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The technological imprinting of educational experiences on student startups

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A B S T R A C T

The literature suggests that the startups of *de novo* entrepreneurs are disadvantaged, but many of the world's leading firms have been founded by students and recent graduates. We hypothesize that academic and industry-based educational experiences shape the innovative activity of student startups and use patent data to measure technological proximity between the patent portfolios of influencers and startups. We find that indirect exposure to the research and development activities of the students' university departments and work term employers results in technological imprinting. Influencer and entrepreneur capabilities affect the magnitude of the imprinting effect: student ventures are technologically more proximate to highly ranked university departments and to more innovative work term employers, and the students' software skills impact their ability to invent in proximity to their work term employer. We also find that multiple layers of imprints are complements, not substitutes. Exposure to inventive activities, even when indirect and brief, results in multiple capabilities-moderated layers of imprints.

1. Introduction

Why some people, and not others, identify entrepreneurial opportunities is one of the fundamental questions of entrepreneurship research (Shane and Venkataraman, 2000). Information asymmetries due to past experiences that vary across individuals are part of the explanation (Agarwal and Shah, 2014). Prior experience as an employee (Agarwal et al., 2004; Dahl and Sorenson, 2014), user (Shah and Tripsas, 2007; Smith and Shah, 2013), academic (Shane, 2004; Stuart and Ding, 2006), and entrepreneur (Westhead et al., 2009) improves entrepreneurial behaviours and outcomes.

According to this framing, the entrepreneurial initiatives of students and recent graduates—de novo entrepreneurs—are without history and therefore disadvantaged. But many of the world's leading firms, including Microsoft, Google, and Meta, have been founded by *de novo* entrepreneurs, and students and recent alumni are creating an increasing number of startups, some of which are very successful (Hsu et al., 2007; Lerner and Malmendier, 2013; Wright and Mustar, 2019). Are these outcomes a consequence of talent and youth, or do university experiences matter? While Gates and Zuckerberg left college before graduating and others have dismissed university education as irrelevant for entrepreneurs (Thiel, 2021), comprehensive US data shows that startups founded in domains related to the student's education do better than those that are founded in unrelated domains (Åstebro et al., 2012). The fundamental question that has not been addressed is whether or not the ventures of alumni entrepreneurs build upon their educational experiences.

We examine the technological antecedents of high-potential student ventures and show that alumni entrepreneurs build upon the research and development (R&D) activities to which they were indirectly exposed as students. We consider the technological imprinting effects of academic and industry-based learning experiences, where the latter consist of a series of four-month, paid work terms at a broad range of employers that include leading technology firms. Using patent data, we construct the patent portfolios of the student ventures, their university departments, and their work term employers. Where ventures are more technologically proximate to the university department or work term employer influencers than would be expected in the absence of a prior relationship, we claim an imprinting effect. Our statistical results are robust to concerns of endogeneity in the formation of ties.

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We contribute to the literatures on high-potential startups, imprinting, and work-integrated learning. The student startups in our sample have been awarded both patents and venture capital (VC) financing, making them rare, but important. Ventures with patents are >25 times more likely to grow than ventures without patents (Guzman and Stern, 2015), and while <1 % of ventures attract VC financing in the US, the country with the most well-developed VC market (Puri and Zarutskie, 2012), VC-funded companies comprise 76 % of publicly-traded companies by market capitalization (Economist, 2021), and contribute disproportionately to innovation, employment, and productivity growth (Haltiwanger et al., 2013; Lerner and Nanda, 2020). Our paper is the first of which we are aware to examine the technological antecedents of this important group of firms.

Imprinting is defined as "a process whereby, during a brief period of susceptibility, a focal entity develops characteristics that reflect prominent features of the environment, and these characteristics continue to persist despite significant environmental changes in subsequent periods" (Marquis and Tilcsik, 2013: 201; Stinchcombe, 1965). Because we are examining lasting impressions made on entrepreneurs at a particularly sensitive point in their lives, we adopt an imprinting lens to theorize about the mechanisms by which the patent portfolios of student ventures come to reflect the patent portfolios of influencer organizations. While qualitative examinations of imprinting have examined multiple sources of imprint (Johnson, 2007; Mathias et al., 2015), quantitative examinations in the entrepreneurship literature generally consider single influencers—parent firms of spinouts (Basu et al., 2015; Chatterji, 2009; Dahl and Sorenson, 2014; Ellis et al., 2017; Feldman et al., 2019; Sapienza et al., 2004), educational institutions (Bai et al., 2020), or academic supervisors (Azoulay et al., 2017). As a consequence of our empirical setting, we are able to consider multiple influencers, variations in imprinter and imprintee capabilities, and the minimum engagement required for an imprinting effect. And while prior studies have examined the consequences of the technological relatedness of ventures to influencers in terms of growth (Sapienza et al., 2004), patent citations (Basu et al., 2015), or investment (Chatterji, 2009), we consider its antecedents as per the suggestion of Ellis et al., that 'future work can explore the inheritance of technological knowledge and the degree to which those who leave to become entrepreneurs form startups in the technological domain of the parent firm' (Ellis et al., 2017: 518).

For the literature on experiential education, we contribute evidence of an effect on entrepreneurs. While many programs exist to incentivize or enable individuals who identify as entrepreneurs and who have already identified opportunities (Buffart et al., 2020), we provide evidence of the entrepreneurial effects of a program designed to prepare students for the workforce and provide employers with fresh talent.

In the theory section that follows, we draw on the literature, and illustrative examples obtained through interviews with some of the entrepreneurs in our sample, to explain why we expect an imprinting effect of educational experiences on student ventures, and how influencer and entrepreneur capabilities will affect its magnitude. We then describe our methods and results, and in the final section discuss the contributions, policy implications, and limitations of our work.

2. The imprinting of educational environments on student startups

The environments to which entrepreneurs are exposed as students, be they academic or industry-based, may leave a technological imprint on the student's venture. While the imprints of the influencer on the venture may be broad, and not purely technical (Dahl and Sorenson, 2014; Feldman et al., 2019), confining our measure of the imprinting effect to the technological dimension allows us to use an entity's patent portfolio as an indicator of its capabilities, and technological proximity between patent portfolios as an indicator of imprinting (Basu et al., 2015; Klepper and Sleeper, 2005).

As shown in Fig. 1, this interorganizational imprint is the result of a sequential series of interpersonal engagements that facilitate tacit knowledge transfer (Ellis et al., 2017; Nonaka and Takeuchi, 1995;

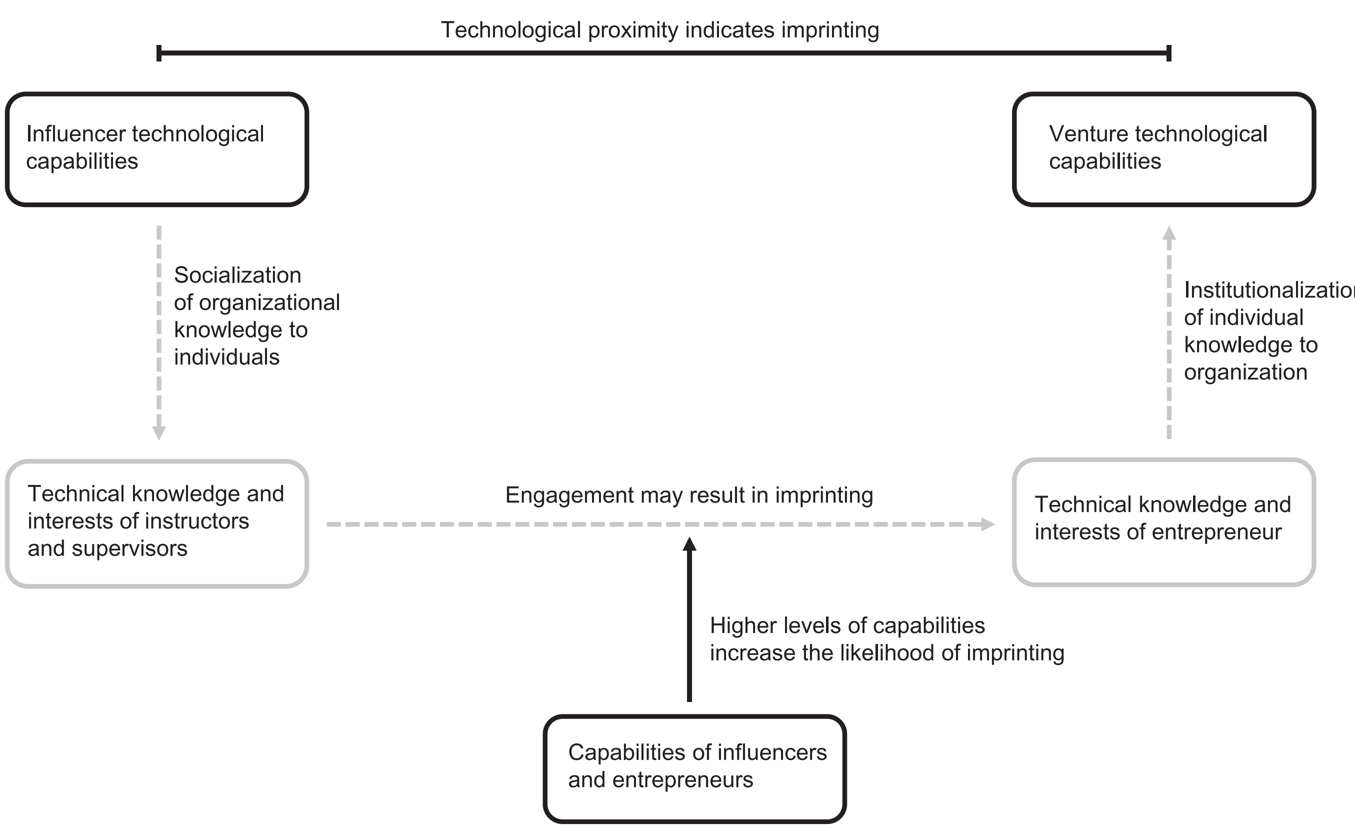

Fig. 1. The Imprinting of Influencer Technological Capabilities on Ventures.

Szulanski, 1996). First, intra-organizational engagement, amongst faculty within the university department or amongst employees in the workplace, socializes the organization's technological knowledge and perspectives, and explains why many instructors and supervisors, not just patent inventors, are able to expose students to the organization's technological capabilities. Second, there is the engagement between instructors or supervisors and the student entrepreneurs on which we focus, which may result in imprinting. And finally, there is the engagement between the student entrepreneurs and their co-founders and employees, which institutionalizes the adopted orientations and behaviours in the new venture and may result in related technology development, which is necessary to the observability of the imprint.

Imprints shape organizational culture, values, and capabilities (Johnson, 2007; Marquis and Huang, 2010; Marquis and Tilcsik, 2013), but capabilities also affect the imprinting process (Basu et al., 2015; Burton et al., 2002; Colombo and Piva, 2020; Klepper and Sleeper, 2005; Xu et al., 2023). Accordingly, we also consider how the capabilities of influencers and entrepreneurs affect the degree to which engagement results in imprinting.

Academic curricula are designed to facilitate learning and many students subsequently work in domains they have studied. So, it is expected that the institutions that educate or employ young people will have an effect on the knowledge, perspectives, and behaviours of graduates. But it is less clear that the inventive activity of graduates who become entrepreneurs will reflect the R&D activities of their former university departments and work term employers. Entrepreneurs pursue novel ideas and may be driven to entrepreneurship by negative experiences in academic or corporate settings and this may push them to explore alternative domains. Second, the student's exposure to the R&D activities may be insufficiently direct or sustained to enable understanding. Work term experiences are multiple and of limited duration, and the student is exposed to only a small subset of the organization's current employees, especially in cases where the employer is a global enterprise. And finally, accredited engineering faculties teach a standardized curriculum so that their graduates are eligible to become professional engineers. Standardized curricula leave little room for professors to share information about their research activities. Notwithstanding these frictions, we posit an imprinting effect.

2.1. *The imprinting of influencer technological capabilities on entrepreneurs*

In our theorizing, we deconstruct the imprinting concept to identify three mechanisms by which entrepreneurs may be imprinted by their environments. First, we expect that academic instructors and workplace managers will, perhaps subconsciously, direct the student's attention to specific domains; second, that they will transmit knowledge and enable skills development; and third that they will provide resources in the form of social connections.

2.1.1. *Attention direction*

A world in which information is abundant creates the need to allocate attention efficiently (Simon, 1986). Few are as overwhelmed with information as students, and so it is natural for them to focus on areas that have been identified as important by their instructors and work term managers. Extended engagement with knowledgeable individuals reveals perspectives that are considered meritorious, phenomena that are considered important, and challenges that are considered worthy (Azoulay et al., 2017). Sometimes professors have occasion to go beyond the curricula, directing the student's attention to recent developments that pique their interest:

"He got me really interested in the area, at least nano-sensors and biotechnology that otherwise I don't know if I would have really been exposed to–just through the bare bones of the curriculum." (Founder 1043, interviewed March 18, 2019)

2.1.2. *Knowledge transfer*

During academic and experiential learning experiences students may learn about new technologies, tools, and approaches and may employ that expertise in their subsequent inventions. Research on knowledge sharing between individuals within organizations has shown that knowledge transfers more readily when it is codified and when the recipient's existing knowledge base is sufficient to absorb the new knowledge (Szulanski, 1996; Zander and Kogut, 1995), and that relationship strength abets the transfer of tacit knowledge (Hansen et al., 2005). Entrepreneurial faculty may take a special interest in entrepreneurially minded students and may make special efforts to engage with them:

> "I would say we got some really good advice from Prof. X. He and Prof. Y started the mechatronics program and were still heavily involved. I certainly had a bit of a different approach and they decided to break the rules a bit and push the envelope to move this stuff forward." (Founder 1052, interviewed March 20, 2019)

At the work term employer, the student may be participating in the development of technology and possibly the generation of new intellectual property. The work term experience may also have made the student aware of the technical limitations of their employer, and possibly other firms in the industry, limitations which they elect to address in subsequent years. Corporate spinouts are more likely when corporations lack strength in either technological or market know-how (Agarwal et al., 2004). Even when employer limitations provide the entrepreneurial impetus, the student may nonetheless develop technologies that are closely related to employer technologies:

> "At the next coop, I worked on a scanning train that scanned the rail as it went along. They told me the data was being processed manually, which I thought was the most insane thing I'd ever heard. And it was also the only manual part of the process; if they could automate that, they could automate the whole thing. I spent the next three years, working on this on my spare time. I was totally obsessed with it, and I got good enough at it that I could go beyond just the study and make a business out of it." (Founder 1006, interviewed November 21, 2018)

2.1.3. *Social connections*

Social networks facilitate search and access to resources, and may also affect cognition and behaviour (Hansen, 1999; Stuart and Ding, 2006). Researchers have examined the developmental networks of entrepreneurs, the networks of mentors and advisors who provide career advice and psychosocial support to young people (Higgins and Kram, 2001). The best of these networks exhibit a diverse range of strong ties that provide superior support and leverage, and research shows that individuals with these so-called entrepreneurial developmental networks have a greater propensity to act on the inputs they receive (Higgins and Kram, 2001). Social connections made at school or at work may reinforce the imprinting effect of the student's educational activities as the imprinted knowledge, perspectives, and behaviours are reinforced and validated by peers and colleagues (Stuart and Ding, 2006). Through work terms, students develop connections with a diverse range of individuals and these connections may facilitate subsequent learning and inventive activity, especially for students who continue to work in proximate domains (McEvily and Marcus, 2005; Singh et al., 2010):

> "I was interacting with a fair bit with guys from startup X and Y during my undergrad and so I guess they would be influential in that they were a little bit ahead of us in the process. There was another company called Z, and all those people are our peer group. And they were the people that we were seeing doing some of the same stuff as us. So it felt like less of a crazy idea because we were seeing these other examples of people who were at the same stage or maybe a

couple of steps ahead of us in the process." (Founder 1009, interviewed December 18, 2018)

Because educational experiences influence where students direct their attention, what they learn, and their social networks, they will influence what they produce, resulting in technological innovations that are more proximate to those of the organizations where they were educated or employed than to other similar organizations.

Hypothesis 1a. Student startup patent portfolios will be technologically more proximate to the patent portfolios of their university departments than to matched departments.

Hypothesis 1b. Student startup patent portfolios will be technologically more proximate to the patent portfolios of their work term employers than to matched organizations.

2.2. How capabilities enable imprinting

No organization takes on all the features of its environment. While entrepreneurs are constrained by the social and technological schemas that are available at the time of venture founding, they play an important role in determining which resources upon which to draw (Stinchcombe, 1965; Johnson, 2007). And while some features of the organizational context may be available to all, some may require expertise to be transmitted and absorbed (Cohen and Levinthal, 1990). In the following, we consider how the capabilities of influencers and entrepreneurs affect the imprinting process and its outcomes.

2.2.1. The effect of influencer capabilities

Researchers have considered the effects of influencer knowledge on imprinting and have shown that influencers with more extensive or more relevant knowledge to transmit engender greater imprinting effects. Klepper and Sleeper (2005) study spinouts in the laser industry and, as evidence of imprinting, show that the type of lasers produced by spinouts are predicted by the type of lasers produced by their parent firms. The authors show that the effect is greater for parent firms with more patents and more years of experience producing the relevant type of laser. Burton et al. (2002) show that spinouts are more likely to innovate, thereby deploying imprinted capabilities, if the parent firm has high entrepreneurial prominence. Colombo and Piva (2020) study the impact of university education on entrepreneurial entry and find a greater effect in fields where the quality of the university was highly rated.

We argue that the capabilities of the university and industry influencers will positively affect imprinting. More capable influencers will undertake more important and more compelling research and will therefore have more distinctive knowledge upon which to draw. They may offer a more engaging and enlightened educational or work experience resulting in a greater motivation to absorb on the part of students. The individuals associated with highly capable influencers may hold more centralized positions in social networks, providing the students with access to more numerous, more qualified, or more diverse connections, again increasing learning opportunities (Sorenson and Audia, 2000). And finally, past associations with highly capable influencers will have greater signaling value. The signaling value of associations with prestigious parties make it easier for ventures to attract resources (Higgins and Gulati, 2006; Stuart et al., 1999), thereby improving their chances of survival and hence the observability of imprinting. For these reasons, we expect that influencer capabilities will have a positive effect on observable technological proximity.

Hypothesis 2a. University department capabilities will have a positive effect on technological proximity between university department and student startup patent portfolios.

Hypothesis 2b. Work term employer capabilities will have a positive effect on technological proximity between work term employer and student startup patent portfolios.

2.2.2. The effect of the entrepreneur's capabilities

Founders may have perspectives or capabilities that affect the degree to which they absorb imprints. Johnson (2007) shows how Pierre Perrin chose to model the Paris Opera as a royal academy, not as a commercial theatre, thereby selecting the source of imprinting and according the new institution a unique status. Basu et al. (2015) study spinouts in the biotechnology industry and, as evidence of imprinting, show that ventures are likely to patent in the domains in which their parent firms patent. They consider the effect of founder technological breadth on the impact of the venture's patents. Even when the imprinted organization is mature, the attributes of individuals may affect the extent of imprinting. Xu et al. (2023) show that the negative effect of Communist Party affiliations on the patent applications of listed Chinese firms is attenuated if the board chair is younger or has higher educational attainment.

A broad range of capabilities are important to entrepreneurship, but we believe that for the creation of student startups, software skills are a differentiating factor. Software skills will affect opportunity identification, inventive activity, and venture capital acquisition as software products can be generated more quickly than hardware products, due in part to shared resources such as Open Source Software (OSS) (McDonald and Eisenhardt, 2020). Participation in GitHub, the leading OSS platform, predicts the number and quality of entrepreneurial ventures in a country (Wright et al., 2023). And because admittance to software engineering is highly competitive, it may serve as an indicator of general technical capabilities (UW Engineering, 2023). Colombo and Piva (2020) show that students who follow specialized technical programs, and therefore have higher levels of entrepreneurially relevant human capital, are more likely to become entrepreneurs than students who follow general technical programs. And highly capable students will have the opportunity to work closely with researchers, facilitating knowledge transfer.

> "A company was producing software for the book my academic supervisor was writing. My friend and I ended up landing coop jobs with them, basically a project to produce a bunch of simulation results for the book." (Founder 1031, interviewed February 4 2019)

We expect that the more capable the student entrepreneur, particularly in software development, the more attuned they will be to the R&D activities of their university department and work term employers and the better able they will be to absorb and build upon what they learn.

Hypothesis 3a. The student's software skills will be positively related to technological proximity between university department and startup patent portfolios.

Hypothesis 3b. The student's software skills will be positively related to technological proximity between work term employers and startup patent portfolios.

2.2.3. Relations between multiple layers of imprint

Past empirical studies of entrepreneurial imprinting have considered the effects of single influencers on spinouts (Agarwal et al., 2004; Basu et al., 2015; Ellis et al., 2017; Klepper and Sleeper, 2005; Sapienza et al., 2004). But the entrepreneurs in our study are exposed to multiple potential imprinters, as they alternate between academic terms and work terms throughout their university degrees. This allows us to examine multiple layers of imprint, for each entrepreneur.[1]

It may be that multiple layers of imprints act as substitutes for one another. Some imprints may be more fit for present challenges,

[1] We thank a reviewer for suggesting that we consider multiple layers of imprint.

comprised of richer content, or more easily absorbed by the entrepreneur. In our setting, for some entrepreneurs the academic curriculum may be too theoretical to be applicable and the industry activities more pertinent, or the entrepreneur may be less gifted academically and more passionate about business. This may lead to weak academic imprints and strong industry imprints. Conversely, the academic material may be more highly curated for pertinence, while the industry material may be routine, driven by the requirements of the business, leading to strong academic imprints and weak industry imprints. If imprints are substitutes for one another, or if individual entrepreneurs are better able to absorb either academic or industry imprints, then the magnitude of academic and industry imprints will be inversely related or unrelated.

Alternatively, it may be that multiple layers of imprint are complementary, each layer adding value in conjunction with other layers. The utility of academic imprints may be enhanced by complementary industry knowledge and vice versa. And if all imprints are potentially valuable then it may be the entrepreneur's capabilities that limit what they can absorb from their environments and how effectively they can build upon what they absorb (Cohen and Levinthal, 1990; Ellis et al., 2017). More capable entrepreneurs will position themselves in more impactful environments, will be better able to absorb the knowledge to which they are exposed, and will be better able to manifest the acquired knowledge in new inventions:

> "I was working in the automotive industry for hydrogen fuel cells in R&D and identified a real-world problem. I came back to school the following term and I knew that there was a professor at the university who could possibly solve this problem. So, then I started a research assistantship with the professor, and I presented it to my old boss, and we started a research collaboration that was pretty cool." (Founder 1028, interviewed January 23, 2019)

If imprints are complementary, or if the entrepreneur's capabilities are a primary determinant of imprint magnitude, then the magnitude of academic and industry imprints will be positively related. In Hypothesis 4 we predict a positive relationship between the magnitude of layers of imprint.

Hypothesis 4. Technological proximity between student startup and university department patent portfolios will be positively related to technological proximity between student startup and work term employer patent portfolios.

3. Methods

3.1. Sample

We conduct our examination on a sample of startups created by graduates of the University of Waterloo (UW), a Canadian university that is known for its cooperative education program, the world's largest, with over 22,000 placements per year (UW Cooperative Education Annual Report, 2018). Quacquarelli Symonds (QS) ranks UW 38th for Engineering and Technology worldwide and 23rd for Computer Science and Information Systems, and Pitchbook and AngelList rank it 21st and second, respectively, in entrepreneurial terms (AngelList, 2021; Pitchbook, 2022; QS, 2021). The university's inventor-owned intellectual property policy, cooperative education program, and role in a thriving entrepreneurial ecosystem has attracted the attention of policy makers and researchers (Bramwell and Wolfe, 2008; Kenney and Patton, 2011).

Each year, Pitchbook, a venture capital data provider, compiles lists of the top universities in terms of the number of alumni who raise VC-financing and the total amount raised. In 2016, Pitchbook identified a total of 346 UW graduates (275 ventures) who had raised a total of over $5 billion in VC-financing over the preceding decade (Pitchbook, 2016). Our sample of student entrepreneurs and ventures is drawn from this list.

UW has complete information on work term employment for 183 of the entrepreneurs who graduated after 2004 (181 entrepreneurs) or dropped out (2 entrepreneurs). Of these, 90 % did at least one four–month work term and 82 % did between four and eight work terms. One–third (62) of these students have US patents assigned to their ventures or on which they are listed as inventors. As we are interested in the technological proximity between startups and work term employers, we restrict our sample to the 55 entrepreneurs who had a patent, who participated in cooperative education, who were expected to complete their university degrees after 2004 (making work term employment data available), and whose work term employers had at least one patent. The last criterion ensures we are able to estimate technological proximity between the venture and work term employer. Eighteen of these entrepreneurs have one patent, 33 have between two and 10 patents, and four entrepreneurs have >10 patents for a total of 298 patents. The students completed a total of 157 work terms with 101 unique work term employers. The 40 ventures that these entrepreneurs (co)founded were launched between 2005 and 2016; in 2016 or earlier had between two and 3000 employees; operated in the manufacturing (6), wholesale or retail trade (5), information and culture (8), professional, scientific, and technical services (19), or other service sectors (2); and were located in Waterloo or Toronto (13), elsewhere in Canada (3), the San Francisco Bay area (14), elsewhere in the US (7), or outside North America (3).

3.2. Matching of university departments and work term employers

We match the student's university department and work term employers with control organizations to test our hypotheses on technological proximity. For each student, we construct the patent portfolios of their startup, their university department and the matched university department, and each of their work term employers and matched organizations. We match university departments and work term employers, rather than ventures, so as to be able to test our hypotheses on the influence of different educational experiences on this set of ventures.

To test the effect of the students' university department we match UW departments with their counterparts at McMaster University, a university that is geographically proximate to UW and comparable in terms of size and quality. McMaster University, founded in 1887, has a student body of approximately 32,000 students (UW has 41,000 students), and is located about 70 km away from UW, in Hamilton, Ontario. QS ranks McMaster University 194th in Engineering and Technology (QS, 2021). To test the effect of the students' work term employers, we needed matched employers that had at least one patent. In 2018, 26,871 US firms spent more than $50,000 on R&D (Shackelford and Jankowski, 2021). As it costs between $1 million and $5 million in R&D spending to produce a patent (Dechezleprêtre et al., 2016), we used Compustat to identify the 3698 firms that spent more than $500,000 per year on R&D as our control reservoir, from which we selected control group employers, to increase the likelihood that firms in our control group would have patents. We used case-control matching to match employers with control group firms on the basis of founding date (within a 15–year window), industrial sector (same 3–digit industry subsector based on the North American Industry Classification System), and the log of the number of employees (to a one order of magnitude difference). Where the employer was a university, hospital, or government department, it was matched with a similar university, hospital, or government department on the basis of size, location, and ranking (for universities) or mandate (for government departments). We reviewed matches for face validity and improved this by manually matching Amazon with Ebay and American Express with Bank of America and Mastercard. Standardized differences of means on the three matching variables ranged from 0.05 to 0.18, below the reliability cutoff of 0.25 for balanced samples (Stuart, 2010).

3.3. Measures

3.3.1. Dependent variable

Our dependent variable, technological proximity, is a measure of the similarity of the patent portfolio of the venture and the patent portfolio of the university department, work term employer, or control group organization. The patent portfolios of the university departments include all patents granted to department faculty between 1976 and 2017, while the portfolios of industry organizations are based on patents granted to the organization within the 13–year window that begins 10 years before the year of the respective work term relationship and ends three years after. University portfolios employ longer time periods so as to capture a sufficient number of patents for each department.

A number of knowledge proximity measures have been used in the literature. Some consider citations between patents and patent classes while others consider the co–occurrence of patent classes, leveraging the fact that patents are often classified in multiple classes (Kay et al., 2014; Leydesdorff et al., 2014). Yan and Luo (2017) analyzed 12 alternative knowledge proximity measures in terms of consistency and granularity and proposed the class–to–patent cosine similarity index, which is better able to represent technological space than alternative measures (Leydesdorff et al., 2017). We use this measure to estimate *Techprox*, the proximity of the patent portfolio of the venture (P_1) to the patent portfolio of the influencer (P_2).

$$\text{Techprox} = \frac{\sum_{i,j} \varphi_{i,j} P_{1i} P_{2j}}{\sqrt{\sum_{i,j} \varphi_{i,j} P_{1i} P_{1j}} \sqrt{\sum_{i,j} \varphi_{i,j} P_{2i} P_{2j}}}$$

where φ_{ij} is the Jaccard index of the proximity of patent class i to patent class j, P_{1i} is the vector describing the venture's portfolio across all patent classes (i), and P_{2j} is the vector describing the potential influencer's portfolio across all patent classes (j). *Techprox* ranges from 0 to 1.

3.3.2. Independent variables

Our independent variables of interest are binary variables that indicate whether or not the venture-potential influencer pair were subject to an educational relationship, and measures of the capabilities of the parties. *UWaterloo* is a binary variable that is 1 if the department is part of UW and 0 otherwise. *Work term* is a binary variable that is 1 if the industry organization was a work term employer and 0 otherwise.

Organizational capabilities are socially embedded and draw upon tacit knowledge and so are difficult to measure without interview or survey data. We follow past studies of organizational imprints on ventures which, lacking direct measures of organizational capabilities, have used proxies such as the number of patents (Klepper and Sleeper, 2005), the number of spinouts (Burton et al., 2002), and the ranking of university departments (Colombo and Piva, 2020). Such indicators are able to distinguish between progenitors in ways that are pertinent to technology-based startups. Our indicator of department capabilities, *Department rank*, is the QS ranking of the department, reverse-coded for a predicted positive effect. QS ranks over 15,000 university departments on the basis of research reputation as assessed by academics, graduate quality as assessed by employers, research citations per publication, H indices, and international joint publications (QS, 2023a, 2023b). We group the students' departments into five groups that correspond to the QS ratings: electrical engineering (the reference group, rated 48), chemical engineering (includes nanotechnology, rated 78), mechanical engineering (rated 76), other STEM (includes physics and astronomy, rated 61), and mathematics and computer science (rated 29).

Our indicator of employer capabilities, *Ln employer patents*, is the natural logarithm of the number of patents held by the organization. While an alternative measure would have been citation-weighted patents, such a measure would increase the skewness in a variable that was already skewed, whereas it is the variability at the low end of the range that is important for our purposes—hence the natural logarithm. Our indicator of *Student software skills* is the sum, across the courses taken by the student, of the proportion of course material that is software related in each course. We determine these subject specific proportions by using curricula to determine, for each subject, the proportion of software courses to total courses. For example, software courses constitute 5 % of mechanical engineering courses, 19 % of applied mathematics courses, and 77 % of computer science courses.

3.3.3. Control variables

We control for up to eight factors that may influence technological proximity. In our models of the effect of the students' university department we control for the department in which they were enrolled using dummy variables (unless *Department rank* is included in the model), the year in which the student graduated (*Graduation year*), *Venture founding year*, and *Ln venture size*, in terms of number of employees. In our models of the effect of the students' work term employer we also control for *Ln employer founding year* and *Ln employer size* (in terms of number of employees), and for *Industrial proximity* and *Geographic proximity* between ventures and paired organizations. In the case of venture size, employer founding year, and employer size we use the natural logarithm of the variable to address skewness.

Firms in similar industries are more likely to create similar technologies so, as is common, we use a standard industry classification system to identify industry proximity. Our industry proximity values range from 1 for pairs of organizations in different sectors to 5 for pairs of organizations in the same 5–digit industry. Our geographic proximity variable ranges from a value of 1 for organizations on different continents, to 6 for organizations in the same city. Both our proximity variables are ordinal that we treat as continuous to retain the ordinal information. Treating ordinal variables as continuous does not compromise the reliability of results if the sample size and number of ordinal categories are sufficient, that is, greater than four (Johnson and Creech, 1983), or five (Rhemtulla et al., 2012). We expect *Industry proximity* and *Geographic proximity* to be positively related to technological proximity. Tables 1 and 2 present the descriptive statistics, and Tables 3 and 4 the pairwise correlations, for the proximity to university department and proximity to work term employer models, respectively. Correlations are based on treated (UW) observations only to show pairwise relationships between the measures of capabilities.

4. Results

Table 5 shows our results which regress *Techprox* on independent variables and control variables. In all cases we use fractional response generalized linear models as our dependent variable is a proportion that ranges from 0 to 1 (Williams, 2019). Model 1.1 through 1.5 consider the imprinting effects of the student's university department and Models 2.1 through 2.5 consider the imprinting effects of the student's work term employers. Models 1.1 and 2.1 include only control variables. Models 1.2 and 2.2 present estimates of the imprinting effect of the student's

Table 1
Descriptive statistics: proximity to university department.

	n	Mean	Standard deviation	Minimum	Maximum
Techprox	110	0.57	0.29	0.06	0.99
UWaterloo	110	0.50	0.50	0	1
Department rank	55	55.34	17.64	29	78
Student software skills	55	8.50	3.56	0.52	14.77
Department	110	2.73	1.62	1	5
Graduation year	110	2009.24	2.56	2005	2014
Venture founding year	110	2010.92	2.36	2005	2016
Venture size	110	133.84	406.74	2	3000
Ln venture size	110	3.56	1.53	0.69	8.01

Table 2
Descriptive statistics: proximity to work term employers.

	n	Mean	Standard deviation	Minimum	Maximum
Techprox	314	0.45	0.34	0.00	1.00
Workterm	314	0.50	0.50	0	1
Employer patents	157	1636.12	4021.40	1	21,905
Ln employer patents	157	4.24	2.95	0	9.99
Student software skills	157	8.62	3.45	0.52	14.77
Department	314	2.66	1.60	1	5
Graduation year	314	2008.65	2.50	2005	2014
Venture founding year	314	2010.64	2.50	2005	2016
Venture size	314	139.34	413.95	2	3000
Ln venture size	314	3.60	1.56	0.69	8.01
Employer founding year	314	1964.65	50.60	1636	2011
Ln employer founding year	314	7.58	0.03	7.40	7.61
Employer size	314	37,118.37	95,287.43	25	613,300
Ln employer size	314	8.52	2.24	3.22	13.33
Industry proximity	314	1.15	0.67	1	5
Geographic proximity	314	2.77	1.18	1	6
Work term hires	314	49.97	146.10	0	1210
Ln work term hires	314	1.80	1.90	0	7.10

UW department and work term employer, respectively. Model 1.2 tests whether the ventures are technologically more proximate to their UW departments than to matched departments (Hypothesis 1a). Model 1.2 provides support for Hypothesis 1a as the *UWaterloo* variable is significant ($p < 0.01$), showing that the patent portfolios of UW student startups exhibit greater technological similarity to the patent portfolios of UW faculty than to those of McMaster University faculty. This suggests that the technological proximity between ventures and university departments observed previously (Åstebro et al., 2012) is not explained by similarity in subject matter across universities, but is the consequence of enrollment, engagement, and imprinting.

Model 2.2 presents the estimates of the technological proximity between the patent portfolios of student startups and industry organizations and shows that the *Work term* variable is significant ($p < 0.001$), indicating that an employment relationship significantly increases technological proximity (Hypothesis 1b). Employment and engagement leads to increased technological proximity between patent portfolios, our indicator of an imprinting effect.

To examine the effect of capabilities and skills (Hypotheses 2a, 2b, 3a, and 3b) we drop matched observations, restricting the sample to observations where influencer organizations and students came into contact with one another. Models 1.3 and 2.3 examine the effect of influencer capabilities and Model 1.3 provides support for Hypothesis 2a as *Department rank* is positive and significant ($p < 0.001$). The more highly ranked the department, the higher the expected level of technological proximity between startup and former employer patent portfolios. We omit *Department* when we include *Department rank* in the model, as the two variables are colinear. Model 2.3 examines effect of employer capabilities and provides support for Hypothesis 2b as *Ln employer patents* is positive and significant ($p < 0.01$). The more innovative the work term employer, as indicated by the number of granted patents, the higher the expected level of technological proximity between startup and former employer patent portfolios. These dosage effects provide additional support for our proposition that student ventures are imprinted by the R&D activities of their university departments and work term employers and point to the importance of influencer capabilities in technological imprinting.

Models 1.4 and 2.4 provide support for Hypotheses 3a and 3b as *Student software skills* is significant ($p < 0.01$, $p < 0.001$, respectively). The greater the student's software skills, the higher the level of technological proximity between startup and influencer employer patent portfolios. But Model 1.5 shows that when both *Department rank* and *Student software skills* are included in the model, *Student software skills* is no longer significant. We attribute this to idiosyncratic collinearity between *Department rank* and *Student software skills*, which are highly correlated (0.77, $p < 0.05$). The most highly ranked science and engineering departments at UW happen to be those that are software intensive. The significance of *Student software skills* persists in Model 2.5, which includes both *Employer patents* and *Student software skills*, providing additional support for Hypothesis 3b.

Figs. 2a, 2b, and 2c show the marginal effects of *Department rank*, *Ln employer patents,* and *Student software skills,* respectively, as these variables range from their minimum to maximum values and other covariates take their mean values. Technological proximity ranges from 0.32 to 0.90 as *Department rank* (reverse coded) ranges from a low of −78 (Chemical engineering) to a high of −29 (Mathematics and computer science) in Model 1.5, a difference of 0.58, which is >50 % of the dependent variable (DV) range. It ranges from 0.43 to 0.68 as *Ln employer patents* ranges from a low of 0 (1 patent) to a high of 10 (21,905 patents) in Model 2.5, a difference of 25 % of the DV range, and it ranges from 0.28 to 0.71 as *Student software courses* ranges from a low of 0.5 (one technical course) to a high of 14.8 (19 computer science courses) in Model 2.5, approximately 10 % of the DV range.

To test Hypothesis 4 on the relationships between multiple layers of imprint we examine correlations between venture-department and venture-employer measures of technological proximity across the entire sample, and when observations are grouped by entrepreneur. The entrepreneurs in our sample undertake between one and eight work terms, with an average of 2.8, and we take the mean venture-employer technological proximity value as our measure of industry-based technological proximity when observations are grouped by entrepreneur. We find strong positive correlations between academic and industry-based proximities (0.59, $p < 0.001$ for the full sample, 0.68, $p < 0.001$ when grouped by entrepreneur), which supports the view that layers of imprint are complementary.

4.1. Robustness tests

Our observations are not independent as specific ventures and

Table 3
Correlations: proximity to university department.

		1	2	3	4	5	6	7
1	Techprox							
2	Department	−0.10						
3	Department rank	0.72	0.02					
4	Student software skills	0.57	−0.04	0.77				
5	Graduation year	−0.39	0.24	−0.24	−0.29			
6	Venture founding year	−0.24	0.18	0.06	−0.03	0.33		
7	Venture size	0.16	0.16	0.16	0.17	−0.23	0.24	
8	Ln venture size	0.06	−0.03	−0.01	0.02	−0.20	−0.44	0.59

$n = 55$; Correlations with an absolute value of >0.29 are significant, $p < 0.05$.

Table 4
Correlations: proximity to work term employers.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Techprox																
2	Employer patents	0.24															
3	Ln employer patents	0.32	0.66														
4	Student software skills	0.44	0.11	0.10													
5	Department	−0.06	−0.20	−0.08	−0.11												
6	Graduation year	−0.25	−0.10	−0.07	−0.30	0.34											
7	Venture founding year	−0.06	0.02	0.05	−0.03	0.20	0.34										
8	Venture size	0.16	−0.08	−0.04	0.16	0.19	−0.21	0.04									
9	Ln venture size	0.05	−0.09	−0.04	−0.03	−0.04	−0.16	−0.43	0.58								
10	Employer founding year	0.30	0.05	−0.06	0.45	−0.07	−0.10	−0.02	0.10	0.06							
11	Ln employer founding year	0.30	0.05	−0.07	0.45	−0.07	−0.11	−0.02	0.10	0.06	0.99						
12	Employer size	0.24	0.13	0.21	0.14	−0.11	−0.16	0.00	0.20	0.17	0.04	0.04					
13	Ln employer size	0.16	0.37	0.42	−0.05	−0.19	−0.19	−0.02	−0.04	−0.04	−0.21	−0.21	0.60				
14	Industry proximity	0.14	−0.03	0.04	0.04	−0.01	−0.03	0.13	0.18	−0.01	0.08	0.08	−0.06	−0.12			
15	Geographic proximity	−0.10	−0.11	−0.11	−0.11	0.04	0.11	−0.08	−0.04	0.03	0.01	0.01	−0.08	−0.12	−0.13		
16	Number work term hires	−0.02	−0.01	0.22	−0.03	−0.01	0.12	0.07	−0.08	−0.08	0.02	0.02	−0.08	0.01	−0.05	0.15	
17	Ln work term hires	0.16	0.18	0.38	0.10	−0.17	−0.01	0.02	−0.05	−0.01	−0.02	−0.02	0.11	0.28	−0.00	0.14	0.73

$n = 157$; Correlations with an absolute value of >0.16 are significant, $p < 0.05$.

entrepreneurs appear multiple times in our samples. In models estimating the effects of university departments we cluster observations by venture, as where a venture has multiple UW co-founders, they are associated with the same department. In models estimating the effects of work term employers we cluster by student as each student has different work term employers. Post-estimation scatter plots of the squared residuals against the predicted values of the dependent variable show no evidence of heteroscedasticity but a clustering of higher values near the mean of the dependent variable, as is common with small samples (Williams, 2020).

We hypothesized that the ventures' patent portfolios would be closer to the portfolios of the entrepreneurs' university departments and work term employers than to those of matched organizations. While we have found support for our hypotheses, before we claim a causal effect, we must consider the possibility that endogeneity in the selection of relationship ties, motivated by latent technological similarities, is the cause. While it is likely that the entrepreneurs in our sample had a sense of their interests and abilities when choosing universities and work term employers, and vice-versa, it is unlikely that they would have been able to identify the specific inventions that they would subsequently create. Our measure of technological proximity is sufficiently fine-grained to distinguish between, for example, the technological footprints of competing firms in the same industry (Sarica et al., 2020). A common interest in software, as is the case for many of the organizations in our sample, would be insufficiently precise to bias our results. There is also a temporal argument as university enrollment and graduation precede the year of the first patent award by an average of 9.9 and 4.9 years, respectively. There is a difference of five years because where work terms are mandatory, UW programs take five years to complete.

In the case of work term employers, we can also provide statistical evidence that selection into work term relationships is not endogenous. Table 6 reports the results of our two-stage regressions. As an instrumental variable, which predicts selection into the employee-employer relationship, but which is not significantly correlated with technological proximity, we use the number of UW work term hires the employer had in the year of the focal work term relationship (*Number work term hires*). Because this number is skewed and may be zero, we employ the natural logarithm, *Ln* (*Number work term hires* + 1). As shown in Model 3.1, this variable is a significant predictor of selection into the employer-employee relationship ($p < 0.001$) and, as shown in Model 3.2, the fitted values of *Work term* are significant in predicting technological proximity ($p < 0.001$). We then run endogeneity post-estimation diagnostics and find that neither the Durbin nor the Wu-Hausman score is significant, supporting our view that selection into work term relationships is not endogenous.

In our main results on the effect of an employment relation, we used 1:1 case control matching in which we identified 157 matched organizations. To ensure that our results are not vulnerable to the matching process we re-estimate the models using 1:5 case control matching in which we identified 413 matched organizations, up to five control group observations for each treatment group observation. Models 4.1 and 4.2 in Table 6 show the results of the tests on this alternative sample, and they are substantially the same as Models 2.1 and 2.2 in Table 5. We also re-estimate the two-stage regression results and again, Models 5.1 and 5.2 do not differ materially from Models 3.1 and 3.2. The endogeneity and heteroscedasticity tests again produce essentially the same results.

5. Discussion

5.1. Contributions

Student entrepreneurs have history and build upon their educational experiences. The entrepreneurs in our sample founded ventures with patents in areas that are technologically proximate to the patented R&D activities of their former university departments and work term employers. Whether consciously or unconsciously, the students gleaned

Table 5
Regression of technological proximity on independent variables and controls.

Model	1.1	1.2	1.3	1.4	1.5	2.1	2.2	2.3	2.4	2.5
Hypothesis		H1a	H2a	H3a	H3a		H1b	H2b	H3b	H3b
	Controls	Department	Department rank	Student software skills	Department and student	Controls	Employer	Employer patents	Student software skills	Employer and student
Independent variables										
UWaterloo		2.99**								
Department rank			5.36***		4.59***					
Work term							5.18***			
Ln employer patents								3.33**		2.99**
Student software skills				3.18**	−0.37				3.67***	3.32**
Control variables										
Chemical engineering	−2.61**	−2.62**				−4.57***	−4.43***			
Mech. engineering	−5.21***	−5.26***				−2.20*	−2.17*			
Other STEM	−2.12*	−2.12*				0.81	0.48			
Math. and comp. sci.	3.21**	3.21**				2.69**	2.61**			
Graduation year	−0.81	−0.81	−1.04	−1.48	−1.03	−0.14	−0.06	−1.55	−0.65	−0.73
Venture founding year	−2.61**	−2.62**	−2.40*	−1.70+	−2.39*	−0.39	−0.38	−0.19	−0.19	−0.26
Ln venture size	−0.40	−0.39	−0.59	−0.58	−0.59	1.11	1.09	0.12	0.50	0.49
Ln emp. Founding year						2.09*	2.20*	4.02***	2.44*	2.50*
Ln employer size						3.31**	3.14**	1.26	2.91**	1.59
Industry proximity						2.08*	1.94+	1.71+	2.29*	1.95+
Geographic proximity						1.50	0.35	−0.16	−0.01	0.10
Constant	2.48*	2.48*	2.57*	2.69**	2.56*	−0.36	−0.17	0.54	0.11	0.24
Model										
n	110	110	55	55	55	314	314	157	157	157
R^2	0.16	0.17	0.18	0.12	0.18	0.11	0.13	0.10	0.11	0.13
X^2	$X^2(7)$ 99.09***	$X^2(8)$ 116.63***	$X^2(4)$ 60.12***	$X^2(4)$ 21.42***	$X^2(5)$ 74.14***	$X^2(11)$ 261.65***	$X^2(12)$ 282.16***	$X^2(8)$ 70.41***	$X^2(8)$ 56.48***	$X^2(9)$ 68.76***

Dependent variable is *Techprox*; cells are t values; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p < 0.1$;
Observations in Models 1.1 through 1.5 are clustered by venture for robust standard errors.
Observations in Models 2.1 through 2.5 are clustered by student for robust standard errors.

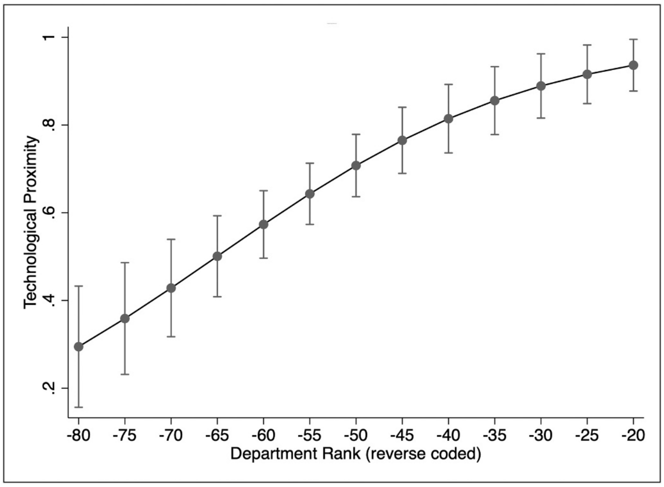

Fig. 2a. Marginal effect of department rank.

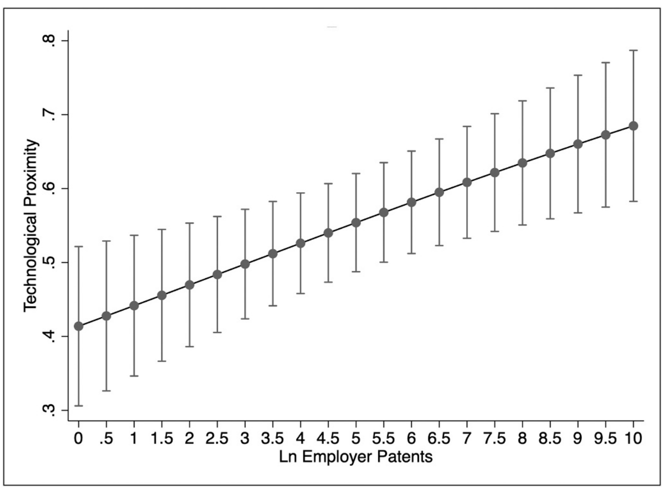

Fig. 2b. Marginal effect of Ln employer patents.

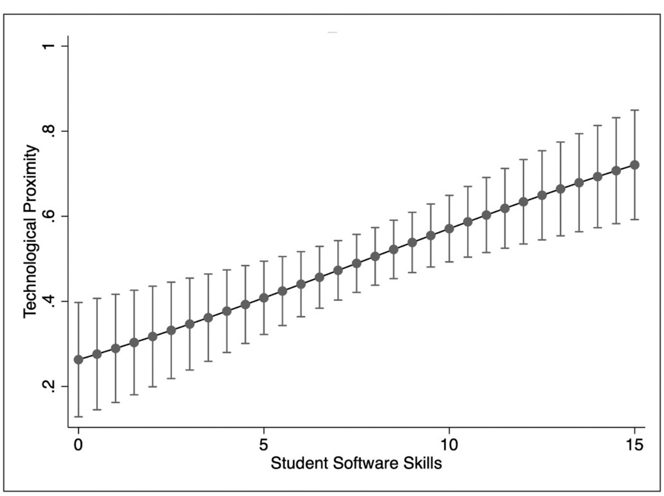

Fig. 2c. Marginal effect of student software skills.

knowledge of the R&D activities to which they were indirectly exposed, and this knowledge shaped the inventive activity of their ventures. They likely absorbed a wealth of additional knowledge, perspectives, and behaviours that are less easily measured and, in their efforts to build companies that correspond to their models of what is important, feasible, and true, have similarly drawn upon this material.

University quality matters. Previous research has shown that university quality is positively related to the incidence of entrepreneurial entry (Colombo and Piva, 2020) and the earnings of alumni entrepreneurs (Åstebro et al., 2012). Our results suggest that this is because students at higher quality institutions are exposed to more relevant, important, and engaging material and leverage this exposure by continuing to work in proximate domains. The graduates of superior universities found more successful companies not only because of the value of their prestigious affiliations and social networks, but also because they build upon the superior material to which they are exposed. Similarly, more innovative companies have a greater effect than less innovative companies.

Capabilities are not essential to all imprinting. But in settings where the source behaviours, values, and knowledge are sophisticated, capabilities may be essential to imprint absorption. Software skills play an important role in venture development and we show that the student's software skills strengthen the magnitude of imprinting.

We consider the relationship between the multiple layers of imprints to which the entrepreneurs in our sample are exposed and show that university and industry imprints are complements not substitutes. Students with superior capabilities are sponges that accumulate multiple complementary layers of imprint, from a range of sources. Less capable students do not substitute more suitable knowledge for less suitable knowledge, they absorb less from all sources. Our evidence supports the theory that individuals are a complex mix of enduring imprints of past experiences (Johnson, 2007; Mathias et al., 2015).

Finally, we provide a baseline for the minimal engagement required for an imprinting effect. The post–docs in Azoulay et al.'s (2017) study of the effect of academic supervisor patenting behaviour on post-doc patenting behaviour are in the relationship for a median of five years. Similarly, the entrepreneurs in Ellis et al.'s study of entrepreneurial proclivity and in Agarwal et al.'s study of spinouts are in working relationships with the ancestor entrepreneurs and spawning firms for multiple years (Agarwal et al., 2004; Ellis et al., 2017). And it is known that the number of years an entrepreneur spends at a source organization predicts the extent of technology transfer from the source organization to the spinout (Roberts, 1988). Our study considers the effects of modest exposures, testing for an imprinting effect in a context where it was not evident that one would be found—a four-month work term—and thereby establishes a lower bound on the magnitude of engagement required for an imprinting effect.

To the literature on work-integrated learning we contribute evidence of an effect of cooperative education on entrepreneurs. In contrast to the many entrepreneurship support programs that may have modest effects on venture clients (Amezcua et al., 2013; Jourdan and Kivleniece, 2017), the entrepreneurial effects of UW's cooperative education program come with no distortionary or adverse effects because they arise serendipitously, as an unintended consequence of activities undertaken for other reasons. The approach is inclusive, low–cost, and receives no government funding. While UW employs over 200 people to manage the recruitment and reporting processes of both cooperative education and post–graduation employment, the costs of the cooperative education program are largely borne by students (UW Cooperative Education, 2021).

Many studies of the genesis of ventures look to establish a measure of the distance between a venture and a spawning organization, be it a university or a former employer of the founders (Agarwal et al., 2004; Azoulay et al., 2017; Basu et al., 2015). To this endeavour we introduce a knowledge proximity measure of proven superiority, that uses the entire USPTO database to weigh the co–occurrence of patent classes in terms of their likelihood (Yan and Luo, 2017).

Table 6
Robustness tests.

Model	3.1	3.2	4.1	4.2	5.1	5.2
Hypothesis		H1b		H1b		H1b
	Fitted values	2SLS	Controls	Employer	Fitted values	2SLS
Independent variables						
Work term				5.99***		
Ln work term hires	22.01***				28.57***	
Work term (fitted values)		3.55***				4.68***
Control variables						
Chemical engineering	0.39	−4.06***	−3.32**	−3.27**	0.51	−3.07**
Mechanical engineering	2.03*	−2.45*	−1.73+	−1.76+	2.08*	−2.05*
Other STEM	−1.05	0.83	1.66+	1.75+	−0.43	1.65+
Math. and comp. sci.	0.30	2.60**	1.46	1.44	0.35	1.30
Graduation year	−1.59	0.05	−0.25	−0.65	−1.58*	−0.01
Ln venture founding year	−0.89	−0.41	−0.59	−0.60	−0.91	−0.44
Venture size	−0.52	1.15	1.02	0.96	−0.48	1.10
Ln employer founding year	−0.31	2.51*	2.78**	2.95**	−0.13	3.06**
Ln employer size	−3.14**	3.18**	3.35**	3.41**	−3.69***	3.32**
Industry proximity	0.78	2.01*	2.25*	2.14*	0.48	2.15*
Geographic proximity	0.40	0.28	0.51	−0.83	1.79+	−1.00
Constant	1.96	−0.33	0.69	−0.56	1.94	−0.42
Model						
n	314	314	570	570	570	570
R^2 (Adjusted R^2)	0.56(Adjusted)	0.33	0.09	0.11	0.62(Adjusted)	0.28
F	F (12,301) 51.72***				F (12,557) 90.36***	
X^2		X^2 (12) 327.76***	X^2 (11) 133.47***	X^2 (12) 155.32***		X^2 (12) 228.41***

Dependent variable is *Techprox*; cells are t values; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p < 0.1$.
2SLS Two stage least squares regression; Observations in Models 3.1 through 5.2 are clustered by student for robust standard errors.

5.2. Policy implications

Most fundamentally, our work points to the importance of exposure to substantive knowledge-based activities for young people. Policy makers need to do everything in their power to expose young people to influencers of the broadest range and highest quality possible. More specifically, our results point to the value of equipping people to behave entrepreneurially prior to their identification as entrepreneurs. In the context of high-potential ventures, this means exposing them to the intricacies of recent technological advances and to a variety of experiences in diverse settings. Cooperative education, as it is offered at UW, may be particularly efficacious at enhancing opportunity identification, because it increases the likelihood of fruitful collisions experienced by students who are smart, energetic, and open to new ideas. Programs that try to support entrepreneurs systematically may, in their focus on measurable progress, diminish prospects for the serendipitous discovery of entrepreneurial opportunities. Like user entrepreneurs (Shah and Tripsas, 2007), many of the entrepreneurs in our sample identify and evaluate the business potential of opportunities prior to identifying as entrepreneurs. This may be preferable to first identifying as an entrepreneur and then searching for an opportunity, because negative feedback on business ideas can threaten entrepreneurial identity, and therefore be resisted (Grimes, 2018).

Our work also points to the potential socioeconomic effects of high-quality universities. While UW is a top Canadian school, it is well down the list of international rankings. Nevertheless, UW has had a remarkable effect on the entrepreneurial ecosystem in the Waterloo region (Bramwell and Wolfe, 2008), in part due to a disproportionate number of both faculty (Kenney and Patton, 2011) and student (AngelList, 2021; Pitchbook, 2022) ventures. Kenney and Patton (2011) credit the university's inventor-owned intellectual property (IP) policy for its strong performance in the number of faculty startups, but the IP policy is unlikely to have a direct effect on ventures launched by undergraduate students who generally do not conduct funded research and so have no obligation or incentive to report their business activities to their educational institution. We believe it is UW's cooperative education program, coupled with its high standards, that is responsible for its disproportionate success in terms of enabling alumni entrepreneurs. The cooperative education program provides complementary learning and networking opportunities and increases the likelihood of serendipitous opportunity identification. Nevertheless, replication of the cooperative education program without the attention to institutional quality may not yield the same results in terms of high-potential entrepreneurs, though it may provide learning benefits to students and their employers.

5.3. Limitations and future research

Our work is subject to limitations that point to opportunities for future research. The generalizability of our results is limited by the fact that the startups in our sample were founded by the graduates of the University of Waterloo. Future studies can examine the degree to which startups founded by the graduates of other universities bear the technological imprints of their educational experiences, thereby illuminating the student startup phenomenon and one of the mechanisms by which universities spur economic development. It may also be possible to trace the technology development activities of inventors to the R&D activities of their alma maters.

Investigations of the antecedents of ventures, including studies of imprinting, may be challenged by survival bias as ventures that do not survive may be excluded from samples. In our case, using Pitchbook data to identify ventures meant that ventures that had not attracted VC financing were excluded from our dataset and we also excluded ventures that had no patents. These omissions may have affected our estimates of the magnitude of the imprinting effect. If ventures that didn't raise funding and didn't patent are led by less capable entrepreneurs then, given our finding that the entrepreneur's capabilities are an important determinant of the magnitude of imprinting, the exclusion of less capable entrepreneurs means we may have over-estimated the magnitude of the average imprinting effect. The average student entrepreneur may absorb less of the R&D activities of influencer organizations than the entrepreneurs in our sample. A comprehensive qualitative study could overcome some of these biases by considering a broader range of student startups. It could also provide a richer understanding how student entrepreneurs build upon their educational experiences to identify and pursue entrepreneurial opportunities.

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CRediT authorship contribution statement

Margaret Dalziel: Conceptualization, Formal analysis, Methodology, Supervision, Writing – original draft. **Nada Basir:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Margaret Dalziel reports financial support was provided by Government of Canada Social Sciences and Humanities Research Council. The authors (Margaret Dalziel and Nada Basir) are employed by the University of Waterloo. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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