible to researchers or prohibitively difficult or expensive to access and process, and which has found its way into the generation of the Entrepreneurship database – in particular the identification of the individuals to be considered as the entrepreneurs behind the companies.

The main conditions for inclusion in the Entrepreneurship database are that the firms are indeed new firms instead of the outcome of mere organizational restructuring, and that their activity levels in terms of employment and turnover are above industry-specific minimum thresholds. The latter implies that the Entrepreneurship Database does not sample new firms that first experience minimum measurable activity in subsequent years.

3.2. University and high-tech industry startups

We define both university and corporate startup entrepreneurs according to the NACE Rev. 1 sectoral classification. For universities we consider sector 80.30 “Higher education” while we define corporate startups from “High-tech industry and knowledge-intensive services” based on Eurostat’s guidelines.[10]

3.3. Explanatory variables

Our data provide a detailed and accurate picture of entrepreneurs in Denmark. We consider four main sets of personal characteristics that may explain university startup activity (Shane, 2004) and startup activity more generally (Sauermann, 2017): (i) human capital (Beckman et al., 2007; Davidsson and Honig, 2003; Evans and Jovanovic, 1983), (ii) income and wealth (Holtz-Eakin et al., 1994; Sauermann 2017), (iii) family background (Dunn and Holtz-Eakin, 2000; Fairlie and Robb, 2007) and (iv) other personal information like gender, previous job mobility or immigration status. In addition, we study (v) the extent to which an individual’s current workplace matters for future startup activity (Elfenbein et al., 2010; Nanda and Sørensen, 2010; Sauermann, 2017; Stuart and Ding, 2006).

3.3.1. Human capital

The quality of the startup team constitutes an important predictor of entrepreneurial choice and startup success (Mustar et al., 2006; Shane and Stuart, 2002). This quality is often measured by age, education, job function and educational background (Beckman et al., 2007; Landry et al., 2006) which all are elements of an individual’s human capital (Davidsson and Honig, 2003).

We consider both the type and the level of formal education (Elfenbein et al., 2010; Sauermann, 2017). All individuals in our data have at least a Bachelor’s degree, so we additionally account for individuals holding an MA or PhD. Stuart and Ding (2006) show that holding a PhD degree increases the likelihood of becoming a USE. Education is positively associated with analytical skills and information about business opportunities (Casson, 1995; Parker, 2009), and provides a larger set of personal opportunities (Gimeno et al. 1997), including a richer set of outside options and promotion opportunities. A meta-analysis shows that most studies find a negative relation between self-employment choice and education (van der Sluis et al., 2008). We focus on three ‘STEMM’ education fields: natural sciences, engineering and health sciences (Colombo and Piva 2012; Elfenbein et al. 2010) and include dummy variables for these fields in our regressions, following our discussion of different opportunities and knowledge bases that come with different education types in Section 2.4.

Past working experience constitutes yet another important part of an individual’s human capital by providing individuals with direct training and professional contacts (Zahra et al., 2007) as well as social ties more generally (Nicolaou and Birley, 2003a). Landry et al. (2006) show a positive association between working experience and entrepreneurial activity. We consider an individual’s overall years of working experience as well as years of self-employment experience, since Shane (2003) associates previous with present startup activity. Our discussion of non-pecuniary motivations for entrepreneurship in Section 2.4 suggests to include a dummy variable that indicates whether an individual receives side-income from self-employment. Such income is typically generated from consultancy side-jobs, and we interpret this variable as measuring “some”’ links to self-employment (Aldridge et al., 2011; Nicolaou and Birley, 2003a). Previous spells of self-employment constitute important heterogeneity among entrepreneurs, since much earlier literature assumes that the individuals are creating a venture for the first time (Mosey and Wright 2007).

We also account for employee age, although Shane (2003, Ch. 2) suggests that working experience should be more informative than age, since the latter explicitly embodies learning. The age effect is unclear a priori, since older employers have accumulated more capital but are also more risk averse (Elfenbein et al. 2010; Sauermann 2017) which is why Levesque and Minniti (2006) include both age and its square. Age had no significant effect on startup activity for Aldridge and Audretsch (2011),

[9] The general Statistics Denmark employer-employee data based on IDA has been applied by, for example, Eriksson and Kuhn (2006)’s analysis of corporate spinoffs.

[10] Eurostat indicators on high-tech industry and knowledge-intensive services. URL: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf

Elfenbein et al. (2010) or Nicolaou and Birley (2003a).[11]

Our final general human capital variable is employee patenting activity, which is a driver of self-employment (George et al., 2002; Landry et al., 2006; Sauermann, 2017; Stuart and Ding, 2006) and which we consider as a proxy for entrepreneurial opportunity (as discussed in Section 2.4). The patent data stem from the European Patent Office's Patstat data that we merged to individual inventors by Statistics Denmark. Our measure of individual patenting activity is an individual's patent stock.

While these variables constitute measures of a person's general human capital, we account for years of tenure as a measure for firm-specific human capital as in Elfenbein et al. (2010) and Sauermann (2017). We additionally consider a dummy variable that is coded 1 if the individual has at least three years of employment at the same workplace, since this is the point in time when tenure decisions are typically reached at Danish universities. Having tenure is positively related to university spinoff activity (Nicolaou and Birley 2003a; Roberts, 1991). Another firm-specific human capital variable is holding a "manager" position, since leadership experience is probably useful in a subsequent self-employment spell. We measure "manager" status by a dummy variable based on the ISCO code that is coded 1 if a person performs top-level leadership work (ISCO code 1). Clearly, the interpretation of managerial positions is likely to be different for university and industry. While the ISCO level 1 codes define managers as individuals in "leadership roles" (translating from Danish to English), they do not distinguish between how "leadership roles" may differ in corporate vs university employment. University professors are e.g. managers even though their leadership role may on average be limited, while managerial status probably involves more leadership in the corporate world.

Finally, beyond our main human capital variables (education field, education length, years of self-employment experience, years of working experience, age, number of patents, years of tenure, manager status), any potentially-remaining unmeasured aspects of human capital can be proxied by income.

3.3.2. Income and wealth

As discussed in Section 2.4, income and wealth may play an important role in an individual's founding decision since they enable prospective founders to overcome resource constraints. Income and wealth facilitate fundraising (Blanchflower and Oswald, 1998; Holtz-Eakin et al., 1994; Sauermann, 2017). Wealth also enables pledging collateral for bank loans (Blanchflower and Oswald, 1998). Landry et al. (2006) find positive effects of wealth on startup activity, while there is no significant association with university spinoff activity in Nicolaou and Birley (2003a). As operationalizations of our income and wealth variables, we include the natural logarithms of (i) personal income, (ii) family income (the total income a family commands over) and (iii) total family assets. To complement the levels of income with relative measures, we include dummy variables for the quintiles of the within-firm income distribution and dummy variables for the quintiles of the family assets distribution in the population.

3.3.3. Family background

We include marital status and the number of children as well as a set of variables that measures the occupations of an individual's parents and partner as variables reflecting a person's family background. Davidsson and Honig (2003) consider them as proxies for social capital which is otherwise empirically hard to precisely measure (Parker 2009, Ch. 4.3). Parker (2009, Ch. 4.5.1) and Budig (2006) report a positive association between having children and being self-employed. Davidsson and Honig (2003) do not find significant effects of marital status on nascent entrepreneurship. We also include mother and father self-employment status to account for inter-generational transmissions of self-employment (Fairlie and Robb, 2007), a variable that may also serve as a proxy for preferences for entrepreneurship following Section 2.4. We also control for present partner self-employment and wage-employment, because of possible similar transmission mechanisms, and since the spouse's employment status reduces the prospective entrepreneur's financial risk exposure, which accordingly makes own entrepreneurial activity more likely (Parker, 2008).

3.3.4. Other personal characteristics

We distinguish between individuals with lineal descendancy in Denmark ("Danes") and "New Danes"[12] who are registered as first- or second-generation immigrants, because these variables have previously been linked to entrepreneurship (Borjas, 1986; Evans, 1989), as has gender (Landry et al., 2006; Minitti and Naude, 2010; Nicolaou and Birley, 2003a). We also include the number of jobs held in the past five years to account for general person-specific mobility (Folta et al., 2010).

3.3.5. Present employer characteristics

We consider a fairly wide range of employer-specific variables that may be associated with an individual's startup decision (Gompers et al., 2005). We include firm size measured by the number of employees, since employees in large firms may be more likely to leave in order to be more independent than in less rigid bureaucracies (Chatterji, 2009), while employees of small firms may leave because of ability and preferences sorting (Elfenbein et al., 2010; Sauermann, 2017) or lack of promotion possibilities (Kacperczyk and Marx, 2016). Former co-workers who left one's present employer to become entrepreneurs may also positively influence mobility (Nanda and Sørensen, 2010; Stuart and Ding, 2006) which is why we account for the share of former co-workers in all workers who left for self-employment at $t-1$. We also consider employer patenting activity, since the more active the employer is the more knowledge can possibly be transferred to a new workplace both from industry (Kaiser et al., 2015) and university (Kaiser et al., 2018). Dummy variables for the geographical location of the employer (Gompers et al., 2005; Klepper and Sleeper, 2005) as well as for the employer's sector of main economic activity (Nocke, 2006) constitute a final set of employer-related variables. Our specifications also include year dummies.

4. Empirical analysis

4.1. Descriptive statistics

We begin with descriptive statistics to compare the characteristics of individuals in year t who found a startup at $t+1$ to individuals who do not start a firm. Table 3 displays the means of the respective variables, as well as a test for identity of the respective type of startup entrepreneur and those individuals who remain with their present employer (called "stayers" hereafter). We use t-tests for the continuous variables and test for the equality of proportions for the dummy variables. The table shows the corresponding p-values.[13] Table 3 shows that many differences between both USEs and CSEs and the respective group of stayers are statistically significant but economically negligible. We hence define statistically significant differences exceeding 30 percent in absolute values as "economically" significant and discuss them in more detail below.

A major difference to existing studies that use more selected data sets is that the mean number of patents is relatively low. A USE holds 0.59

[11] Given that we exactly measure education and working experience we can also include age without it being collinear with education and working experience.

[12] We are grateful to the Editor for suggesting this term.

[13] Note that some cells in the table do not contain figures, since they relate to less than ten observations which would violate Statistics Denmark's secrecy restrictions.

Table 3
Descriptive statistics.

			University			Corporation			Tests for differences		
			Mean Stayer	Mover	p-val. stayer =mover	Mean Stayer	Mover	p-val. stayer =mover	p-val. uni mover =corp. mover	mover=stayer	university=corporate
										(2)&(4)=(1)&(3)	(1)&(2)=(3)&(4)
		Dummy	(1)	(2)	(1)=(2)	(3)	(4)	(3)=(4)	(2)=(4)		
Human capital	Education field: Natural sciences	1	0.449	0.419	0.206	0.414	0.439	0.100	0.489	0.744	0.000
	Education field: Engineering	1	*0.191*	*0.313*	0.000	0.417	0.440	0.138	0.000	0.000	0.000
	Education field: Health	1	*0.360*	*0.267*	0.000	*0.169*	*0.122*	0.000	0.000	0.000	0.000
	Education length: Bachelor	1	*0.437*	*0.316*	0.000	0.229	0.192	0.002	0.000	0.000	0.000
	Education length: Master	1	0.464	0.600	0.000	0.732	0.780	0.000	0.000	0.000	0.000
	Education length: PhD	1	0.099	0.084	0.256	*0.039*	*0.028*	0.023	0.000	0.000	0.000
	Years of self-employment experience	0	0.554	0.402	0.220	0.087	0.132	0.076	0.033	0.065	0.000
	Some self-employment experience	1	0.673	0.737	0.002	0.539	0.577	0.012	0.000	0.025	0.000
	Years of working experience	0	17.945	17.428	0.173	18.471	18.584	0.614	0.009	0.992	0.000
	Age	0	42.308	39.967	0.000	40.154	40.562	0.144	0.313	0.006	0.000
	Number of patents	0	*0.197*	*0.587*	0.000	0.388	0.431	0.489	0.218	0.002	0.000
	Years of tenure	0	4.367	4.289	0.785	4.924	4.341	0.000	0.874	0.010	0.000
	"Tenure" (more than 3 years at employer)	1	0.351	0.353	0.928	0.449	0.392	0.000	0.155	0.030	0.000
	Manager	1	*0.023*	*0.046*	0.021	*0.063*	*0.124*	0.000	0.000	0.000	0.000
Income and wealth	Gross annual income in DKK	0	502201	578555	0.076	584770	759323	0.000	0.000	0.000	0.000
	Top 80-100% in employer income distribution	1	0.171	0.157	0.413	*0.165*	*0.124*	0.000	0.096	0.000	0.000
	Top 60-80% in employer income distribution	1	0.178	0.166	0.476	*0.182*	*0.118*	0.000	0.018	0.000	0.018
	Top 40-60% in employer income distribution	1	0.197	0.196	0.995	0.214	0.165	0.000	0.154	0.001	0.000
	Top 20-40% in employer income distribution	1	0.220	0.181	0.031	0.218	0.226	0.544	0.041	0.541	0.264
	Top 20% in employer income distribution	1	0.234	0.300	0.002	*0.221*	*0.367*	0.000	0.011	0.000	0.000
	Gross annual family income in DKK	0	604189	619794	0.526	599469	708266	0.000	0.006	0.000	0.012
	Total family assets in DKK	0	2938753	2965818	0.885	2762192	3661413	0.000	0.023	0.001	0.000
	Top 80-100% in family asset distribution	1	0.151	0.212	0.002	0.167	0.181	0.236	0.170	0.003	0.000
	Top 60-80% in family asset distribution	1	0.187	0.183	0.844	0.170	0.164	0.600	0.378	0.438	0.000
	Top 40-60% in family asset distribution	1	0.192	0.166	0.134	0.221	0.207	0.261	0.054	0.176	0.000
	Top 20-40% in family asset distribution	1	0.201	0.216	0.416	0.238	0.206	0.010	0.650	0.221	0.000
	Top 20% in family asset distribution	1	0.269	0.223	0.019	0.204	0.242	0.004	0.420	0.701	0.000
Family background	Married	1	0.613	0.627	0.540	0.635	0.673	0.008	0.086	0.005	0.000
	# of children	0	0.882	1.071	0.000	1.121	1.157	0.289	0.150	0.000	0.000
	Father self-employed	1	0.052	0.064	0.316	0.061	0.078	0.031	0.306	0.011	0.000
	Father wage-employed	1	0.215	0.254	0.057	0.202	0.198	0.701	0.018	0.531	0.000
	Father unemployed or retired	1	0.240	0.285	0.036	0.329	0.318	0.418	0.198	0.150	0.000
	Mother self-employed	1	0.024	0.038	0.121	0.023	0.029	0.241	0.387	0.066	0.081
	Mother wage-employed	1	0.238	0.283	0.036	0.221	0.200	0.086	0.001	0.715	0.000
	Mother unemployed or retired	1	0.337	0.404	0.004	0.456	0.476	0.187	0.009	0.000	0.000
	Spouse self-employed	1	0.018	-	0.409	0.015	0.020	0.261	0.304	0.599	0.000
	Spouse wage-employed	1	0.256	0.300	0.042	0.349	0.381	0.031	0.002	0.000	0.000
	Spouse unemployed or retired	1	*0.134*	*0.113*	0.398	0.111	0.139	0.070	0.375	0.316	0.000
Other personal character-istics	1st generation new Dane	1	*0.088*	*0.049*	*0.000*	0.081	0.062	0.009	0.287	0.000	0.000

(*continued on next page*)

Table 3 (*continued*)

			University			Corporation			Tests for differences		
			Mean Stayer	Mover	p-val. stayer =mover	Mean Stayer	Mover	p-val. stayer =mover	p-val. uni mover =corp. mover	mover=stayer (2)&(4)=(1)&(3)	university=corporate (1)&(2)=(3)&(4)
		Dummy	(1)	(2)	(1)=(2)	(3)	(4)	(3)=(4)	(2)=(4)		
	2nd generation new Dane	1	0.005	-	0.799	0.005	-	0.276	0.350	0.378	0.685
	Female	1	*0.318*	*0.159*	0.000	*0.281*	*0.136*	0.000	0.249	0.000	0.000
	# of different workplaces	0	8.750	9.523	0.000	7.508	8.201	0.000	0.000	0.000	0.000
Present employer characteri-stics	# employees own employer	0	1242	1108	0.026	*191.357*	*121*	0.000	0.000	0.000	0.000
	# patents own employer	0	142.843	133	0.286	*65.417*	*32.989*	0.000	0.000	0.000	0.000
	Share co-workers who became self-employed	0	0.005	0.006	0.000	*0.009*	*0.014*	0.001	0.000	0.000	0.000
	# obs.		126669	453	127122	168768	1083	169851	1536	296973	296973

Notes: Table 3 displays the means of our explanatory variables for USEs (column (1)) vs university stayers (column (2)) and CSEs (column (3)) vs corporate stayers (column (4)). It also shows tests for equality of the respective means. "–" refers to too few observations to be compatible with Statistics Denmark's confidentiality requirements. Economically (defined as an absolute difference of more than 30%) and statistically significant differences between USEs/CSEs and the respective group of stayers are in italics. Economically and statistically significant differences between USEs and CSEs and are in bold face.

patents on average while the related figure for CSEs is 0.43. To compare, Bonardo et al. (2011) find that the median number of university spinoff patents is six while that of independent startups is two. Their data does, however, relate to European high-tech SMEs that went public, while we use much broader population data that, most importantly, does not focus on high-tech startups that had an IPO.

4.1.1. USEs and stayers

For university employees, almost all differences between USEs and stayers relate to human capital. In particular, holding a degree in engineering and being a manager is more prevalent among USEs than among university stayers (note that here we are comparing university employees to one another, which implies that potentially different interpretations of managerial roles across university and industry contexts are less relevant here).[14] The number of own patents is also higher among USEs than among the respective group of stayers. As predicted in Section 2.4 and summarized in Table 2, there are significant differences in education with holding a Master's degree being positively related to startup activity. Females are less likely to become USEs.

4.1.2. CSEs and stayers

Relating CSEs to corporate stayers shows that overall differences relate less to human capital variables compared to university employees. As for USEs, there are differences in education for CSEs as well, with CSEs being less likely to hold a degree in health and less likely to hold a PhD. Individuals positioned in the upper deciles of the within-firm income distribution, males and employees of less patent active and – consistent with the "small firm effect" discussed in Section 2.3 – smaller firms are more likely to leave for an own startup. As predicted in Section 2.4, CSEs are more likely to be managers compared to individuals who stay with their corporate employer. They are also employed by firms with a higher share of former workers who left for self-employment.

4.1.3. USEs and CSEs

Overall, differences between startup entrepreneurs from university or business and their respective groups of stayers are small. This maps into relatively few differences between USEs and CSEs, where USEs are more likely to hold a PhD or a Bachelor degree, hold a health-related degree, command over more years of self-employment experience, belong to the 60-80 percent highest earners within their employer, have a wage-employed mother, and to be employed at a larger and more patent-active institution compared to CSEs. By contrast, CSEs are more likely to be managers[15], to hold a Master's degree, and to have had colleagues who left for self-employment.

4.1.4. Movers vs stayers and university vs corporate employees

Finally, Table 3 compares all employees who found firms (regardless of their origin) to those employees who remain with their employer; i.e. we compare columns (2) and (4) to columns (1) and (3). We also provide an overall comparison of university and corporate employees (movers and stayers combined) by comparing columns (1) and (2) to columns (3) and (4).

4.2. Regression analysis

While the univariate statistics discussed above provide a first picture of the characteristics of USEs and CSEs, we use OLS linear probability models in our main analysis. We prefer OLS over logit or probit models since OLS coefficients directly translate into marginal effects. We estimate binary choice probit models in a robustness check and find that there is no qualitative difference at all between them and our main OLS results.[16]

Below, we discuss both our (i) "overall" estimation results based on the same data as our descriptive analysis and (ii) evidence from selected subsamples of individuals in an attempt to move our data closer to the existing literature where, e.g., a stereotypical USE is a high-status research-active professor of a certain age and career development and not – as could potentially be the case in our main analysis – a university administrator with an academic degree.

4.2.1. Overall results

Table 4 presents our OLS estimation results for our complete data

[14] This is hinted at by the summary statistics in Table 3. For USEs, the proportion of managers is 0.023 for stayers and 0.046 for movers. For CSEs, the proportion is 0.063 for stayers and 0.124 for movers.

[15] This is consistent with the notion that starting a CSE requires more resources than starting a USE (as discussed in Section 2.3), although this might also simply be due to the different roles managers have at university vs industry.

[16] Estimation results are therefore only available upon request.

set.[17] We first estimate separate models for university (column (1)) and corporate employees (column (2)) for the propensity to become a startup entrepreneur. We secondly estimate a joint model which interacts all explanatory variables with a dummy variable for being a corporate employee. The non-interacted coefficients and standard errors of that model are identical to the coefficient estimates for the separate university employee model (column (1)). The interacted coefficients displayed in column (3) are deviations from the coefficients for university employees.[18] A positive coefficient means that the respective variable is more strongly related to a corporate employee's decision to start a firm than to a university employee's decision.

We include the same set of variables as in our descriptive statistics, Table 3. The omitted base categories of our sets of dummy variables are natural sciences, holding a Bachelor's degree, lowest quintile in the employer income distribution and lowest quintile in the family wealth distribution. We take the logarithm of annual personal and family income, employer firm size and employer patent stock and include squared terms of total working experience, age, tenure, log annual income and log employer size. We cluster standard errors at the present employer level.

4.2.1.1. Movers and stayers. Our estimation results reflect the differences between USEs and CSEs and the respective groups of individuals remaining with their employer that were discussed in our descriptive statistics. Consistent with our predictions from Section 2.4, university employees who are engineers, have gained some self-employment experience, hold more patents, have switched workplaces more frequently and are managers, are more likely to become founders than university stayers.

Some of these significant results could relate to knowledge-based theories of entrepreneurship (e.g. having a Master's degree and patents), while other results may have more to do with non-pecuniary motivations for entrepreneurship that are distinct from knowledge-based motivations (Frederiksen et al., 2016). In this vein, having previous self-employment experience, as well as having a larger number of previous workplaces, could make individuals more mobile in the pursuit of entrepreneurial opportunities (Frederiksen et al., 2016), as discussed in Section 2.3. In addition, being among the top 40-60 percent in the family wealth distribution negatively affects the self-employment decision, indicating that university employees with either lower or higher family wealth are more likely to found USEs. One possible interpretation is that having low family wealth pushes an individual to pursue income-generating opportunities, while having high family wealth encourages entrepreneurship by providing an individual with the resources needed to take risks in pursuing entrepreneurial opportunities.

For CSEs (Table 4, column (2)) we find that manager status, earning a high relative income, having a self-employed father (one of our proxies for non-pecuniary motivations for entrepreneurship from Section 2.4), and being employed at a small firm increases the likelihood of leaving for self-employment. On the one hand, some of these results suggest that individuals with more (managerial and leadership) experience and greater resources and networks are better positioned to start a new venture (as pointed out in Section 2.4). On the other hand, and consistent with the "small firm effect" (Kacperczyk and Marx, 2016), the results could suggest that larger firms may perform better at retaining their employees, because they provide more scope for exploring opportunities within the firm, as well as more attractive pay and promotion possibilities.

4.2.1.2. USEs and CSEs. The interaction model in column (3) shows that the effects of holding an engineering background, and holding own patents on the likelihood of starting an own business is statistically significantly smaller for corporate employees than for university employees. In line with our resource constraints arguments put forward in Section 2.4 (i.e. that CSEs must overcome barriers raised by their former employers, and for this they require resources), we find that higher relative income is to a statistically significantly larger degree related to leaving for a startup for CSEs rather than USEs. Perhaps surprisingly, few statistically significantly different coefficients are found for the other variables we consider, which implies that there are negligible differences between USEs and CSEs in terms of their other observed characteristics.[19]

4.2.2. Subsample analyses

In order to move our data closer to what has previously been used in the literature, we therefore re-estimate our models on a large set of subsamples that restrict attention to university and corporate STEMM graduates who start a firm in a high-tech sector (instead of any sector); become full-time entrepreneurs (instead of part-time); are aged above 40, 30-39, or below 30 (instead of in any age); have degrees in either sciences, engineering or health; either hold a BA, MA or PhD; are either female or male; belong to the 20 percent highest-paid employees at their present workplace; belong to the 20 percent highest-paid employees overall; hold a patent; hold corporate or university part-time jobs when in self-employment or are managers. We also consider combinations of these sample selections.

Given the large number of additional estimation results, we present most of the corresponding results in OSM Appendix B. While it is challenging to summarize a total of 29 different subsamples (times three regressions: USE, CSE, and USE vs CSE), the results clearly demonstrate that the lack of statistical significance is not due to our use of "too broad" estimation samples. Contrarily, using more selective samples *decreases* the number of statistically significant coefficients. The results also show substantial differences in the observed characteristics of different types of individuals that make them more or less inclined to move into entrepreneurship. Importantly, we find almost no differences between university and corporate startup entrepreneurs once we restrict our samples. While our main results show that university and corporate startup entrepreneurs may not be much different in their observed characteristics overall, our subsample analyses provide further evidence for such a lack of differences. It hence seems that differences between USEs and CSEs vanish once population data is used instead of potentially unrepresentative subsamples (Elfenbein et al. 2010; Rothaermel et al. 2007).

One subsample, however, worth highlighting on is the subsample of subsequent high-tech-sector founders, especially since only 30% of all USE or CSE founders start firms in a high-technology industry – which arguably constitutes the biggest difference to most other studies that focus on formal knowledge transfer (with Hvide and Jones, 2018 being a notable exception). Instead of lumping leaving for entrepreneurship together, we now separate leaving for a high-tech startup from leaving for a non high-tech startup. In order to account for these three different types of mobility (leaving for high-tech, leaving for non high-tech and staying) we estimate a multinomial probit model instead of our linear probability model, defining staying as the comparison state with the corresponding coefficients normalized to 0. Table 5 shows our results for this subsample. Note that the coefficient estimates cannot be quantitatively compared to our main linear probability model and that they

[17] A direct empirical consequence of the relatively low number of startup events is that the corresponding coefficient estimates become small. To maintain readability, we rescale many of our continuous explanatory variables as shown in our results table.

[18] The results of the interaction model are to be interpreted in a difference-in-difference estimation sense (Donald and Lang, 2007) with the first difference being the initial selection into university vs corporate employment and the second difference being the selection into entrepreneurial activity.

[19] However, we cannot rule out that USEs and CSEs may differ in terms of unobserved variables.

Table 4
OLS estimation results.

		(1) University spinoff entrepreneurs Coeff.	p-val.	Std. err.	(2) Corporate spinoff entrepreneurs Coeff.	p-val.	Std. err.	(3) Difference university and corporate spinoff entrepreneur Coeff.	p-val.	Std. err.
	Corporate startup entrepreneur (d)	-	-	-	-	-	-	-0.00347	0.701	0.009
Human capital	Education field: Engineering	0.002***	0.000	0.001	-0.001	0.066	0.000	-0.003***	0.000	0.001
	Education field: Health	-0.001	0.363	0.001	-0.001	0.258	0.001	0.000	0.900	0.001
	Education length: Master	0.002***	0.000	0.000	0.001	0.148	0.000	-0.001	0.111	0.001
	Education length: PhD	0.000	0.443	0.001	0.000	0.960	0.001	0.000	0.738	0.001
	Years of self-employment experience	-0.012	0.384	0.014	0.140*	0.026	0.063	0.153*	0.018	0.065
	Years of self-employment experience^2	0.102	0.172	0.075	-0.836**	0.004	0.292	-0.938**	0.002	0.301
	Some self-employment experience	0.001*	0.017	0.000	0.000	0.931	0.001	-0.001	0.131	0.001
	Years of working experience	0.014	0.200	0.011	0.006	0.644	0.012	-0.008	0.616	0.016
	Years of working experience^2	-0.050	0.105	0.031	-0.048	0.178	0.036	0.002	0.959	0.047
	Age	-0.053	0.762	0.176	-0.121	0.594	0.227	-0.068	0.813	0.287
	Age^2	-0.356	0.845	1.826	1.238	0.632	2.583	1.594	0.614	3.162
	Number of patents	0.027*	0.036	0.013	-0.006	0.108	0.004	-0.032**	0.013	0.013
	Years of tenure	-0.013	0.359	0.014	0.006	0.717	0.016	0.019	0.377	0.022
	Years of tenure^2	0.064	0.161	0.045	-0.023	0.685	0.058	-0.087	0.235	0.073
	"Tenure" (more than 3 years at employer)	0.000	0.713	0.001	-0.001	0.099	0.001	-0.002	0.183	0.001
	Manager	0.003*	0.045	0.002	0.004***	0.001	0.001	0.001	0.748	0.002
Income and wealth	Gross annual income in DKK	0.001	0.891	0.010	-0.018	0.487	0.025	-0.019	0.487	0.027
	Top 60-80% in employer income distribution	0.000	0.869	0.001	0.000	0.936	0.001	0.000	0.862	0.001
	Top 40-60% in employer income distribution	0.000	0.796	0.001	0.001	0.352	0.001	0.000	0.703	0.001
	Top 20-40% in employer income distribution	0.000	0.665	0.001	0.002**	0.002	0.001	0.003*	0.032	0.001
	Top 20% in employer income distribution	0.001	0.472	0.001	0.005***	0.000	0.001	0.004***	0.001	0.001
	Gross annual family income in DKK	0.007	0.804	0.030	0.053	0.130	0.035	0.046	0.322	0.046
	Total family assets in DKK	-0.007	0.582	0.012	0.007	0.619	0.014	0.014	0.460	0.018
	Top 60-80% in family asset distribution	-0.001	0.072	0.001	0.000	0.863	0.001	0.001	0.242	0.001
	Top 40-60% in family asset distribution	-0.002*	0.036	0.001	0.000	0.548	0.001	0.001	0.245	0.001
	Top 20-40% in family asset distribution	-0.001	0.300	0.001	-0.001	0.192	0.001	0.000	0.754	0.001
	Top 20% in family asset distribution	-0.001	0.231	0.001	0.001	0.288	0.001	0.002	0.115	0.001
Family background	Married	0.000	0.739	0.000	0.001	0.161	0.001	0.001	0.378	0.001
	# of children	0.031	0.144	0.021	-0.034	0.173	0.025	-0.065*	0.047	0.033
	Father self-employed	0.000	0.949	0.001	0.002*	0.026	0.001	0.002	0.102	0.001
	Father wage-employed	0.000	0.952	0.001	0.000	0.420	0.001	0.000	0.572	0.001
	Mother self-employed	0.002	0.202	0.001	0.001	0.630	0.002	-0.001	0.590	0.002
	Mother wage-employed	0.000	0.604	0.001	-0.001	0.170	0.001	-0.001	0.189	0.001
	Spouse self-employed	-0.001	0.473	0.001	0.001	0.683	0.002	0.002	0.472	0.002
	Spouse wage-employed	0.000	0.820	0.001	0.000	0.714	0.001	0.000	0.672	0.001
Other personal character-istics	1st generation new Dane	-0.001	0.135	0.001	0.000	0.574	0.001	0.000	0.694	0.001
	2nd generation new Dane	0.000	0.864	0.002	0.004	0.166	0.003	0.005	0.215	0.004
	Female	-0.002***	0.000	0.000	-0.003***	0.000	0.000	0.000	0.498	0.001
	# of different workplaces	0.029***	0.000	0.007	0.041***	0.000	0.008	0.012	0.267	0.011
Present employer character-istics	# employees own employer	-0.020	0.064	0.011	-0.020***	0.000	0.006	0.000	0.979	0.012
	# employees own employer^2	0.015	0.072	0.008	0.011	0.107	0.007	-0.004	0.728	0.011
	# patents own employer	0.003	0.713	0.008	-0.011	0.087	0.006	-0.014	0.174	0.010
	Share co-workers who became self-employed	0.066	0.066	0.036	0.009	0.208	0.007	-0.057	0.116	0.036
	# obs.	127122			169851			296973		

Notes: Table 4 displays the coefficient estimates as well as the corresponding p-values and standard errors for university spinoff entrepreneurs, corporate spinoff entrepreneurs and the difference in the coefficient estimates between university and corporate spinoff entrepreneurs. Column (3) is a joint model which interacts all explanatory variables with a dummy variable for being a corporate employee. The non-interacted coefficients and standard errors of that model (column (3)) are identical to the coefficient estimates for the separate university employee model (column (1)). The interacted coefficients displayed in column (3) are deviations from the coefficients for university employees. The asterisks *, ** and *** correspond to marginal significances at the 0.05, 0.01 and 0.001 percent level. Standard errors are clustered at the present employer level.

neither translate directly into marginal effects.

Splitting up the different types of leavers leads to ever fewer statistically significant results for leavers of either kind relative to the probability of staying, both for university and corporate startup entrepreneurs. While this could be due to a substantial reduction in the number of observations for the two leaver states, some variables that are statistically insignificantly different from 0 in the main model do become significant once we distinguish between the two alternative leaver modes.

For corporate employees, having a degree in engineering or health and years of tenure are negatively associated with leaving for an own high-tech startup while present employer patent stock, a self-employed father, annual family income, and the share of previous co-workers who left for self-employment are positively linked to leaving for an own high-tech startup. By contrast, and unsurprisingly so given the larger share in non high-tech rather than high-tech founders, the results for non high-tech startup entrepreneurs from corporations are much in line with our main findings.

University leavers to non high-tech industries are likely to hold degrees in engineering, a Master degree, have frequently changed workplaces, be male and have an employer with a higher share of previous workers who became self-employed. These are quite different associations compared to high-tech university startup entrepreneurs, who are more likely to have some self-employment experience, possess either high or low family assets, be male and have a non-employed father, and who are less likely to have a degree in health. Overall, leaving for an own high technology startup does not seem to be well explained by the variables we consider, which is somewhat in contrast to our findings for corporate startup entrepreneurs. That might suggest that university policies and technology transfer offices might play a larger role here than corporate policies do for their spinoffs.

Comparing the differences between university and corporate startup entrepreneurs in terms of either starting a high-tech or a non high-tech firm shows that there are few statistically significant differences between university and corporate employees in the variables that are associated with starting a non high-tech business.

Individuals employed at a university who hold a master's degree, are engineers, are males and are employed at a workplace with many employees who left for self-employment are more likely to become non high-tech entrepreneurs compared to corporate employees, reflecting the differences we discussed above.

There are also several differences between university and corporate employees and their probability to become high-tech entrepreneurs (relative to staying with their respective employers). Here, corporate employees who are not engineers, have less self-employment experience, are in the middle of the family assets distribution and have an employer who holds many patents are more likely to become high-tech entrepreneurs compared to university employees. Having a self-employed or a wage-employed father makes corporate employees more inclined to become high-tech founders compared to university employees.

Differentiating between workers who leave for high-tech and non high-tech self-employment hence does not generate a larger set of factors that are associated with either type of startup activity. It does, however, show that there are not only differences between USEs and CSEs as well as stayers and leavers, but also between different types of leavers. Most importantly, high-tech startup activity is not well explained by the variables we use in our models which might highlight the importance of factors that are unobserved (to us), such as university startup promotion activity. This contrasts with our findings for corporate high-tech startup activity for which we find a substantially larger set of variables related to this type of startup activity.

4.3. Robustness analyses

Our main results indicate that there are few variables that distinguish university startup entrepreneurs from university stayers, corporate startup entrepreneurs from corporate stayers, and USEs from CSEs. We explore whether this finding of non-significance is driven by (i) our use of a large set of explanatory variables whereby a removal of sets of variables might affect the statistical significance of other sets of variables, even though this issue is alleviated in large samples (O`Brien, 2007); and (iii) possible ignorance of self-selection problems.

4.3.1. Selected sets of variables

Our main results consider five main sets of explanatory variables: human capital, income and wealth, family background, other personal characteristics and present employer characteristics. Our robustness checks additionally distinguish the income and wealth variables. We run 14 (times three – for each comparison USE vs university stayer, CSE vs corporate stayer, and USE vs CSE) additional regressions which omit these different subsets of variables. These additional regression results are shown in Appendix A in the Online Supplementary Materials (OSM). Our two key findings are that (i) variables which are statistically significant in our main regressions retain their significance in the robustness check regressions, and (ii) there are generally no variables that become statistically significant once subsets of variables are removed. In addition, coefficient sizes remain almost exactly the same across the different estimations. Our overall finding of insignificant differences in our main analysis is hence not driven by our large set of explanatory variables.

4.3.2. CEM weighting

Finally, our estimations may be affected by endogeneity, whereby workers may sort into university or corporate employment while taking into account their expectations about possible future spells of self-employment. We therefore match individuals working at either universities or the private sector according to their observed characteristics using Coarsened Exact Matching (CEM, Iacus et al., 2012). Of course, our CEM estimates should not be interpreted as causal effects because we cannot rule out a possible confounding influence of unobserved variables. CEM weighting leaves our main estimation results quantitatively and qualitatively unchanged once we apply "non-exact" matching, e.g. matching on the quartiles of work experience, age, years of tenure, family wealth and the number of job changes, instead of exactly matching on these variables. Exact matching yields even fewer differences between USEs and CSEs compared to our baseline model. We believe this is a natural consequence of making individuals even more homogeneous via matching.[20]

5. Conclusions

New firm formation by university and corporate employees can make a considerable contribution to knowledge flows and economic dynamism (Zahra et al., 2007; Hvide and Jones, 2018). Despite a considerable literature on the characteristics of entrepreneurial founders in general, there remains a gap in our knowledge of the characteristics of founders of USEs and CSEs, and how these compare to individuals who stay with their employer. This seems worth investigating, because incentivizing startups from university employees could be quite different from incentivizing (or preventing) startups from corporate employees. We study these characteristics using a relatively comprehensive set of explanatory variables on human capital, as well as income and wealth, family background and present employer characteristics. In order to make meaningful comparisons, we compare university employees to individuals working in the corporate high-tech sector. Our focus is on all individuals with at least a Bachelor's degree in natural sciences, engineering and health.

A first observation is that USE and CSE events are quite rare: 0.36% of our observations for university employees correspond to USE entry, while 0.64% of our observations for firm employees correspond to CSE entry.[21] The higher frequency of CSEs relative to USEs is *prima facie* surprising, because USEs are often supported by the parent organization, while CSEs often are discouraged by the parent organization. Without support from universities and government, USEs would be even rarer (Fini et al., 2020). However, the higher frequency of CSEs could be due to non-pecuniary factors affecting the choice of an entrepreneurial career that are less relevant for USEs (Table 2).

While startup rates are quite different between universities and corporate high-tech employees, we document that there actually are overall very few differences in the factors associated with startup choice

[20] Estimations are available upon request. We additionally exactly match on the "some" self-employment experience dummy, manager status, spouse self-employment and residing in the Greater Copenhagen area. We included all variables in the matching procedure which have a statistically significant effect on both selection into university vs industry and the propensity to become a startup entrepreneur (Dehejia and Wahba, 1999).

[21] 453/(126,669 + 453) and 1083/(168'768+1083) respectively, see Table 3. Note that we may underestimate actual founding behavior since we only observe individuals annually, which implies that an individual that founds multiple firms within a given year cannot be distinguished from an individual that founds a single firm within a given year.

Table 5
Multinomial probit estimation results – high-tech vs non high-tech entrepreneurship.

		(1) University startup entrepreneur non high-tech (base: university stayer)			high-tech			(2) Corporate startup entrepreneur non high-tech (base: university stayer)			high-tech			(3) Difference universityand corporate spinoff non high-tech entrepreneur			Difference universityand corporate spinoff high-tech entrepreneur		
		Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.
	Corporate startup entrepreneur (d)													0.757	0.788	2.815	-5.131	0.148	3.547
Human capital	Education field: Engineering	0.588***	0.000	0.147	0.326	0.103	0.200	0.040	0.694	0.102	-0.364***	0.001	0.105	-0.548**	0.002	0.179	-0.690**	0.002	0.226
	Education field: Health	0.256	0.335	0.265	-1.319***	0.001	0.395	0.173	0.191	0.133	-0.556*	0.041	0.272	-0.082	0.781	0.296	0.763	0.111	0.479
	Education length: Master	0.777***	0.001	0.230	-0.083	0.742	0.253	0.126	0.260	0.112	0.126	0.311	0.124	-0.652**	0.011	0.255	0.209	0.457	0.281
	Education length: PhD	0.104	0.600	0.198	0.333	0.433	0.425	-0.172	0.553	0.291	0.380	0.371	0.425	-0.276	0.432	0.352	0.047	0.938	0.601
	Years of self-employment experience	-5.631	0.310	0.055	0.088	0.681	0.213	0.165	0.121	0.107	.559*	0.015	0.231	0.222	0.065	0.120	0.472	0.133	0.314
	(Years of self-employment experience)2	0.004	0.138	0.003	-0.011	0.392	0.013	-0.013	0.222	0.011	-0.090	0.065	0.049	-0.017	0.122	0.011	-0.079	0.116	0.050
	Some self-employment experience	0.226	0.169	0.164	0.543**	0.012	0.216	0.022	0.870	0.133	-0.062	0.608	0.121	-0.204	0.333	0.211	-0.605**	0.014	0.247
	Years of self-employment experience	0.026	0.483	0.037	0.069	0.220	0.056	0.010	0.709	0.028	.559*	0.916	0.030	-0.016	0.731	0.046	-0.066	0.300	0.064
	(Years of self-employment experience)2	-0.001	0.227	0.001	-0.002	0.300	0.002	-0.001	0.434	0.001	-0.001	0.503	0.001	0.001	0.633	0.001	0.001	0.524	0.002
	Age/1000	0.875	0.214	0.704	-1.809	0.120	1.165	0.137	0.776	0.481	.559*	0.415	0.543	-0.738	0.386	0.852	1.367	0.287	1.284
	$(\text{Age}/1000)^2$	-0.113	0.148	0.078	0.131	0.313	0.130	-0.006	0.905	0.053	0.031	0.623	0.063	0.106	0.258	0.094	-0.100	0.489	0.144
	Number of patents	0.024	0.000	0.004	0.027	0.085	0.015	-0.019	0.552	0.031	-2.124	0.691	0.053	-0.043	0.178	0.032	-0.048	0.389	0.056
	Years of tenure	-0.087	0.074	0.048	0.090	0.187	0.068	-0.012	0.732	0.035	6.741	0.125	0.044	0.075	0.212	0.060	-0.022	0.784	0.081
	(Years of tenure)2	0.004	0.010	0.001	-0.004	0.142	0.003	0.001	0.475	0.001	0.004	0.018	0.002	-0.003	0.137	0.002	0.000	0.899	0.003
	"Tenure" (more than 3 years at employer)	0.208	0.507	0.313	-0.164	0.659	0.373	-0.106	0.543	0.175	-0.373*	0.048	0.188	-0.314	0.380	0.358	-0.209	0.617	0.417
	Manager	0.474	0.064	0.256	0.749	0.087	0.438	0.505***	0.000	0.126	0.073	0.687	0.181	0.030	0.915	0.285	-0.676	0.153	0.473
Income and wealth	Gross annual income in DKK	-0.014	0.745	0.043	0.310	0.112	0.195	0.004	0.930	0.048	-4.951	0.059	0.026	0.018	0.777	0.064	-0.360	0.068	0.197
	Top 60-80% in employer income distribution	0.081	0.719	0.224	-0.606	0.084	0.350	-0.030	0.860	0.169	-0.082	0.666	0.189	-0.110	0.693	0.280	0.524	0.187	0.398

(*continued on next page*)

Table 5 (*continued*)

		(1) University startup entrepreneur non high-tech (base: university stayer)			high-tech			(2) Corporate startup entrepreneur non high-tech (base: university stayer)			high-tech			(3) Difference universityand corporate spinoff non high-tech entrepreneur			Difference universityand corporate spinoff high-tech entrepreneur		
		Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.
	Top 40-60% in employer income distribution	0.054	0.850	0.285	-0.362	0.318	0.363	-0.005	0.975	0.166	0.141	0.422	0.175	-0.059	0.857	0.329	0.503	0.211	0.402
	Top 20-40% in employer income distribution	-0.203	0.589	0.377	-0.453	0.387	0.523	0.306*	0.054	0.159	0.397*	0.026	0.178	0.510	0.212	0.408	0.850	0.123	0.552
	Top 20% in employer income distribution	0.111	0.748	0.345	-0.076	0.883	0.512	0.700***	0.000	0.162	0.562***	0.001	0.176	0.590	0.121	0.380	0.638	0.238	0.541
	Gross annual family income in DKK	-0.003	0.010	0.127	0.102	0.010	0.190	0.021	0.010	0.106	.505**	0.010	0.128	0.024	0.010	0.165	0.403	0.010	0.228
	Total family assets in DKK	-0.022	0.010	0.035	-0.016	0.010	0.036	-0.002	0.010	0.036	-0.009	0.010	0.026	0.021	0.010	0.050	0.008	0.010	0.044
	Top 60-80% in family asset distribution	-0.353	0.153	0.247	-0.114	0.649	0.250	-0.303	0.060	0.161	0.318*	0.031	0.147	0.050	0.865	0.294	0.431	0.136	0.289
	Top 40-60% in family asset distribution	-0.275	0.226	0.227	-0.544*	0.034	0.256	-0.224	0.088	0.132	0.158	0.309	0.155	0.050	0.847	0.262	0.702*	0.019	0.299
	Top 20-40% in family asset distribution	-0.126	0.450	0.167	-0.053	0.835	0.255	-0.311*	0.029	0.143	0.053	0.749	0.165	-0.185	0.399	0.219	0.106	0.727	0.304
	Top 20% in family asset distribution	-0.093	0.617	0.187	-0.269	0.431	0.342	0.008	0.956	0.145	0.230	0.243	0.197	0.101	0.667	0.236	0.499	0.205	0.394
Family background	Married	0.080	0.612	0.158	-0.053	0.823	0.235	0.123	0.321	0.124	0.097	0.529	0.154	0.043	0.831	0.201	0.150	0.594	0.281
	# of children	0.048	0.010	0.076	0.120	0.010	0.081	-0.064	0.010	0.049	-0.048	0.010	0.057	-0.111	0.010	0.090	-0.168	0.010	0.099
	Father self-employed	0.318	0.178	0.236	-0.931*	0.042	0.457	0.270	0.135	0.181	0.360*	0.030	0.166	-0.047	0.873	0.297	1.291**	0.008	0.485
	Father wage-employed	0.267	0.081	0.153	-0.490*	0.017	0.206	0.003	0.980	0.133	0.140	0.279	0.129	-0.263	0.193	0.202	0.630**	0.010	0.243
	Mother self-employed	0.479	0.093	0.285	0.158	0.807	0.647	-0.231	0.472	0.321	0.347	0.139	0.235	-0.710	0.098	0.429	0.189	0.783	0.687

(*continued on next page*)

Table 5 (*continued*)

		(1) University startup entrepreneur non high-tech (base: university stayer)			high-tech			(2) Corporate startup entrepreneur non high-tech (base: university stayer)			high-tech			(3) Difference universityand corporate spinoff non high-tech entrepreneur			Difference universityand corporate spinoff high-tech entrepreneur		
		Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.	Coeff.	p-val.	Std. err.
	Mother wage-employed	0.074	0.730	0.215	0.115	0.599	0.220	-0.093	0.515	0.143	-0.150	0.275	0.137	-0.167	0.516	0.258	-0.265	0.305	0.259
	Spouse self-employed	-0.141	0.745	0.435	-0.541	0.588	0.998	0.002	0.995	0.342	0.202	0.558	0.345	0.143	0.795	0.553	0.743	0.481	1.054
	Spouse wage-employed	0.021	0.918	0.201	0.097	0.747	0.301	0.104	0.400	0.124	-0.256	0.109	0.160	0.084	0.723	0.236	-0.354	0.299	0.341
Other personal characteristics	1st gen. new Dane	-0.333	0.269	0.302	-0.436	0.295	0.416	-0.106	0.600	0.202	-0.038	0.862	0.218	0.228	0.530	0.363	0.398	0.396	0.469
	2nd gen. new Dane	0.296	0.682	0.723	-11.648***	0.000	0.281	0.505	0.309	0.496	0.590	0.175	0.435	0.209	0.811	0.876	12.821***	0.000	0.518
	Female	-0.716***	0.000	0.151	-1.221***	0.000	0.233	-0.273*	0.025	0.122	-1.156***	0.000	0.180	0.443*	0.022	0.194	0.065	0.825	0.294
	# of different workplaces	0.093***	0.010	0.017	0.036	0.010	0.027	.078***	0.010	0.014	.037*	0.010	0.017	-0.015	0.010	0.022	0.001	0.010	0.032
Present employer characteristics	# employees own employer	-0.040	0.217	0.032	-0.035	0.340	0.037	.023**	0.013	0.009	0.003	0.811	0.011	0.017	0.619	0.034	0.038	0.325	0.038
	(# employees own employer)2	0.000	0.179	0.000	0.000	0.527	0.000	0.000	0.476	0.000	-0.031*	0.049	0.000	0.000	0.409	0.000	-0.001	0.149	0.000
	# patents own employer	-0.007	0.010	0.025	0.026	0.010	0.033	0.001	0.009	0.013	.0442***	0.010	0.014	0.009	0.010	0.028	.070*	0.010	0.035
	Share co-workers who became self-employed/ 100	.068*	0.034	0.032	-0.030	0.762	0.100	-0.008	0.222	0.006	.011**	0.015	0.005	-0.076*	0.020	0.033	0.042	0.677	0.100
	# obs.	127122						169851											

Notes: Table 5 displays multinomial logit estimation results for the probability of founding a non high-tech or a high-tech business vs staying with the current employer (base category). The coefficient estimates hence need to be interpreted relative to not leaving for self-employment. Columns (3) refer to joint models which interact all explanatory variables with a dummy variable for being a corporate employee. It hence reflects the differences in the probability to becoming a corporate spinoff entrepreneur relative to becoming a university spinoff entrepreneur. The non-interacted coefficient estimates are identical to the ones related to the USE estimates and hence not displayed for brevity.

between both types of employees – and even fewer differences exist if we consider more narrowly defined subsamples (like holding a management position, a PhD or a patent, or employees who found high tech companies). Even though there are compelling theoretical reasons for expecting that startup motivations differ for CSEs and USEs (Section 2.3) nevertheless the empirical evidence suggests that there are few differences between USEs and CSEs. In addition, possible performance differences between university and corporate startups are unlikely to be driven by differences in the observed characteristics of the respective founders, which in turn might suggest that performance differences may be caused by inheritance effects documented by Agrawal et al. (2016), Clarysse et al. (2011a, b) and Wennberg et al. (2011) who account for a narrower set of founder characteristics. Future research should simultaneously consider both these institutional factors and the personal characteristics of the founders to explain possible performance differences between USEs and CSEs.

For CSEs, general human capital matters less than for USEs. Instead, for CSEs, present employer characteristics play an important role, as large and patent-active firms are the least likely to lose employees to entrepreneurial activity. This indicates that such large R&D active corporations constitute on average more attractive workplaces for STEMM graduates than a possible own startup. They may offer complementary assets and allow specialization. Given that we also show that the corporate employee most likely to leave for entrepreneurship is in a leadership position with a high within-firm income – i.e. a corporation's best employees in terms of rank and pay – an effective HR policy to prevent those employees from leaving could include increased R&D efforts to improve the research attractiveness, and sustained firm growth to create promotion opportunities. Firm growth and innovation are at the same time common industrial policy targets.[22]

For university-employed STEMM graduates, those most likely to leave to found their startup are engineers, with a Master's degree, who hold patents, who have gained some self-employment experience via jobs on the side, are individuals in management positions, with either low or high (compared to median) family wealth, and who have been mobile in the past. However, present employer characteristics do not significantly relate to the startup activities of university employees. Even though this may be related to relatively low variation across universities, it in turn implies that the observed characteristics which distinguish future entrepreneurs from those remaining in university employment are beyond the direct scope of human resource management, policy makers and university administration. Except for family wealth, all characteristics with significant relation to the entrepreneurial decisions of university employees are, however, observable in CVs, which could potentially allow policy makers to target specific individuals and university administrators to establish HR policies targeted at a well-defined group of university employees.

We submit our main analysis to a stack of robustness checks, most importantly checks where we narrow down the population under investigation to e.g. holders of PhDs or patents, founders of high-tech firms etc. While this of course generates results that differ from the main findings, these robustness checks overwhelmingly show that narrowing in the data leads to even fewer differences between USEs vs CSEs as well as between stayers and founders.

In general, our results for USEs may interest policymakers, because university-based entrepreneurs may respond more to policy initiatives and stimuli. Mathisen and Rasmussen (2019, p14) observed that "USOs are very active users of governmental support programs, including being favored by public VC funds, staying longer as tenants in incubators and using public R&D funding schemes."

More generally, our analysis differs from prior research in that we observe few differences between CSEs and USEs. Hence, prior work on the differences between CSEs and USEs may have been context-specific. We therefore hope to stimulate future work on the founding of USEs vs CSEs, to better understand the generalizability of prior findings.

Our analysis is not without limitations. This study contributes to the literature by investigating the differences between USEs and CSEs using large-sample data with relatively comprehensive information on human capital, income and wealth, family background and present employer characteristics. However, other salient dimensions are not measured in our data, regarding the motivations, choices, and knowledge of the individuals themselves. For example, we have no direct observations on knowledge flows or technology transfer. Future work could perhaps combine employer-employee register data (such as ours) with representative survey data (including information on psychological traits, motives, knowledge stocks, characteristics of the business idea and the technology/IP being transferred, etc) and perhaps also data from university Technology Transfer Offices (TTOs). Furthermore, while this paper takes a descriptive empirical approach, future research could apply empirical methods for rigorous causal inference.

A closer comparison of USEs and CSEs could also investigate how the meaning of some variables (such as managerial experience and hierarchical status) varies from university to corporate contexts.

Overall, our in-depth analysis of representative data on the founding decisions of USEs compared to CSEs improves our understanding of these phenomena, and contributes towards improving our understanding of employee entrepreneurship.

CRediT authorship contribution statement

Alex Coad: Conceptualization, Writing – review & editing. **Ulrich Kaiser:** Conceptualization, Funding acquisition, Methodology, Project administration, Writing – original draft, Writing – review & editing. **Johan Kuhn:** Conceptualization, Funding acquisition, Methodology, Data curation, Formal analysis, Software, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

None.

Acknowledgement

We gratefully acknowledge financial support from the social science research program "The Socioeconomic Impact of Research in Denmark" of the Novo Nordisk Foundations. Alex Coad gratefully acknowledges support from the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2018S1A3A2075175). This research benefited from helpful comments by Hans Christian Kongsted, Martin Murmann, Thomas Blomgren Hansen, Martin Junge, Ammon Salter, Cédric Schneider, Sotaro Shibayama, Paula Stephan and Valentina Tartari, as well as three anonymous referees, and participants of the workshops on "Investments, Incentives and the Impact of Danish Research" held in Copenhagen June 10, 2018, and the "Socioeconomic Impact of Research" held in Hillerød Jan. 16-17, 2019.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2021.104347.

[22] In addition, corporate HR that has the goal of retaining employees could perhaps focus on employees with a self-employed father who have frequently switched workplaces and who hold a degree in health or natural sciences, i.e. information that (with the exception of father employment status) is readily available to HR managers. We remind the reader, however, that our results are conditional associations rather than causal estimates, and therefore due caution is needed when making causal interpretations from our descriptive results.

References

Agarwal, R., Echambadi, R., Franco, A., Sarkar, M., 2004. Knowledge transfer through inheritance: spin-out generation, development, and survival. Acad. Manage. J. 47, 501–522.

Agarwal, R., Shah, S., 2014. Knowledge sources of entrepreneurship: firm formation by academic,user and employee innovators. Res. Policy 43, 1109–1133.

Agarwal, R., Campbell, B.A., Franco, A.M., Ganco, M., 2016. What do I take with me? The mediating effect of spin-out team size and tenure on the founder–firm performance relationship. Acad. Manage. J. 59 (3), 1060–1087.

Ateljevic, I., Doorne, S., 2000. Staying within the fence': lifestyle entrepreneurship in tourism. J. Sustain. Tour. 8 (5), 378–392.

Audretsch, D.B., Keilbach, M., 2008. Resolving the knowledge paradox: knowledge-spillover entrepreneurship and economic growth. Res. Policy 37 (10), 1697–1705.

Aldridge, T.T., Audretsch, D., 2011. The Bayh-Dole act and scientist entrepreneurship. Res. Policy 40, 1058–1067.

Åstebro, T., Thompson, P., 2011. Entrepreneurs, jacks of all trades or hobos? Res. Policy 40 (5), 637–649.

Beckman, C.M., Burton, M.D., O'Reilly, C.A., 2007. Early teams: the impact of team demography on VC Financing and going public. J. Bus. Ventur. 22 (2), 147–173.

Benz, M., Frey, B.S., 2008. The value of doing what you like: evidence from the self-employed in 23 countries. J. Econ. Behav. Organ. 68 (3-4), 445–455.

Blanchflower, D., Oswald, A., 1998. What makes an entrepreneur? J. Labor Econ. 16 (1), 26–60.

Bodas Freitas, I.M., Geuna, A., Rossi, F., 2013. Finding the right partners: institutional and personal modes of governance of university–industry interactions. Res. Policy 42 (1), 50–62.

Boehm, D., Hogan, T., 2014. A jack of all trades': the role of PIs in the establishment and management of collaborative networks in scientific knowledge commercialization. J. Technol. Transf. 39 (1), 134–149.

Bonardo, D., Paleari, S., Vismara, S., 2011. Valuing university-based firms: the Effects of academic Affiliation on IPO performance. Entrepreneurship Theory and Practice 35, 755–776.

Borjas, G., 1986. The self-employment experience of immigrants. J. Hum. Resour. 21 (4), 485–506.

Braun, E., Macdonald, S., 1982. Revolution in Miniature. Cambridge University Press.

Budig, M.J., 2006. Intersections on the road to self-employment: gender, family and occupational class. Soc. Forces 84 (4), 2223–2239.

Byun, H., Raffiee, J., Ganco, M., 2019. Discontinuities in the value of relational capital: the effects on employee entrepreneurship and mobility. Organ. Sci. 30 (6), 1368–1393.

Casson, M., 1995. Entrepreneurship and Business Culture. Edward Elgar, Aldershot.

Chatterji, A.K., 2009. Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. Strat. Manage. J. 30 (2), 185–206.

Christensen, C.M., 1993. The rigid disk drive industry: a history of commercial and technological turbulence. Bus. Hist. Rev. 67 (4), 531–588.

Clarysse, B., Moray, N., 2004. A process study of entrepreneurial team formation: the case of a research-based spin-off. J. Bus. Ventur. 19 (1), 55–79.

Clarysse, B., Wright, M., van de Velde, E., 2011a. Entrepreneurial origin, technology knowledge, and the growth of spin-off companies. J. Manage. Stud. 48 (6), 1420–1442.

Clarysse, B., Tartari, V., Salter, A., 2011b. The impact of entrepreneurial capacity, experience and organizational support on academic entrepreneurship. Res. Policy 40 (8), 1084–1093.

Colombo, M.G., D'Adda, D., Piva, E., 2010. The contribution of university research to the growth of academic start-ups: an empirical analysis. J. Technol. Transf. 35 (1), 113–140.

Colombo, M., Piva, E., 2012. Firms' genetic characteristics and competence-enlarging strategies: a comparison between academic and non-academic high-tech start-ups. Res. Policy 41 (1), 79–92.

Dahl, M.S., Sorenson, O., 2012. Home sweet home: entrepreneurs' location choices and the performance of their ventures. Manage. Sci. 58 (6), 1059–1071.

Dahl, M.S., Sorenson, O., 2014. The who, why, and how of spinoffs. Ind. Corp. Change 23 (3), 661–688.

Davidsson, P., Honig, B., 2003. The role of social and human capital among nascent entrepreneurs. J. Bus. Ventur. 18 (3), 301–331.

Dehejia, R.H., Wahba, S., 1999. Causal effects in nonexperimental studies: reevaluating the evaluation of training programs. J. Am. Statist. Assoc. 94 (448), 1053–1062.

Donald, S.G., Lang, K., 2007. Inference with difference-in-differences and other panel data. Rev. Econ. Stat. 89, 221–233.

Dorner, M., Fryges, H., Schopen, K., 2017. Wages in high-tech start-ups–do academic spin-offs pay a wage premium? Res. Policy 46 (1), 1–18.

Dunn, T., Holtz-Eakin, D., 2000. Financial capital, human capital, and the transition to self-employment: evidence from intergenerational links. J. Labor Econ. 18 (2), 282–305.

Druilhe, C., Garnsey, E.W., 2003. Do academic spin-outs differ and does it matter? J. Technol. Transf. 29 (3-4), 269–285.

Elfenbein, D.W., Hamilton, B., Zenger, T.R., 2010. The small firm effect and the entrepreneurial spawning of scientists and engineers. Manage. Sci. 56 (4), 659–681.

Ensley, M.D., Hmieleski, K.M., 2005. A comparative study of new venture top management team composition, dynamics and performance between university-based and independent startups. Res. Policy 34, 1091–1105.

Eriksson, T., Kuhn, J.M., 2006. Firm spin-offs in Denmark 1981-2000 - patterns of entry and exit. Int. J. Ind. Organ. 24, 1021–1040.

Evans, M., 1989. immigrant entrepreneurship: effects of ethnic market SIZE and isolated labor pool. Am. Sociol. Rev. 54 (6), 950–962.

Evans, D.S., Jovanovic, B., 1983. An estimated model of entrepreneurial choice under liquidity constraints. J. Polit. Econ. 97 (4), 808–827.

Fairlie, R., Robb, A., 2007. Why are black-owned businesses less successful than white-owned businesses? The role of families, inheritances, and business human capital. J. Labor Econ. 25, 289–323.

Feldman, M., Feller, I., Bercovitz, J., Burton, R., 2002. Equity and the technology transfer strategies of American research universities. Manage. Sci. 48, 105–121.

Fini, R., Grimaldi, R., Santoni, S., Sobrero, M., 2011. Complements or substitutes? The role of universities and local context in supporting the creation of academic spin-offs. Res. Policy 40 (8), 1113–1127.

Fini, R., Grimaldi, R., Meoli, A., 2020. The effectiveness of university regulations to foster science-based entrepreneurship. Res. Policy 49 (10), 104048. Forthcoming.

Folta, T.B., Delmar, F., Wennberg, K., 2010. Hybrid Entrepreneurship. Manage. Sci. 56 (2), 253–269.

Franco, M., Filson, D., 2006. Spin-outs: knowledge diffusion through employee mobility. RAND J. Econ. 37, 841–860.

Frederiksen, L., Wennberg, K., Balachandran, C., 2016. Mobility and entrepreneurship: evaluating the scope of knowledge–based theories of entrepreneurship. Entrepreneurship Theory Pract. 40 (2), 359–380.

Ganco, M., 2013. Cutting the Gordian knot: the effect of knowledge complexity on employee mobility and entrepreneurship. Strat. Manage. J. 34 (6), 666–686.

Ganco, M., Ziedonis, R.H., Agarwal, R., 2015. More stars stay, but the brightest ones still leave: Job hopping in the shadow of patent enforcement. Strat. Manage. J. 36 (5), 659–685.

Garvin, D.A., 1983. Spin-offs and the new firm formation process. Calif. Manage. Rev. 25 (2), 3–20.

George, G., Zahra, S.A., Wood, D.R., 2002. The effects of business-university alliances on innovative output and financial performance: a study of publicly traded biotechnology companies. J. Bus. Ventur. 17 (6), 577–609.

Geuna, A., Rossi, F., 2011. Changes to university IPR regulations in Europe and the impact on academic patenting. Res. Policy 40 (8), 1068–1076.

Gimeno, J., Folta, T., Cooper, A., Woo, C., 1997. Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms. Adm. Sci. Q. 42 (4), 750–783.

Gompers, P., Lerner, J., Scharfstein, D., 2005. Entrepreneurial spawning: public corporations and the genesis of new ventures, 1986 to 1999. J. Finance 60 (2), 577–614.

Gubitta, P., Tognazzo, A., Destro, F., 2016. Signaling in academic ventures: the role of technology transfer offices and university funds. J. Technol. Transf. 41, 368–393.

Hall, B.H., von Graevenitz, G., Helmers, C., 2021. Technology entry in the presence of patent thickets. Oxford Economic Papers 73 (2), 903–926.

Hayter, C.S., Lubynsky, R., Maroulis, S., 2017. Who is the academic entrepreneur? The role of graduate students in the development of university spinoffs. J. Technol. Transf. 42 (6), 1237–1254.

Hayter, C.S., Parker, M.A., 2019. Factors that influence the transition of university postdocs to non-academic scientific careers: an exploratory study. Res. Policy 48 (3), 556–570.

Helfat, C.E., 2007. Stylized facts, empirical research and theory development in management. Strat. Organ. 5 (2), 185–192.

Holtz-Eakin, D., Joulfaian, D., Rosen, H., 1994. Entrepreneurial decisions and liquidity constraints. RAND J. Econ. 25 (2), 334–347.

Hvide, H.K., Jones, B.F., 2018. University innovation and the professor's privilege. Am. Econ. Rev. 108 (7), 1860–1898.

Iacus, S.M., King, G., Porro, G., 2012. Causal inference without balance checking: coarsened exact matching. Polit. Anal. 20 (1), 1–24.

Kacperczyk, A., Marx, M., 2016. Revisiting the small-firm effect on entrepreneurship: evidence from firm dissolutions. Organ. Sci. 27 (4), 893–910.

Kaiser, U., Kongsted, H.C., Rønde, T., 2015. Does the mobility of R&D labor increase innovation? J. Econ. Behav. Organ. 110, 91–105.

Kaiser, U., Kongsted, H.C., Laursen, K., Ejsing, A.-K., 2018. Experience matters: the role of academic scientist mobility for industrial innovation. Strat. Manage. J. 39 (7), 1935–1958.

Klepper, S., 2002. The capabilities of new firms and the evolution of the US automobile industry. Ind. Corp. Change 11 (4), 645–666.

Klepper, S., Sleeper, S., 2005. Entry by Spinoffs. Manage. Sci. 51 (8), 1291–1306.

Klepper, S., Thompson, P., 2010. Disagreements and intra-industry spinoffs. Int. J. Ind Organiz. 28 (5), 526–538.

Landry, R., Saihib, M., Amaraa, N., Ouimet, M., 2006. Evidence on how academics manage their portfolio of knowledge transfer activities. Res. Policy 39, 1387–1403.

Laspita, S., Breugst, N., Heblich, S., Patzelt, H., 2012. Intergenerational transmission of entrepreneurial intentions. J. Bus. Ventur. 27, 414–435.

Lazear, E., 2005. Entrepreneurship. J. Labor Econ. 23 (4), 649–680.

Levesque, M., Minniti, M., 2006. The effect of aging on entrepreneurial behavior. J. Bus. Ventur. 21 (2), 177–194.

Lindholm, A.D., 1997. Growth and inventiveness in technology-based spin-off firms. Res. Policy 26, 331–344.

Malchow-Møller, N., Schjerning, B., Sørensen, A., 2011. Entrepreneurship, job creation and wage growth. Small Bus. Econ. 36, 15–32.

Mathisen, M.T., Rasmussen, E., 2019. The development, growth, and performance of university spin-offs: A critical review. J. Technol. Transf. 44 (6), 1891–1938.

Minniti, M., Naude, W., 2010. What do we know about the patterns and determinants of female entrepreneurship across countries? Eur. J. Dev. Res. 22, 277–293.

Mosey, S., Wright, M., 2007. From human capital to social capital: a longitudinal study of technology-based academic entrepreneurs. Entrepreneurship Theory Pract. 31, 909–935.

Müller, K., 2010. Academic spin-off's transfer speed — analyzing the time from leaving university to venture. Res. Policy 39, 189–199.
Mustar, P., Renault, M., Colombo, M.G., Piva, E., Fontes, M., 2006. Conceptualising the heterogeneity of research-based spin-offs: a multi-dimensional taxonomy. Res. Policy 35 (2), 289–308.
Nanda, R., Sørensen, J., 2010. Workplace peers and entrepreneurship. Manage. Sci. 56 (7), 1116–1126.
Nicolaou, N., Birley, S., 2003a. Social Networks in organizational emergence: the university spinout phenomenon. Manage. Sci. 49 (12), 1702–1725.
Nicolaou, N., Birley, S., 2003b. Academic networks in a trichotomous categorisation of university spinouts. J. Bus. Ventur. 18 (3), 333–359.
Nicolaou, N., Souitaris, V., 2016. Can perceived support for entrepreneurship keep great faculty in the face of spinouts? J. Prod. Innov. Manage. 33 (3), 298–319.
Nightingale, P. (2014). What is technology? Six definitions and two pathologies. Six Definitions and Two Pathologies. SPRU Working Paper Series #19, University of Sussex, UK.
Nightingale, P., Coad, A., 2016. Challenging assumptions and bias in entrepreneurship research. Chapter 6. edited by. In: Landström, H., Parhankangas, A., Fayolle, A., Riot, P. (Eds.), Challenging Entrepreneurship Research. Routledge, Oxon, UK.
Nocke, V., 2006. A gap for me: entrepreneurs and entry. J. Eur. Econ. Assoc. 4 (5), 929–956.
O'Brien, R.M., 2007. A caution regarding rules of thumb for variance inflation factors. Qual. Quant. 41 (5), 673–690.
Ouimet, P., Zarutskie, R., 2014. Who works for startups? The relation between firm age, employee age, and growth. J. Financ. Econ. 112 (3), 386–407.
Parhankangas, A., Arenius, P., 2003. From a corporate venture to an independent company: a base for a taxonomy for corporate spin-off firms. Res. Policy 32, 463–481.
Parker, S.C., 2008. Entrepreneurship among married couples in the United States: a simultaneous probit approach. Labour Econ. 15 (3), 515–537.
Parker, S.C., 2009. The Economics of Entrepreneurship. Cambridge University Press.
Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A., Krabel, S., Kitson, M., Llerena, P., Lissoni, F., Salter, A., Sobrero, M., 2013. Academic engagement and commercialisation: a review of the literature on university–industry relations. Res. Policy 42 (2), 423–442.
Rappert, B., Webster, A., Charles, D., 1999. Making sense of diversity and reluctance: academic industrial relations and intellectual property. Res. Policy 28 (9), 873–890.
Rasmussen, E., Mosey, S., Wright, M., 2014. The influence of university departments on the evolution of entrepreneurial competencies in spin-off ventures. Res. Policy 43 (1), 92–106.
Reynolds, P.D., 2005. Understanding business creation: Serendipity and scope in two decades of business creation studies. Small Bus. Econ. 24 (4), 359–364.
Roberts, E., 1991. Entrepreneurs in High Technology, Lessons from MIT and Beyond. Oxford University Press, Oxford.
Roche, M.P., Conti, A., Rothaermel, F.T., 2020. Different founders, different venture outcomes: a comparative analysis of academic and non-academic startups. Res. Policy, 104062. https://doi.org/10.1016/j.respol.2020.104062.
Rothaermel, F.T., Agung, S.D., Jiang, L., 2007. University entrepreneurship: a taxonomy of the literature. Ind. Corp. Change 16 (4), 691–791.
Sauermann, H., 2017. Fire in the belly? Employee motives and innovative performance in start-ups versus established firms. Strat. Entrepreneurship J. 12 (4), 1–32.
Shah, S.K., Agrawal, R., Echambadi, R., 2019. Jewels in the crown: exploring the motivations and team building processes of employee entrepreneurs. Strat. Manage. J. 40 (9), 1417–1452.
Shane, S., 2003. A General Theory of Entrepreneurship: the Individual-Opportunity Nexus. Edward Elgar, Cheltenham.
Shane, S., 2004. Academic Entrepreneurship: University Spin-Offs and Wealth Creation. Edward Elgar, Cheltenham, UK.
Shane, S., Stuart, T., 2002. Organizational endowments and the growth of university start-ups. Manage. Sci. 48, 154–170.
Shaw, K.L., 2019. Bosses matter: the effects of managers on workers' performance. IZA World Labor. https://wol.iza.org/articles/bosses-matter-the-effects-of-managers-on-workers-performance.
Siegel, D.S., Wright, M., 2015. Academic entrepreneurship: time for a rethink? Br. J. Manage. 26 (4), 582–595.
Starr, E., Ganco, M., Campbell, B.A., 2018. Strategic human capital management in the context of cross-industry and within-industry mobility frictions. Strat. Manage. J. 39 (8), 2226–2254.
Staniforth, D., Hariand, T., 1999. The work of an academic: jack of all trades, or master of one? Int. J. Acad. Dev. 4 (2), 142–149. https://doi.org/10.1080/1360144990040209.
Steffenson, M., Rogers, E., Speakman, K., 1999. Spin offs from research centers at a research university. J. Bus. Ventur. 15, 93–111.
Stern, S., 2004. Do scientists pay to be scientists? Manage. Sci. 50 (6), 835–853.
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. Sociol. 112 (1), 97–144.
Teece, D., 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Res. Policy 15 (6), 285–305.
Van der Sluis, J., van Praag, M., Vijerberg, W., 2008. Education and entrepreneurship selection and performance: a review of the empirical literature. J. Econ. Surv. 22 (5), 795–841.
Visintin, F., Pittino, D., 2014. Founding team composition and early performance of university–based spin–off companies. Technovation 34, 31–43.
Walker, E., Brown, A., 2004. What success factors are important to small business owners? Int. Small Bus. J. 22 (6), 577–594.
Wennberg, K., Wiklund, J., Wright, M., 2011. The effectiveness of university knowledge spillovers: performance differences between university spinoffs and corporate spinoffs. Res. Policy 40, 1128–1143.
Wright, M., Siegel, D.S., Mustar, P., 2017. An emerging ecosystem for student start-ups. J. Technol. Transf. 42 (4), 909–922.
Zahra, S.A., van de Velde, E., Larraneta, B., 2007. Knowledge conversion capability and the performance of corporate and university spin-offs. Ind. Corp. Change 16 (4), 569–608.