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When do serial entrepreneurs found innovative ventures? Evidence from patent data

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Abstract Experienced entrepreneurs are typically considered to be wellsprings of both wealth creation and innovation. However, given that prior research has provided evidence of an inverse relationship between economic performance and innovation performance, innovation performance of experienced entrepreneurs requires greater scrutiny. In this study, we examine the question: under what conditions do serial entrepreneurs produce impactful innovations in their subsequent ventures? Using data on 334 VC-funded companies, our study suggests that the familiarity garnered by founders through their prior industry experience may limit the venture's propensity to produce impactful innovation. Our findings contribute to the literature on serial entrepreneurship and innovation.

Keywords Serial entrepreneurship · Impactful innovation · Founder experience · Spillovers

JEL classifications L26 · O31 · O00 · O32

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1 Introduction

Experienced entrepreneurs are often considered to be the drivers of enterprise and change in industries (McGrath and MacMillan 2000). However, it is unclear when prior entrepreneurial experience influences the propensity of individuals to create innovative new ventures.[1] Even though prior entrepreneurial experience can increase the ability of entrepreneurs to pursue a broader choice set of lucrative opportunities (Gruber et al. 2008; Ucbasaran et al. 2008b, 2009) and create more successful ventures (Delmar and Shane 2006; Lafontaine and Shaw 2016), it may also make them more inclined towards exploiting their existing knowledge as opposed to exploring new ideas (March 1991) and to favor the conventional over more innovative approaches to solving problems (Baron and Ensley 2006; Audia and Goncalo 2007). As noted by Autio et al. (2014: p.1098), "The real question, then, … [is] not whether entrepreneurs innovate, but rather, when and where they do so."

We examine this question in the context of serial entrepreneurs (Westhead et al. 2005b, c; Parker 2014). Serial entrepreneurs—those individuals who have wholly or partly owned a business in the past and who then go on to found another new venture (Hyytinen and Ilmakunnas 2007)—are often lionized in the media and described as "economic artists…bringing together economic resources rather than putting paint on canvas"

[1] We conceptualize innovation as "a new idea, which may be a recombination of old ideas, a scheme that challenges the present order, a formula, or a unique approach" (Van de Ven 1986: 591).

(Chaplin 2001). Their rich experience and deep knowledge of entrepreneurship enable them to recognize and act on opportunities (Politis 2005), with greater potential to impact our economy and society as compared to first-time entrepreneurs (Eesley and Roberts 2012; Hyytinen and Ilmakunnas 2007).

Schumpeter (1934) argued that impactful innovations can lead to economic spillovers that may exert considerable influence on the state of an economy. Impact of innovations can be understood as the ongoing influence of ideas generated through inventions (Ghosh et al. 2013; Audia and Goncalo 2007) that underlie future innovations in the form of new technologies (Ahuja and Lampert 2001: 522).[2] While most inventions make no impact, a few may generate great value for society and serve as a harbinger for technological progress (Scherer and Harhoff 2000). Many prior studies have examined the implications of prior entrepreneurial experience on the subsequent survival and *economic performance* of the later venture (e.g., Delmar and Shane 2006; Gruber et al. 2008; Lafontaine and Shaw 2016; Paik 2014; Toft-Kehler et al. 2014; Eggers and Song 2015; Eesley and Roberts 2012), but it is unclear *when* prior entrepreneurial experience impacts the *innovation performance* of the later venture (for an exception, see Ucbasaran et al. 2009).[3] Hence, while most entrepreneurs are primarily interested in the economic performance of their ventures, the innovation performance of such ventures is also vital because it has the potential to generate spillovers in a Schumpeterian sense. Given that some prior work suggests an inverse relationship between innovation and economic performance of new ventures (Hyytinen et al. 2015), the innovation performance of ventures is an important area for further research.

Additionally, even though extant work has shown that prior entrepreneurial experience enables entrepreneurs to identify a greater number of market opportunities for their subsequent ventures (e.g., Gruber et al. 2008; McGrath and MacMillan 2000; Ucbasaran et al. 2008b) and the innovativeness of the opportunity identified (Ucbasaran et al. 2009), the conditions under which entrepreneurs are able to leverage these opportunities to create novel and impactful start-ups are still not clear. Thus, our broad research question is when do serial entrepreneurs produce high-impact innovations in their subsequent ventures? Investigating the relationship between prior entrepreneurial experience and innovation impact holds great potential to advance our ability to understand the various ways in which prior entrepreneurial experience influences value creation in new ventures. Our study synthesizes insights from the literatures on serial entrepreneurship (e.g., Eggers and Song 2015; Gruber et al. 2008; Ucbasaran et al. 2009), external knowledge sourcing (e.g., Franke et al. 2014; Jeppesen and Lakhani 2010; Gruber et al. 2013), and the cognition of innovation literature (e.g., Arts and Veugelers 2015; Audia and Goncalo 2007; Stuart and Podolny 1996).

Our study examines entrepreneurship in technologically intensive industries, where ventures typically emerge from unique technical insights and technology is the basis of entrepreneurial opportunity (Beckman et al. 2012). The extent of relatedness between the prior founding experience and the focal venture of the serial entrepreneur has been shown to influence the propensity of entrepreneurs to pursue novel opportunities (e.g., Audia and Goncalo 2007; Benner and Tushman 2003) and may influence how well they understand how to shape the opportunity (Gruber et al. 2013). Therefore, we answer the call by Ucsbasaran and colleagues (Ucbasaran et al. 2009: 112) to examine the role this important contingency plays in determining the innovativeness of ventures founded by serial entrepreneurs.

Our results have important implications for both theory and practice. Our study shows that an entrepreneur's choices of industry and technology across successive ventures can have contrasting implications for the innovation and economic performance of the later venture. By examining when serial entrepreneurs pursue the creation of innovativeness ventures, our study helps forge the link between the literature on the dark side of innovativeness in new ventures (e.g., Boyer and Blazy 2014; Buddelmeyer et al. 2010; Hyytinen et al. 2015; Reid and Smith 2000), and the literature on decision-making following business failure (Eggers and Song 2015; Gompers et al. 2010; Parker 2014), thus uncovering new avenues for research. Our findings demonstrate that not only is the value of experience

[2] We study innovation by examining the patenting activity (inventions) of the firms in our sample. Although patents represent an intermediate innovation output, they have been found to be highly correlated with alternative measures of innovation performance (Hagedoorn and Cloodt 2003) and as such are considered reasonable proxies of firm innovation performance in high tech industries by scholars (Harhoff et al. 1999; Jaffe and Trajtenberg 2002).

[3] The limited evidence on the implications of prior entrepreneurial experience on innovation performance has principally relied on self-reported survey data for measuring the innovativeness of the venture.

defined by its context as suggested by Dencker and Gruber (2015), but that, in some cases, the presence of some kinds of prior experience can diminish the value that can be potentially derived from other types of prior experience. This study also helps to deepen our understanding of the role of the individual in serial entrepreneurship, which is an important avenue for future research (Eggers and Song 2015; Ucbasaran et al. 2008a).

2 Theory

2.1 Significance of technology and industry contexts for new ventures

Many entrepreneurs express a commitment to innovation for their entrepreneurial pursuits. For example, a serial entrepreneur notes in a popular press article (Fallon 2015), "Serial entrepreneurship breeds intellectual curiosity. I like to think about it as innovation versus creation, where innovation is improving upon existing ideas and creation is starting fresh. Societal demands are constantly changing, and technology is continually advancing. However, there is a gap that takes place in leveraging these technology changes to properly address new demands…[S]erial entrepreneurs are focused on creation and leveraging these technologies to create new solutions optimized to address the market need." However, research also suggests that entrepreneurial experience can reduce entrepreneurs' focus on innovation-related considerations such as novelty of the idea, superiority of the product/technology, or potential to change an industry (Baron and Ensley 2006). In this study, we suggest that the extent of relatedness across technology and industry contexts in successive ventures play a key role in shaping the conditions that define the innovativeness of firms founded by serial entrepreneurs.

Technology and industry are widely acknowledged as key contexts influencing entrepreneurial innovation (Autio et al. 2014). The *technological context* of the venture is defined by its knowledge landscape, encompassing the different technologies that underlie the venture's technology (Rosenkopf and Almeida 2003: 752; Agarwal et al. 2004). Familiarity with a technology imparts an understanding of how the technology works and makes it easier for entrepreneurs to troubleshoot problems with product development, increase predictability of the development process, and anticipate customer experience and ease of use of the technology (Gruber et al. 2013; Meyer and Roberts 1986). Prior research has indicated that a deep understanding of their core underlying technology enables firms to "generate new scientific discoveries and technological breakthroughs" (Agarwal et al. 2004: 503). Such an understanding also enhances firm competitiveness by enabling them to maximize product performance through finding the optimal combination of functionality, cost, and reliability (Rosenberg 1994) and by improving firms' ability to respond to product improvements by competitors (Cohen and Levinthal 1990). In the context of serial entrepreneurship, this process may be facilitated by an entrepreneur's pursuit of the commercialization of a product based on a familiar technology in their subsequent new venture (Eesley and Roberts 2012; Gruber et al. 2013).

The *industry context* of a venture is defined by the customer wants, needs, and processes around which the entrepreneurial action occurs (Cooper et al. 1995; Wennberg et al. 2011; Wiklund and Shepherd 2003). Users of new technologies are unlikely to be able to articulate their needs, and hence an entrepreneur's understanding of what the customer needs is often the basis of real market opportunities (Shane 2000). For example, Shane (2000) studied how the same technology 3DPTM, licensed by MIT, was commercialized in 8 different markets, depending on heterogeneity across entrepreneurs' assessment about the potential market for the technology. Moreover, an understanding of customer needs and willingness to pay enables an accurate assessment of the attractiveness of entrepreneurial opportunities in specific markets (Kirzner 1997). Greater industry relatedness can endow entrepreneurs with valuable industry-specific knowhow about important technologies, prevalent business strategies, competitive landscape, employment practices, customer preferences, relationships with suppliers and distributors, etc. (Helfat and Lieberman 2002; Cooper et al. 1994). When the entrepreneur operates in an industry they are familiar with, they are more likely to be able to leverage past relationships or other ties with key stakeholders such as customers, suppliers, distributors, channel partners, and financial resource providers within the industry setting (Cooper et al. 1994; Delmar and Shane 2006; Eesley and Roberts 2012). These insights, which are usually tacit in nature, are often vital for successfully exploiting an opportunity and are not likely to be available to outsiders inexperienced with industry norms (Delmar and Shane 2006).

In sum, prior entrepreneurial experience provides serial entrepreneurs with both general knowledge related to entrepreneurial process and specific knowledge about the technology and industry targeted by the new venture. Since some aspects of prior entrepreneurial knowledge are specific to the technology and industry contexts, the relevance and value of that knowledge for improving the later venture's outcomes is contingent on the extent of its relatedness to prior ventures.

2.2 Implications of changing context

One important factor exposed by prior research is that a significant number of serial entrepreneurs change key aspects of their venture context, such as industry, when they initiate subsequent ventures (Eggers and Song 2015; Gompers et al. 2010). Given the strong learning benefits associated with starting a subsequent venture in a familiar context (Eesley and Roberts 2012), this choice of changing context does appear to be curiously unproductive. Entrepreneurs who pick familiar venture contexts as opposed to more novel ones are better able to look to the past to formulate expectations of future states, thus lowering the overall uncertainty they face. Eggers and Song (2015) suggested that such behavior could be driven by prior venture failure. They argued that serial entrepreneurs who experience business failure are likely to attribute the failure to factors outside the entrepreneur's control, leading them to change the contexts such as industry in later ventures. Such substantive changes in venture context are likely to lead to detrimental performance outcomes for serial entrepreneurs—including the failure of the entrepreneur's later venture (Eggers and Song 2015)—and may well lead to "performance persistence" in entrepreneurship (Gompers et al. 2010). However, it remains to be explored how such changes in venture context impact the innovativeness of the subsequent ventures founded by the serial entrepreneur.

2.3 Technology relatedness and innovation impact

Development of novel applications in technology ventures is typically aided by familiarity with the underlying technology (Gruber et al. 2013). This familiarity comes from acquiring knowledge about specific technologies that individuals have worked on in their prior inventions, which not only enriches their knowledge of successful and unsuccessful combinations of technology components, but also stimulates insight into how to reuse the components to create novel but useful technological combinations (Arts and Veugelers 2015; Cohen and Levinthal 1990; Hargadon 2003) Familiarity with the technology allows entrepreneurs to build on their existing knowledge, reduce large upfront developmental costs (Winter et al. 2007), and make successful deployment of the technology in the market more likely (Gruber et al. 2013). The process of applying technological knowhow to new applications—termed "technology leveraging" (Gruber et al. 2013)—involves two steps: (i) developing an abstract understanding of the firm's technological base and functionality, delinked from any specific product application; and (ii) relinking the technological resources (potentially refined and reconfigured) to new industries and applications (Danneels 2002; Galunic and Rodan 1998). Technology leveraging is significantly harder when individuals have low familiarity with the focal technology since the low technology familiarity translates into a weaker ability to apply the technology in novel ways (Gruber et al. 2013; Menon and Pfeffer 2003). Although individuals with low technology familiarity are likely to engage in exploratory search for new technological combinations, their *capacity* to identify promising combinations of technological components in the vicinity of an entity's existing knowledge base is much weaker (Arts and Veugelers 2015). This may result in lower quality technological combinations being generated which are less likely to generate impactful knowledge (March 1991; Stuart and Podolny 1996).

In the context of serial entrepreneurship, the serial entrepreneur is more likely to be familiar with the underlying technology of the venture when there is high relatedness in the technology domains across successive ventures they founded. Conversely, serial entrepreneurs are less likely to be familiar with the underlying technology of the venture when there is low relatedness in the technology domains across successive ventures they founded. Applied to this context, the above discussion suggests that when serial entrepreneurs start new ventures in less related technological domains, they are less likely to achieve impactful innovations as compared to serial entrepreneurs who venture out into more related technological domains for their subsequent ventures.

As technology relatedness increases, so does the capacity to identify novel and useful combinations of technological components (March 1991; Stuart and Podolny 1996; Arts and Veugelers 2015). For serial entrepreneurs, when the degree of technology familiarity across their successive ventures is high, it implies a concomitant increase in their ability to translate exploratory search into impactful knowledge (Audia and Goncalo 2007). We argue that the increasing technology familiarity will be accompanied by an increasing *propensity* to exploit this existing knowledge. This is because individuals with high levels of familiarity with a specific knowledge domain are more likely to favor exploitation when creating new knowledge (March 1991; Stuart and Podolny 1996). This knowledge search strategy has lower uncertainty and higher reliability of outcomes (Katila and Ahuja 2002), making impactful innovations more likely (Arts and Veugelers 2015).

However, at very high levels of technology relatedness, there is a very high propensity to exploit existing knowledge with minimal exploration of new technological combinations. This can stymie innovation by reducing the number of available technological combinations, thereby yielding incremental rather than novel ideas (Audia and Goncalo 2007). In this scenario, the limited scope of ideas makes the generation of impactful innovations less likely (Rosenkopf and Nerkar 2001; March 1991).

In sum, we argue that increased capacity for technology leveraging at higher levels of technology relatedness may lead to an initial positive relationship between the extent of technology relatedness between successive ventures founded by a serial entrepreneur and the potential for innovation impact. However, we also argue that when the extent of relatedness between prior and later ventures is too high, this effect could reverse and turn negative due to the entrepreneur's concomitantly increasing propensity to exploit available technological resources. Hence, we expect an inverted U–shaped relationship between the extent of technology relatedness across the serial entrepreneur's prior and later ventures and the innovation impact of the later venture. This leads to our first hypothesis:

Hypothesis 1: Technology relatedness between prior and later ventures is curvilinearly (inverted U shaped) associated with later venture's innovation impact.

2.4 Industry relatedness and innovation impact

Several studies in the entrepreneurship and innovation literatures offer preliminary evidence that greater industry knowledge can attenuate creativity by increasing a founder's embeddedness within industry routines and increase their propensity to exploit existing industry technological knowhow. For example, prior research has shown that the greater the distance between the industry context of the problem and the problem solver, the greater the novelty of the ideas (Franke et al. 2014; Poetz et al. 2014). Specifically, when comparing the novelty of ideas generated by roofers, inline skaters, and carpenters to improve the comfort and use of carpenters' safety gear, it was the inline skaters—the group farthest from the context of the target problem—who came up with the most innovative ideas, with the carpenters providing the least innovative solutions (Franke et al. 2014). Exposure to new domains can enable individuals to break perceptual set (Katona 1940), avoid "functional fixedness" (Duncker 1945), explore new cognitive pathways by increasing one's "network of possible wanderings" (Newell and Simon 1972), and critically peruse well-used performance "scripts" (Amabile 1998). A quotation from the Nobel Prize–winning social entrepreneur and founder of the Grameen Bank, Muhammad Yunus, illustrates this idea well. Recounting what he thought enabled him to found the bank, Yunus said, "The most important thing, I feel, is that I knew nothing about banking…that way, I could create this [Grameen Bank]. If I was trained as a banker, it would be impossible to do things that I do now because the mind will say, 'No, No, you are not supposed to do that, that's not banking'" (Yunus 2007). Indeed, Ben-David (1960, p.557) notes, "[I]nventions are usually made by outsiders, that is, by men who are not engaged in the occupation which is affected by them and are, therefore, not bound by professional customs and traditions."

Although research reviewed earlier in this paper has indicated several mechanisms by which founders' higher familiarity with a focal industry can benefit a focal firm's *economic* performance, these benefits do not necessarily translate into *more impactful innovation* outcomes. This is because increasing familiarity with industry norms and key players and deeper understanding of a target market's needs is more likely to increase a founder's embeddedness within industry routines and increase their propensity to exploit existing industry technological knowhow, rather than to challenge it through novel applications (Aldrich and Kenworthy 1999; Franke et al. 2014; Audia and Goncalo 2007). Hence, we expect the influence of industry relatedness on innovation impact to be linearly negative.

Hypothesis 2: Industry relatedness between prior and later ventures is negatively associated with later venture's innovation impact.

2.5 Interactive effect of technology and industry relatedness on innovation impact

In our first hypothesis, we suggested that technological relatedness is curvilinearly related to innovation impact. This is because some familiarity with the underlying technology is necessary to help the founder have a thorough understanding of its properties and limitations (Danneels 2002; Galunic and Rodan 1998). This strengthens their *capacity* to identify promising combinations of technological components in the vicinity of an entity's existing knowledge base increases which can enable the entrepreneur to develop a more varied opportunity set of potential solutions for the target market (Danneels 2007; Gruber et al. 2013). However, when the technology relatedness is very high, it can lead to an increasing *propensity* to exploit this existing knowledge in future innovation efforts thereby stymieing the problem-solving process by constraining the solution set to mental schemes and problem-solving strategies that have proven helpful in the past (Jeppesen and Lakhani 2010). This can impede the venture's capacity to produce truly novel solutions (Audia and Goncalo 2007; Chrysikou and Weisberg 2005). The two counteracting forces lead to the curvilinear influence of technological relatedness on innovation impact. In our second hypothesis, we argued that there is a negative relationship between industry relatedness and innovation impact, since higher levels of industry relatedness are associated with both greater levels of embeddedness within existing industry norms and ideas and lower exploration of new technological ideas and applications, thus making the generation of impactful innovations less likely. We now bring these two hypotheses together to discuss the interactive relationship between technology and industry relatedness on innovation impact.

We suggest that high levels of industry relatedness strengthen the entrepreneur's propensity towards exploitation of existing technological knowledge, thereby resulting in a less pronounced positive relationship hypothesized between lower levels of technology relatedness and innovation impact. High industry relatedness between successive ventures started by the serial entrepreneur is associated with greater awareness of industry norms, key players, and needs of the target market (Cooper et al. 1994; Delmar and Shane 2006). This awareness is likely to further increase a founder's embeddedness within industry routines and increase their propensity to exploit their technological knowledge to create solutions that best align with existing industry technology standards (Aldrich and Kenworthy 1999; Baron and Ensley 2006). Thus, high industry relatedness is likely to strengthen the founder's propensity to rely on known technological combinations as opposed to exploring novel combinations of technology components. This propensity for exploitation is likely to reduce the novelty and impact of the ideas that they generate (Levinthal and March 1993; March 1991, 2011).

In contrast, low industry relatedness across ventures founded by the serial entrepreneur could benefit the innovativeness of the subsequent venture in two ways. First, low industry relatedness can enable individuals to avoid deterrents to creative thinking such as functional fixedness (Duncker 1945) and engage in problem-solving with an open mind, leading to more innovative solutions (Franke et al. 2014). For example, in a study designed by 3M to find ways to reduce infections after surgery, the most innovative and helpful idea was provided by a specialist in theatrical makeup, who was also knowledgeable about approaches to dealing with facial skin infections (Lilien et al. 2002). Second, low industry relatedness is likely to catalyze entrepreneurs to be more willing to explore new ideas and novel applications (Austin et al. 2012; March 1991; Merton and Barber 2004). Indeed, as shown by Gruber et al. (2013), possessing lower levels of industry familiarity but high levels of technology familiarity can allow entrepreneurs to break through the "prior knowledge corridor" and identify more varied opportunity sets. This reasoning suggests that when serial entrepreneurs found later ventures characterized by high levels of technology relatedness and low levels of industry relatedness, it creates conditions that can lead to the discovery of novel innovations that are impactful.

In sum, we suggest that while technology relatedness has a curvilinear relationship to innovation impact, this relationship will be attenuated when a serial entrepreneur's successive ventures are situated in highly related industries. This is because greater industry relatedness may strengthen the entrepreneur's propensity to exploit existing knowledge of technological combinations to conform to existing industry norms but thereby making the generation of impactful innovations less likely. Conversely, when a serial entrepreneur's successive ventures are situated in less related industries, the lower industry relatedness may weaken the entrepreneur's propensity to exploit existing knowledge of technological combinations, thus prompting exploratory search for new technological combinations and thereby making the generation of impactful innovations more likely. This leads to the following hypothesis:

> *Hypothesis 3: Industry relatedness moderates the inverted U-shaped relationship between technology relatedness and innovation impact in such a way that the inverted U-shaped relationship will be flatter in ventures with high industry relatedness than those with low industry relatedness.*

3 Data and research methodology

3.1 Sample and data sources

Our data consist of all US-based venture capital (VC)–funded firms, drawn from the Dow Jones Venture Source database, that were started by serial entrepreneurs in the period 1990 to 2005, spanning six knowledge-intensive industries: biopharmaceuticals, communications and networking, software, medical devices and equipment, semiconductors, and electronics and computer hardware. In constructing this sample, to maintain our focus on serial entrepreneurs, we only consider firms where the entrepreneur founded firms one after another within the study time period, as opposed to taking a portfolio approach (Westhead and Wright 1998; Westhead et al. 2005a). Portfolio entrepreneurs, who run multiple businesses concurrently, have different incentives, needs, and aspirations than serial entrepreneurs (Carter and Ram 2003; Sarasvathy et al. 2013; Westhead et al. 2005b; Parker 2014). Given our focus on understanding how the extent of relatedness between successive ventures founded by an entrepreneur impacts the venture's innovation performance, we limit our sample to include only serial entrepreneurs to minimize unnecessary heterogeneity in our sample. We supplement the founder data obtained from Venture Source with data on (a) venture capital investments from the ThompsonOne VentureXpert database, which is an established source for venture capital investment data (Kaplan and Lerner 2017), and (b) patent data on the founders' firms from USPTO. We include only those firms for which reliable performance data and patent data were available.[4] The resulting sample consists of 334 firms founded by 160 serial entrepreneurs, giving us 182 entrepreneur-company dyads, where each dyad represents the serial entrepreneur and the firm she founded. Although our primary sample includes firms founded by entrepreneurial teams, we rely on prior studies (e.g., Gruber et al. 2008) that indicate that serial entrepreneurs have a large influence on the search behavior of other founding team members. In robustness tests, we also test whether our results hold when we consider (a) those firms that have only one founder (solo-founded) and (b) those firms whose entrepreneurs have had only one prior founding experience and the results stayed consistent.

[4] Firms were considered to have unreliable performance data when the outcome from the prior venture was not established prior to the founding of the later venture.

3.2 Dependent variable

Innovation impact We follow prior research in the innovation literature by measuring innovation impact through 5-year citation counts (excluding self-citations) of patents granted to the ventures (e.g., Basu et al. 2015; Kortum and Lerner 2000; Arts and Veugelers 2015; Conti et al. 2013). The number of citations received by a patent is a measure of its technological importance (Albert et al. 1991) as well as its value to the firm (Harhoff et al. 1999).

3.3 Independent variables

Industry relatedness We use two alternate measures of industry relatedness that are drawn from prior literature. Our primary measure of industry relatedness is based on the Standard Industry Classification (SIC) code of the successive ventures founded by the focal serial entrepreneur. This measure is operationalized by creating a binary variable that is set to one if the two ventures are in the same 2-digit SIC code, and zero otherwise (Pahnke et al. 2015; Palepu 1985). In alternate models, we also test our model for 1-digit SIC code overlap as well as the inter-industry relatedness index developed by Bryce and Winter (2009) to assess the extent to which two successive ventures launched by a focal serial entrepreneur share known resource synergies. Our results are consistent across the different model specifications.

Technology relatedness We conceptualize technology relatedness as the distance between the knowledge domains spanned by the entrepreneur's two successive ventures, as captured by their patent filings. This measure is operationalized as the *Euclidean distance between patent classes* (Rosenkopf and Almeida 2003).

We construct this measure using the patent class information for each patent filed by the two ventures in the first five years after founding. Technology relatedness is then calculated as:

$$\left(\sqrt{\sum_i (\text{focal venture patent proportion} - \text{prior venture patent proportion})_i^2}\right.$$

where i is a distinct patent class and *patent proportion* refers to the proportion of patents in a specific patent class relative to all patents filed by the venture. The results are standardized to provide a continuous scale from 0 to 1. We then reverse-code these values such that values close to 0 reflect low technology relatedness and values close to 1 reflect high technology relatedness across successive ventures founded by a focal entrepreneur.

3.4 Control variables

We control for the *later venture's number of patents*, and the amount of venture capital funding received (*funding amount*) by the later venture. We logged the funding variable in order to correct for skewness of its distribution. To control for the entrepreneur's prior experience, we control for the number of prior ventures founded, *venture count*, and the performance of the immediate prior venture, *prior venture success* and *prior venture innovation impact.* Following prior literature (e.g., Arora and Nandkumar 2011; Eesley et al. 2014), we code prior venture success as a binary classification scheme to group firms as successful or unsuccessful.[5] Prior venture innovation impact is coded along the same lines as the dependent variable. To account for entrepreneur's innate *talent*, we follow Eesley and Roberts (2012) and compute this measure by running a regression with individual entrepreneur-level fixed effects on the aggregate amount of venture capital funding obtained by the entrepreneur over successive ventures.[6] The fixed effects thus obtained are then saved and utilized as a measure for talent in the main regression model. We control for the *time elapsed* between founding of the two successive ventures (Toft-Kehler et al. 2014; Amaral et al. 2011). Using data from the NBER zip-code-distance database, we control for the *geographical distance* (Stuart and Sorenson 2003; Toft-Kehler et al. 2014) between the two successive ventures, calculated as the physical distance between the zip codes associated with the founder's successive ventures. We control for team size and the functional and educational diversity of founding team members, which were operationalized using the Blau (1977) index.[7] Finally, we incorporate dummy variables to capture industry-level and geographic heterogeneity.

3.5 Addressing Endogeneity concerns

Prior research (e.g., Eggers and Song 2015) has identified prior venture failure as a key driver for changing venture contexts that may also be associated with the focal venture's performance. This would suggest that entrepreneurs with lower human capital are likely to experience venture failure and then change the venture context of the later venture. To test this idea, we ran an ordinary least squares regression predicting the level of industry and technology relatedness between the serial entrepreneur's successive ventures based on the outcome of the prior venture and various human capital indicators.[8] The results of this regression are summarized in Table 1. We find that, while prior venture success is significantly related to greater industry relatedness across successive venture contexts, there is no association between prior venture performance and technology relatedness between successive ventures. Instead, technology relatedness is significantly associated with being actively involved in technology generation as an inventor. Since this association between prior venture performance and industry relatedness may be endogenous with the venture's performance (Eggers and Song 2015), we take several steps to account for it.

First, following prior research (Aggarwal and Hsu 2013; Pahnke et al. 2015), we undertake a matching approach through coarsened exact matching (CEM) to match ventures whose founders had failed versus those whose founders had succeeded in the prior venture.

[5] A firm is considered successful if either of the following events occurred: (i) the firm went public, or (ii) the firm was acquired in a deal whose purchase price was greater than the total amount of capital raised by the firm. Successful firms were coded as 1 and unsuccessful firms were coded as 0.

[6] These consisted of indicators of the serial entrepreneurs' human capital including education (type and number of educational degrees), inventor status (binary variable indicating whether or not the entrepreneur was an inventor), and work experience (type and number of years).

[7] Functional categories included were finance and accounting, production and operations, technology development, marketing, and general management. Educational categories included were Ph.D., masters, undergraduate degree, and other.

[8] The variables for the type of founder education were coded as binary variables while the variables for the number of prior experiences were coded as count variables.

Table 1 Predicting industry and technology relatedness between serial entrepreneur's prior and later ventures

	Model 1 Industry relatedness	Model 2 Technology relatedness
Time elapsed	0.028	−0.010+
	(0.086)	(0.005)
Geographical distance	0.000	−0.000
	(0.000)	(0.000)
Total funding	−0.095	0.037**
	(0.176)	(0.011)
MD	0.649	0.006
	(0.766)	(0.054)
Ph.D.	0.306	0.009
	(0.524)	(0.034)
MBA	−0.905	−0.070
	(0.565)	(0.044)
Master's	−0.210	0.053
	(0.472)	(0.039)
Inventor	−0.402	0.093**
	(0.435)	(0.034)
Talent	0.009	−0.003
	(0.076)	(0.005)
Prior venture count	−0.339**	0.007
	(0.124)	(0.007)
Prior venture success	0.934*	0.019
	(0.392)	(0.031)
Team size	−0.026	−0.022+
	(0.166)	(0.012)
Team diversity (functional specialization)	−1.660*	0.020
	(0.729)	(0.057)
Team diversity (educ. level)	−0.593	−0.041
	(0.826)	(0.063)
Constant	3.361+	0.522***
	(1.746)	(0.090)
Industry dummies	Yes	Yes
Location dummies	Yes	Yes
Observations	175	175
Log likelihood	−97.74	
Pseudo *R*-squared	0.196	
R-squared		0.303

Model specification—model 1: logistic regression; model 2 specification: OLS regression; robust standard errors in parentheses (). ***$p < 0.001$; ** $p < 0.01$; * $p < 0.05$; +$p < 0.1$, two-tailed *t* tests

Iacus et al. (2009) note that CEM has beneficial statistical properties, such as fewer assumptions and lower bias, than other comparable matching techniques. To implement this, we exact-matched our data using three criteria, i.e., industry, geography, and founding year, while ensuring that, for every venture in our sample whose founder had experienced prior venture failure (treatment), we incorporate at least one "matched" firm whose founder had experienced prior venture success. Through this process, our sample size dropped from 182 to 175 observations. Our analysis reported here is based on these 175 observations, though using all 182 observations yields similar results.

Second, we apply an instrumental variable strategy centered on the general availability of financial resources in the prior industry context for a focal serial entrepreneur. The literature in entrepreneurship has underscored that availability of industry-level financing is an important driver of industry choice (Hsu 2007; Shane and Cable 2002), yet the availability of industry-level financing cannot be theoretically associated with the eventual performance of the later venture. As a result, we follow Hamilton and Nickerson (2003) and use a two-stage least squares model to account for the potentially endogenous decision to change industries across successive venture contexts. To proxy for funding availability in the industry of the prior venture, we draw on data from VentureXpert and calculate the amount of funding disbursed by venture capitalists in the four-digit SIC code pertaining to the industry associated with the prior venture, one year prior to the launch date of the later venture. In the first stage of the model, we regress industry relatedness against the logged amount of funding available based on the record of VC financing activity in the industry associated with the prior venture. We use the ivreg2 command in Stata 14 to test for instrument quality. Our instrument is "strong," based on the size of the F statistic and the significance of the Kleibergen-Paap rk LM statistic (Stock and Yogo 2005). The residuals obtained from this first stage are used to proxy for the choice of industry relatedness free of the influence of financing constraints. In the second stage of the model, we regress the later venture performance variables against the controls and then incorporate the independent variables of interest. The following sections explain our analysis in more detail.

4 Analysis and findings

Our dependent variable, innovation impact, is derived from patent citation data and takes on only non-negative values and is a count variable. Since a likelihood ratio test indicated overdispersion, we used the negative binomial regression for the analysis (Greene 2003).

Table 2 provides the pairwise correlation matrix and descriptive statistics of the variables in the study. An inspection of the correlations does not reveal any multicollinearity concerns. However, to rule out potential concerns about multicollinearity due to the presence of interactions in the regression models, we examined the variance inflation factor (VIF) for the full model. The VIF values give an indication of the correlation of each variable with other regressors included in the model that could potentially inflate the variance of the estimated coefficient for that variable. Typically, VIF values less than 10 indicate that multicollinearity is not a concern in the regression model (Kennedy 2008). For our full model, the mean VIF value is 1.31 and the maximum is 1.92, suggesting that multicollinearity is not a serious problem in the analysis.

Table 3 presents the results of the negative binomial regression on innovation impact of the later venture. In Table 3, model 1 is the baseline model with only control variables. Models 2 and 3 introduce respectively the linear and squared term pertaining to technology relatedness. Model 4 introduces the direct effect of industry relatedness. Model 5 introduces the interaction between technology and industry relatedness. For a conservative test of the study's hypotheses, we evaluated all results using two-tailed t tests and robust standard errors.

Hypothesis 1 predicted that technology relatedness should have a curvilinear relationship with later venture innovation impact. In model 3 (Table 3), the coefficient of the linear term for technology relatedness is positive and significant (model 3; $\beta = 12.56$; $p < 0.001$) while the squared term is negative and significant (model 3; $\beta = -8.62$; $p < 0.01$). We verified that the inflection point lay within the range of the data and the slopes on both sides of the inflection point are significant (Haans et al. 2016). Thus, hypothesis 1 is supported. Figure 1 is a graphical representation of the relationship between technology relatedness and new-venture innovation impact. Interestingly, the results show an optimal technology relatedness of approximately 0.7, suggesting that a mix of familiar and unfamiliar technologies is most optimal for developing impactful innovations.

Hypothesis 2 proposed that industry relatedness across successive ventures started by a serial entrepreneur should be negatively associated with later venture innovation impact. We do not find that industry relatedness between the two ventures has a significantly negative influence on later venture innovation impact (model 4, $\beta = 0.02$, $p > 0.1$). Hence, hypothesis 2 is not supported.

Model 5 in Table 3 includes the interaction between industry and technology relatedness and its impact on innovation impact. The first interaction term is positive and significant (model 5, $\beta = 22.23$, $p < 0.05$), and the second is negative and significant (model 5, $\beta = -19.35$, $p < 0.05$). Figure 2 provides a graphical representation of this relationship and shows that the inverted U-shaped relationship between technology relatedness and innovation impact has a steeper slope for firms with low industry relatedness than for firms with high industry relatedness, thus providing graphical evidence for H3.

4.1 Additional analysis

As mentioned previously in our paper, we ran our models with an alternative operationalization of industry relatedness, the inter-industry relatedness index (Bryce and Winter 2009). The results of this analysis were consistent with our main analysis and are reported in Table 4 (models 1 and 2). To address the possibility that our results may be confounded by the number of prior ventures started by the entrepreneur, we test our hypotheses on the subset of firms whose founders had only one prior founding experience. This limited the sample to 94 entrepreneur-company dyads. The results for these tests were consistent with our previously reported analysis (Table 4, model 3). Since our results could also be confounded by the size of the entrepreneurial team, we re-ran our analysis on the set of entrepreneurs with only solo founding experiences, which limited our sample to 41 entrepreneur-company dyads.[9] The results were consistent with our main analysis (Table 4, model 4). Our findings were also supported when we used an alternative operationalization for the dependent variable and used the *average* number of patent citations per firm patent as opposed to the sum of all citations to a focal venture's patents.[10]

In additional analysis, we evaluated whether our variables of interest—technological and industry relatedness between successive ventures—can also explain

[9] Given the small size of this sample, we were unable to get the models to converge with all our control variables intact. Hence, we dropped the location and industry dummies to obtain the regression estimates for this model.

[10] These results are available from the authors on request.

Table 2 Correlation table[a]

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Innovation Impact	123.34	260.88	1																	
2	Technology relatedness	0.59	0.2	0.12	1																
3	Industry relatedness	0.58	0.49	−0.03	0.12	1															
4	Time elapsed	4.24	2.78	−0.07	−0.14	0.05	1														
5	Geographical distance	311.68	703.79	−0.05	−0.03	0.01	−0.16	1													
6	Total funding	3.59	1.19	0.18	0.23	−0.08	−0.01	0.01	1												
7	Talent	1.68	2.72	0.19	0.01	0	−0.09	−0.05	−0.05	1											
8	MD	0.1	0.3	0.13	0.05	0.12	0.06	0.01	0.08	0.02	1										
9	Ph.D.	0.42	0.5	0.12	0.13	0.1	−0.18	−0.01	0.1	0.06	0.03	1									
10	MBA	0.14	0.35	−0.09	−0.2	−0.12	0	−0.01	−0.04	−0.09	−0.02	−0.28	1								
11	Master's	0.3	0.46	−0.05	0.04	−0.03	0.05	−0.04	0.01	−0.09	−0.09	−0.51	0.09	1							
12	Inventor	0.71	0.46	0.11	0.23	0.05	0.05	−0.02	−0.13	−0.03	0.21	0.22	−0.17	−0.1	1						
13	Venture count	1.9	1.43	0.18	0.03	−0.15	−0.07	0.06	0.13	−0.02	−0.05	0.03	0.03	−0.04	−0.09	1					
14	Prior venture success	0.59	0.49	−0.07	0.01	0.16	0.16	−0.01	0.01	−0.04	0.11	−0.02	−0.03	−0.04	0.08	0.02	1				
15	Team size	2.47	1.19	−0.01	−0.1	0.01	0	−0.01	0.06	−0.03	−0.05	0.08	−0.09	0.06	−0.08	0.07	0.03	1			
16	Team diversity (func.)	0.45	0.26	0.13	0.06	−0.14	0.06	0.01	0.02	0.1	0.01	−0.14	0.05	0.02	0	0.06	0.14	0.05	1		
17	Team diversity (educ. lev.)	0.32	0.23	0.1	−0.04	0.01	0	−0.08	−0.01	−0.03	−0.04	0.05	−0.07	0.1	0.11	0	0	−0.05	−0.07	1	
18	Patent count	14.68	18.5	0.65	0.17	−0.07	−0.03	0	0.22	0.11	0.02	0.08	−0.01	−0.08	−0.02	0.12	−0.08	−0.16	0.11	0.06	1
19	Prior venture innovation impact	117.7	305.42	0.08	0.11	−0.03	0.21	0.1	−0.01	−0.12	0.09	−0.05	0.06	0.04	0.09	0.04	0.19	−0.07	0.14	0.03	0.13

Correlations equal to or greater than 0.20 are significant at the 0.05 level

Table 3 Analysis of innovation impact of ventures founded by serial entrepreneurs

	Model 1	Model 2	Model 3	Model 4	Model 5
Technology relatedness—H1		2.891***	12.564***	12.543***	9.162*
		(0.851)	(3.694)	(3.694)	(4.290)
Technology relatedness squared—H1			− 8.625**	− 8.629**	− 5.458
			(3.319)	(3.321)	(3.794)
Industry relatedness—H2				0.029	− 5.761*
				(0.287)	(2.546)
Technology relatedness × industry relatedness—H3					22.232*
					(9.436)
Technology relatedness squared × industry relatedness—H3					− 19.351*
					(8.410)
Time elapsed	− 0.122**	− 0.106*	− 0.139**	− 0.139**	− 0.128*
	(0.047)	(0.046)	(0.048)	(0.048)	(0.051)
Geographical distance	− 0.000*	− 0.000	− 0.000+	− 0.000+	− 0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total funding	0.315***	0.180+	0.218*	0.221*	0.174+
	(0.094)	(0.101)	(0.098)	(0.105)	(0.103)
Talent	0.041	0.029	0.039	0.039	0.035
	(0.052)	(0.049)	(0.050)	(0.050)	(0.051)
Venture count	0.114	0.140	0.138	0.140	0.167
	(0.113)	(0.112)	(0.111)	(0.112)	(0.128)
Prior venture success	− 0.456+	− 0.401	− 0.256	− 0.250	− 0.385
	(0.239)	(0.244)	(0.242)	(0.244)	(0.274)
Team size	0.097	0.201+	0.102	0.100	0.063
	(0.118)	(0.115)	(0.130)	(0.133)	(0.135)
Team diversity (functional specialization)	− 0.070	0.072	− 0.078	− 0.073	− 0.086
	(0.552)	(0.550)	(0.540)	(0.537)	(0.547)
Team diversity (educ. level)	− 0.102	− 0.026	− 0.138	− 0.137	0.029
	(0.704)	(0.658)	(0.686)	(0.686)	(0.686)
Patent count	0.075***	0.073***	0.070***	0.069***	0.072***
	(0.012)	(0.010)	(0.009)	(0.009)	(0.009)
Prior venture innovation impact	− 0.000	− 0.001*	− 0.000	− 0.000	− 0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.249	− 1.111	− 3.266**	− 3.266**	− 2.075
	(0.813)	(0.906)	(1.102)	(1.102)	(1.350)
Industry/location dummies	Yes	Yes	Yes	Yes	Yes
Observations	175	175	175	175	175
Log likelihood	− 735.5	− 731.3	− 728.8	− 728.6	− 726.7
Pseudo *R*-squared	0.082	0.090	0.094	0.095	0.010

Model specification—negative binomial; robust standard errors in parentheses (). ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$, two-tailed t tests. Values of industry relatedness are residuals (Y-Ypredicted) from the stage 1 estimation

the *economic performance of the later ventures*. We operationalize economic performance of later ventures by a successful venture exit (Arora and Nandkumar 2011; Eesley et al. 2014). A firm is considered successful if either of the following events occurred: (i) the firm went public or filed to go public by August 2015, or (ii)

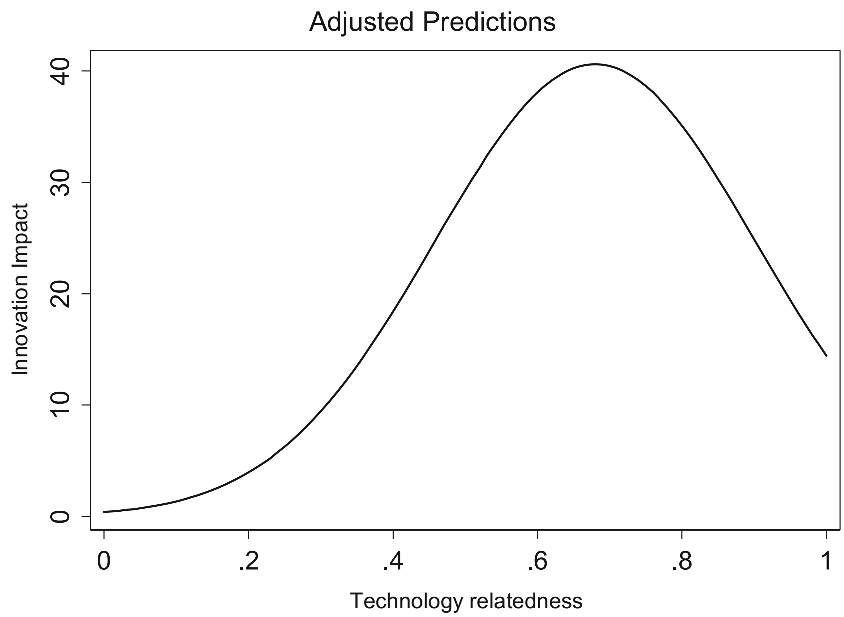

Fig. 1 Plot of the curvilinear relationship between technology relatedness and innovation impact

the firm was acquired in a deal where the purchase price was greater than the total amount of capital raised by the firm. Since economic success is a binary variable, we used logistic regression for this analysis, presented in Table 5.

Table 5, model 1 presents the results for the regression of the control variables on later venture's economic success, as demonstrated through a successful exit. As may be expected, the size of funding received from venture capitalists is strongly predictive of economic success. Similar to prior studies (e.g., Eesley and Roberts 2012; Gompers et al. 2010), we note the significance of the talent variable, suggesting that an entrepreneur's innate ability may have a significant influence on the venture's potential to achieve economic success. We also find that greater amounts of funding and the success of the prior venture as well as greater diversity in the educational specialization of the founding team are predictive of economic success. Models 2 and 3 incorporate the direct effect of the linear and curvilinear specification of technology relatedness. We find that technology relatedness is positively associated

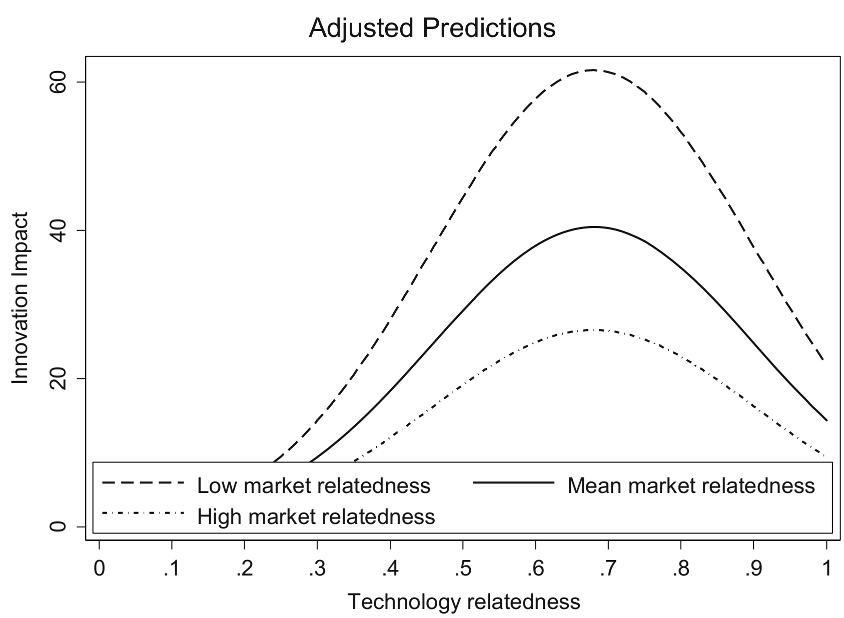

Fig. 2 Plot of the effect of technology and industry relatedness on innovation impact

Table 4 Robustness checks—analysis of innovation impact

	Model 1	Model 2	Model 3	Model 4
Technology relatedness—H1	12.859**	9.157+	3.387	8.074
	(3.918)	(4.733)	(4.532)	(14.879)
Technology relatedness squared—H1	− 9.831**	− 7.015+	− 0.429	− 7.646
	(3.349)	(4.238)	(3.942)	(11.138)
Industry relatedness—H2	− 0.165*	− 2.066**	− 4.169	− 16.447
	(0.082)	(0.697)	(3.640)	(10.565)
Technology relatedness × industry relatedness—H3		5.784*	23.372+	63.729+
		(2.370)	(12.627)	(36.978)
Technology relatedness squared × industry relatedness—H3		− 4.111*	− 24.106*	− 51.221+
		(1.935)	(10.585)	(28.388)
Time elapsed	− 0.203***	− 0.214***	− 0.141*	− 0.403
	(0.041)	(0.040)	(0.070)	(0.247)
Geographical distance	− 0.000*	− 0.000*	0.000	− 0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Total funding	0.179+	0.162	0.199	− 0.061
	(0.109)	(0.107)	(0.168)	(0.297)
Talent	0.044	0.047	0.020	0.366**
	(0.052)	(0.050)	(0.080)	(0.114)
Venture count	0.087	0.065		0.575+
	(0.109)	(0.110)		(0.319)
Prior venture success	− 0.284	− 0.298	− 0.498	− 1.804
	(0.253)	(0.252)	(0.360)	(1.768)
Team size	0.002	− 0.044	0.227	
	(0.109)	(0.109)	(0.157)	
Team diversity (functional specialization)	0.549	0.524	0.726	− 2.812
	(0.505)	(0.503)	(0.961)	(1.749)
Team diversity (educ. level)	− 0.173	− 0.348	0.856	− 7.222*
	(0.706)	(0.694)	(0.850)	(2.926)
Firm patent count	0.073***	0.073***	0.062***	0.043***
	(0.017)	(0.017)	(0.009)	(0.012)
Prior venture innovation impact	− 0.000	− 0.000	− 0.000	− 0.003+
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	− 3.118**	− 1.611	1.030	9.679
	(1.183)	(1.431)	(1.102)	(1.102)
Industry/Location dummies	Yes	Yes	Yes	No
Observations	175	175	94	41
Log likelihood	− 726.63	− 722.91	− 380.24	− 147.41
Pseudo *R*-squared	0.097	0.10	0.13	0.20

Model specification—negative binomial; robust standard errors in parentheses (). ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$, two-tailed t tests. Values of industry relatedness are residuals (Y-Ypredicted) from the stage 1 estimation. Models 1 and 2 report results with an alternative operationalization of industry relatedness, the inter-industry relatedness index (Bryce and Winter 2009). Model 3 reports results for ventures whose founders had only one prior founding experience. Model 4 reports results for ventures with entrepreneurs with only solo founding experiences. Given the small size of this sample, we were unable to get the models to converge with all our control variables intact. Hence, we were compelled to drop the location dummies and industry dummies for this robustness test to obtain the regression estimates for this model

Table 5 Analysis of economic success of ventures founded by serial entrepreneurs

	Model 1	Model 2	Model 3	Model 4	Model 5
Technology relatedness—H1		3.173**	− 1.509	2.658*	5.354*
		(1.228)	(5.363)	(1.188)	(2.152)
Technology relatedness squared—H1			4.266		
			(4.573)		
Industry relatedness—H2				1.202**	3.337*
				(0.445)	(1.457)
Technology relatedness × industry relatedness—H3					− 3.843
					(2.432)
Time elapsed	− 0.021	0.009	0.012	− 0.006	− 0.014
	(0.074)	(0.082)	(0.082)	(0.085)	(0.085)
Geographical distance	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total funding	0.402*	0.283	0.257	0.300	0.212
	(0.187)	(0.191)	(0.187)	(0.196)	(0.181)
Talent	0.204**	0.209**	0.209**	0.203*	0.199*
	(0.078)	(0.076)	(0.078)	(0.080)	(0.083)
Venture count	0.004	0.051	0.067	0.132	0.089
	(0.126)	(0.138)	(0.142)	(0.136)	(0.148)
Prior venture success	1.108**	1.089**	1.092**	0.901*	0.861*
	(0.413)	(0.412)	(0.418)	(0.410)	(0.426)
Team size	0.043	0.113	0.146	0.121	0.094
	(0.186)	(0.198)	(0.204)	(0.203)	(0.188)
Team diversity (functional specialization)	1.419+	1.536*	1.691*	2.079*	1.938*
	(0.810)	(0.780)	(0.797)	(0.828)	(0.779)
Team diversity (educ. level)	0.177	0.217	0.324	0.378	0.302
	(0.893)	(0.969)	(0.988)	(0.949)	(0.976)
Firm patent count	0.012	0.009	0.010	0.011	0.007
	(0.010)	(0.010)	(0.010)	(0.012)	(0.013)
Constant	− 1.649	− 4.193*	− 3.311	− 5.398*	− 6.766**
	(1.660)	(2.045)	(2.283)	(2.205)	(2.225)
Industry/location dummies	Yes	Yes	Yes	Yes	Yes
Observations	175	175	175	175	175
Log likelihood	− 96.08	− 91.74	− 91.24	− 87.79	− 89.76
Pseudo *R*-squared	0.199	0.235	0.239	0.268	0.251

Model specification—logistic regression; robust standard errors in parentheses (). ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$, two-tailed t tests. Values of industry relatedness are residuals (Y-Ypredicted) from the stage 1 estimation

with later venture success (model 2, $\beta = 3.173$, $p < 0.01$). We do not find support for the curvilinear specification of technology relatedness (model 3, $p > 0.1$) and hence this specification is subsequently dropped. Model 4 incorporates the variable for industry relatedness, which we find has a positive effect on later venture economic success (model 4, $\beta = 1.202$, $p < 0.01$). However, we do not find support for the interactive effect of technology and industry relatedness on later venture economic success (model 5, $p > 0.1$).

5 Discussion

In this study, we sought to investigate the conditions under which ventures founded by serial entrepreneurs vary in their innovation impact. Since entrepreneurial innovation is contingent on the venture context (Autio et al. 2014) and the type of prior entrepreneurial experience (Ucbasaran et al. 2009; Westhead et al. 2005c; Baron and Ensley 2006), we specifically examined the extent of industry and technology relatedness across successive ventures founded by serial entrepreneurs. We found that technology relatedness is curvilinearly (inverted U-shaped) associated with innovation impact while industry relatedness is negatively associated with innovation impact. We also found evidence that at intermediate to high levels of technology relatedness, low levels of industry relatedness helped to strengthen rather than attenuate innovation impact, such that later ventures characterized by low levels of industry relatedness but high levels of technology relatedness across successive ventures founded by the serial entrepreneur are more likely to be associated with impactful innovations. We discuss the implications of these results below.

5.1 Theoretical contributions and implications for research

This study makes several contributions. First, it builds upon and extends research on entrepreneurship that has examined the dark side of innovativeness in new ventures by focusing on the inverse relationship between innovativeness and venture survival (e.g., Boyer and Blazy 2014; Buddelmeyer et al. 2010; Hyytinen et al. 2015; Reid and Smith 2000). Our study complements the findings from this literature and extends it by shedding light on the conditions that lead serial entrepreneurs, who are often regarded as drivers of enterprise and change in industries (McGrath and MacMillan 2000), to pursue the creation of such innovative ventures. Our study shows that ventures with high innovation impact are more likely to be founded by entrepreneurs who are well-versed in the underlying venture technology and who are open to new industry contexts. Often such entrepreneurs may have failed in their prior entrepreneurial venture and made the decision to switch to a new industry context (Eggers and Song 2015). Many of these innovative ventures may indeed go on to fail, based on economic indicators, but have high innovation impact, through knowledge spillovers. Our study thus helps forge the link between the literature on the dark side of innovativeness in new ventures (e.g., Boyer and Blazy 2014; Buddelmeyer et al. 2010; Hyytinen et al. 2015; Reid and Smith 2000), and the literature on decision-making following business failure (Eggers and Song 2015; Gompers et al. 2010; Parker 2014), thus opening new avenues for research in entrepreneurship that can focus on the nexus of business failure and the innovation performance of new ventures.

Second, our findings contribute to the entrepreneurship literature by clarifying conditions under which prior experience constrains innovation. Several scholars (e.g., Aldrich and Kenworthy 1999; Baron and Ensley 2006; Marvel 2012; Franke et al. 2014) have noted the stultifying role of industry knowledge on an entrepreneur's willingness to innovate and defy conventional industry norms. Our research extends this work by suggesting that the degree of an entrepreneur's familiarity with the industry can adversely impact the otherwise positive relationship between the entrepreneur's technology familiarity and the venture's potential innovation impact. This weakening effect of industry relatedness occurs through its influence on latent psychological factors such as the propensity to exploit (as opposed to explore) ideas at increasing levels of technology relatedness. This insight suggests that not only is the value of experience defined by its context as suggested by Dencker and Gruber (2015), but, in some cases, the presence of certain types of prior experience together can have a negative synergistic effect on value creation by the entrepreneur in subsequent ventures.

Third, our study helps to deepen our understanding of the role of the individual in serial entrepreneurship which has been noted as an important avenue for research (Eggers and Song 2015; Ucbasaran et al. 2008a). Eggers and Song (2015) showed that entrepreneurs who experience prior venture failure are more likely to change industries and that later ventures started by such entrepreneurs were less likely to be economically successful. In contrast, entrepreneurs who experienced prior venture success were less likely to change industries, which made it more likely that their later venture would be economically successful. This phenomenon has been called "performance persistence in entrepreneurship" (Gompers et al. 2010). Our study complements this body of research by highlighting the contrasting implications for innovation performance. On the one hand, our results suggest that while successful entrepreneurs are less likely to change industries and are more likely to experience economic success, their later ventures are less likely to have a high innovation impact. On the other hand, entrepreneurs who experience prior failure are more likely to change industries, which makes economic success less likely but improves their chances of generating high innovation impact. Our findings complement research which shows that the effect of venture failure on the *individual entrepreneur* can be more complex (Ucbasaran et al. 2013) by providing evidence that venture failure can help bolster *social good* by serving as a source of technological progress upon which other firms can build (Hoetker and Agarwal 2007; Knott and Posen 2005). However, it is feasible that experienced entrepreneurs may be better able to appropriate value in ways that are still optimal for the venture, even though they have no effect on the venture's broader impact. This is an important avenue for future research.[11]

5.2 Contribution to practice

Our findings have important implications for practice. While prior research has indicated that entrepreneurs who fail in their prior ventures are more likely to pick unfamiliar external contexts for subsequent ventures, which makes economic success less likely (Eggers and Song 2015). Our results show that by the same token, serial entrepreneurs who embrace greater risk through lower relatedness across successive venture contexts are more likely to innovate technologically. While both wealth-creation and innovation have great value for society, it is important to realize that successes are not all painted with the same brush—nor are failures. These two types of contributions can, however, lead to some misalignment between the goals of policymakers (if they want positive spillovers) and entrepreneurs and their investors (who might be chasing economic returns).[12] Whereas entrepreneurs and their investors can only appropriate value from their efforts and investments if the firm succeeds economically, a failed firm that generates knowledge spillovers can still contribute to a more broad-based social good.

Our findings also have implications for policymakers. Although many associate innovativeness with economic performance, our study lends further credence to the notion that this may not be a typical outcome (cf. Hyytinen et al. 2015). Start-ups can fail economically, despite having high innovation impact. Evidence suggests that ideas generated by failed firms eventually became integral parts of successful products and projects in successful firms (Gilbert et al. 2004; Holbrook 1995; Holbrook et al. 2000). Their investments in pursuit of innovation continue to pay dividends in terms of generating knowledge spillovers, long after they cease to exist. Such spillovers can be generated through the creation of new start-ups that build on those ideas or through the release of valuable knowledge embedded in human capital that join incumbent firms (Acs et al. 2009; Plummer and Acs 2014). Hence, rather than focusing primarily on new venture's economic success and its ensuing job creation potential, policymakers should also consider initiatives that can help to subsidize start-ups' investments in innovation, given their potential to generate knowledge spillovers regardless of the eventual economic success of the venture.

5.3 Research limitations

An important limitation of this study is our reliance on VC-funded firm data to source our sample of serial entrepreneurs which imposes limits on the generalizability of the study. Firms that obtain VC funding are usually high-potential firms in high-growth industries and thus cross a higher threshold for quality and potential for growth than many firms that do not receive VC funding. An advantage of this approach was that examining VC-funded firms allowed us to have a certain level of homogeneity in the quality of human capital that the entrepreneurs possess. In addition, VC-funded ventures are significantly more likely to pursue patents than non-VC-funded ventures (Engel and Keilbach 2007; Graham et al. 2009; Kortum and Lerner 2000), an attribute which enabled us to rely on patent data for tracking innovation impact. Nevertheless, in future research, we would like to see if the results would be different for non-VC-funded firms.

Another limitation of our study is our reliance on the immediate prior venture's context for determining an entrepreneur's familiarity with the specific industry and technology domain. Although we take several steps to address this limitation including controlling for the entrepreneur's human capital and innate talent, we hope subsequent work will take alternative approaches to examine and measure an entrepreneur's familiarity with different aspects of a venture's context and study its impact on entrepreneurial innovation. A third limitation is that our study relies on patent data for measuring technology relatedness and innovation impact.

[11] We thank an anonymous reviewer for this insight.

[12] We thank an anonymous reviewer for this insight

Although patents represent an intermediate innovation output, they have been found to be highly correlated with alternative measures of innovation performance (Hagedoorn and Cloodt 2003) and as such are considered reasonable proxies of firm innovation performance in high tech industries by scholars (Harhoff et al. 1999; Jaffe and Trajtenberg 2002; Jaffe et al. 2000). However, examining whether our findings extend to alternate operationalization of innovation performance is an important avenue for future research.

6 Conclusion

Our study helps to shed light on the conditions that lead serial entrepreneurs to innovate and how ventures founded by such entrepreneurs may vary in their innovation impact. In so doing, the study draws attention to a broader set of mechanisms by which serial entrepreneurs, even those who persist and repeatedly fail, contribute to the public good, in ways inadequately captured by pure economic indicators. We hope our study encourages further interest and scholarly investigation of this important topic.

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