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# Pre-entry experience and the heterogeneity in startup performance: Evidence from the nascent artificial intelligence industry

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ABSTRACT

We examine the performance differences among startups in nascent industries, taking account of the distinct knowledge contexts from which they arise. Specifically, we investigate the effect of pre-entry experience on the performance of startups originating within the same industry (i.e. inside–industry spinouts) and those from related knowledge contexts along the value chain (i.e. outside–industry spinouts). Analyzing a novel dataset that includes all U.S. artificial intelligence industry startup entrants during the period 1980 to 2014, we find that inside–industry spinouts and outside–industry spinouts have comparable survival and successful exit rates, outperforming startups with no pre-entry experience related to AI. Exploring the heterogeneity among outside–industry spinouts, we also find that the higher survival rate of this category of entrants is driven by startups founded by individuals who previously worked for firms operating in upstream supplier industries. We discuss the implications of our findings for research on strategy and industry evolution.

## 1. Introduction

Pre-entry experience – defined as experience accumulated prior to entry into a market, industry, or niche – has long been recognized as an important determinant of entrant innovative capacity and overall performance, especially for startups (Helfat and Lieberman, 2002). Prior research particularly emphasizes the role of resources and capabilities that individual founders accumulate through prior employment in other companies in shaping the pre-entry experience of startup entrants (Cao and Posen, 2023; Ganco and Agarwal, 2009). Research across a range of industries shows that startups launched by former employees of incumbent firms in the same industry perform better than other startups (Agarwal et al., 2004; Franco and Filson, 2006; Dahl and Sorenson, 2014). It has been argued that the performance advantages of this type of startup derive from the key resources they *inherit* from industry incumbents.[1] These resources include technological know-how (Klepper and Sleeper, 2005; Gambardella et al., 2015), knowledge related to market and regulation (Bahoo-Torodi and Torrisi, 2022; Chatterji, 2009), organizational routines and managerial practices (Feldman et al., 2019; Honoré, 2022), and social ties to external actors (Phillips, 2002; Sorenson and Audia, 2000).

Despite valuable insights from prior work, two important gaps remain in our understanding of the effect of pre-entry experience on startup performance. First, although much attention has been paid to one type of pre-entry experience – that is, the previous employment experience of founders in the same industry – less is known about how founders' experience outside the focal industry context might influence the performance of startups. In particular, while research on academic entrepreneurship has examined the entry and exit rates of startups originating in the upstream university context (e.g. Agarwal and Shah, 2014; Roche et al., 2020), recent findings suggest that some startups may have originated from other knowledge contexts such as those related to the focal industry value chain (Adams et al., 2024; Cattani et al., 2024). These contexts might include upstream supplier industries that provide technical knowledge as a core input for the focal industry's products (e.g. Alcacer and Oxley, 2014), or downstream user industries

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[1] Several different terms have been used in the literature to refer to this category of entrants including intra-industry spinoffs (Klepper and Sleeper, 2005), employee spinouts (Adams et al., 2016) and entrepreneurial spinouts (Kaul et al., 2024). Unlike corporate spinoffs, these independent startups do not have any formal ties with other incumbent firms at the time they are established (Agarwal et al., 2004).

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where knowledge of user preferences and demand serves as a basis for entry into the upstream industry (e.g. Adams et al., 2016). Second, while prior research has explored the effect of pre-entry experience on the performance of startups in established industries (Bayus and Agarwal, 2007; Ganco and Agarwal, 2009), there is a void in our understanding of this relationship in the context of nascent industries where technology and market demand are highly uncertain, making the required resource profiles to successfully operate in these environments somewhat indeterminate (Moeen and Agarwal, 2017; Moeen et al., 2020).

The present study attempts to fill these gaps by examining the consequences of pre-entry experience accumulated within the focal industry or leveraged across industry boundaries for startup entrants in nascent industries. Our analysis investigates the performance of startups launched by former employees of firms active in the focal industry (i.e. inside–industry spinouts) and startups originating from related knowledge contexts along the value chain (i.e. outside–industry spinouts). We conjecture that the performance of startup entrants is shaped by two main factors: pre-entry experience which determines the startup's stock of resources and capabilities at the time of its establishment, and post-entry experience derived from learning-by-doing during startup operations. Specifically, we argue that access to core resources is critical for reducing the uncertainties related to technology (Anderson and Tushman, 1990; Utterback and Suárez, 1993) and market demand (Christensen and Bower, 1996; von Hippel, 1986) typical of nascent industries. Hence, we suggest that startups originating in the focal industry and startups from vertically related contexts (e.g. academic institutions, upstream suppliers, downstream user industries) will be less likely to fail compared to startups with no or little relevant pre-entry experience in the target industry. Further, since learning efficacy increases with length of experience in the industry and the available stock of knowledge, we suggest that compared to other startups, both inside– and outside–industry spinouts will be more likely to achieve a successful exit.

The empirical setting for our study is the nascent U.S. artificial intelligence (AI) industry which has experienced significant growth in recent years. Our analysis is based on a unique dataset that includes all startup entrants into this industry between 1980 and 2014. The findings support our hypotheses that inside– and outside–industry spinouts are less likely to fail and are more likely to exit via acquisition or initial public offering (IPO) compared to the startups with no pre-entry experience related to AI. A focus on the heterogeneity in the outside–industry spinout category further reveals that the survival advantage of these entrants is driven by startups founded by former employees of upstream firms that supply core components and key technologies to the focal industry.

This study contributes to two literature streams. First, it adds to the strategy literature by examining how the pre-entry experience of startups may condition their performance outcomes *across* industry boundaries. Prior research emphasizes the survival advantages of inside–industry spinouts over other startup entrants (Agarwal et al., 2004; Chatterji, 2009; Franco and Filson, 2006). Our analysis provides evidence supporting the argument that founders' prior employment experience in knowledge contexts related to but outside the focal industry is also important for determining the survival and successful exit chances of startups (Adams et al., 2016; Donegan et al., 2019; Hashai and Zahra, 2022). Second, it adds to the literature on industry evolution (Agarwal and Bayus, 2002; Gort and Klepper, 1982; Malerba et al., 2016), specifically research on nascent industries (Moeen and Agarwal, 2017; Moeen et al., 2020). Prior work highlights different actors including startups that contribute to the emergence and evolution of new industries (see Agarwal et al., 2025 for a recent review). Our study contributes by suggesting that in nascent industries, a large proportion of startup entrants are outside–industry spinouts, and also that these startups bring a range of different resources and capabilities which influence the evolution of the new industry. Our findings indicate that supplier industry spinouts exhibit higher survival rates than other startups, suggesting that this category of startups may play a disproportionately important role in shaping the evolution of the nascent industries' knowledge base and structure.

## 2. Startup entrants: A taxonomy

The literature proposes several different taxonomies of industry entrants. For example, based on the type of relationship between the potential entrant and the industry incumbent, Helfat and Lieberman (2002) proposed a taxonomy that distinguishes between diversifying entrants (e.g. incumbent firms entering a new industry), parent company ventures (e.g. parent spinoffs), and de novo entrants (i.e. startups with "no legal relationship with established firms in the industry" (Helfat and Lieberman, 2002: 731). Focusing exclusively on the last category of entrants, subsequent research further distinguishes between startups launched by former employees of incumbent firms active in the same industry and other startups (e.g. Klepper and Sleeper, 2005). Agarwal and Shah (2014) identify two other sources of entrepreneurial knowledge, namely academic and user contexts, which may serve as the basis for a startup creation. However, these taxonomies overlook other sources of knowledge for entrepreneurship such as upstream and downstream industries related to a focal industry along the value chain (Adams et al., 2024).

To try to fill this gap and building on Cattani et al. (2024), we extend the taxonomy of independent startups (see Fig. 1). We distinguish between startups founded by ex-employees of incumbent firms active in the focal industry (i.e. inside–industry spinouts), startups launched by former employees in a vertically related context (i.e. outside–industry spinouts), and startups established by individuals with no prior experience related to the focal industry (i.e. other startups). We then consider the employment context of outside–industry spinout founders and distinguish between startups from academic institutions and those from vertically related industries. In line with the literature, we define academic spinouts as startups founded by faculty and staff members or university researchers (Roberts, 1991), supplier industry spinouts as startups founded by employees of an incumbent firm operating in an upstream supplier industry (Adams et al., 2019), and user industry spinouts as startups founded by employees of an incumbent firm in a downstream user industry (Adams et al., 2016).[2]

The types of resources and capabilities held by startup entrants vary based on pre-entry experience (Cattani et al., 2024; Helfat and Lieberman, 2002). In contrast to diversifying entrants which benefit from their incumbency in a related industry (e.g. Klepper and Simons, 2000) or experience in other markets in the same industry (e.g. Sosa, 2009), the founder's prior employment experience is the main source of pre-entry experience for startup entrants. Previous research suggests that this individual experience acts as the basis for entry and represents the stock of resources and capabilities available to startups at the time of establishment (Agarwal and Shah, 2014). To delve more deeply into the types of resources and capabilities held by different types of startups, we build on the distinction between core resources and complementary capabilities proposed initially by Teece (1986) and further developed by Helfat and Lieberman (2002). In terms of the nature of the complementary capabilities held by the startup at the time of entry, we distinguish between generic capabilities which are fungible and can be deployed for a broad range of uses, and specific capabilities which can be applied in a

[2] In the case of academic spinouts, although the pre-entry experience is not accumulated in an industrial context, we include these spinout types in our analysis since academic institutions represent an upstream context and source of scientific knowledge that can form the basis for startup creation in the focal industry. The literature highlights the role of university basic and applied research as an important source of knowledge for entrepreneurship (Agarwal and Shah, 2014) and industry emergence in particular (Moeen and Agarwal, 2017).

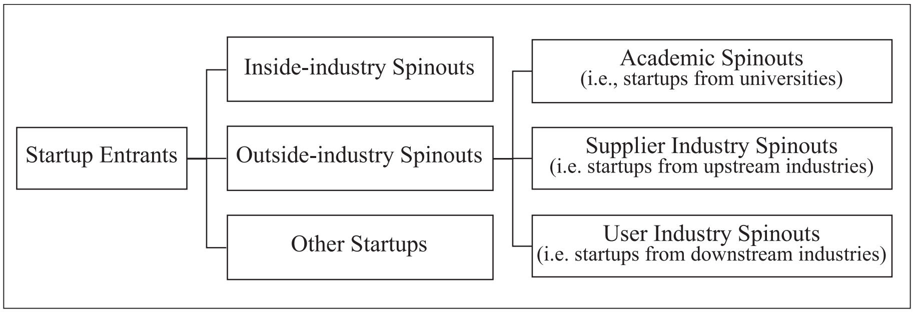


**Fig. 1.** A Taxonomy of Startup Entrants.

particular industry or a narrow range of markets (Cattani et al., 2024; Pisano, 2017; Teece, 1982).

Core resources refer to "knowledge that fundamentally underlies and is required to create a product or service" (Helfat and Lieberman, 2002: 732). They can take the form of scientific knowledge (Moeen and Agarwal, 2017), technical knowledge (Henderson and Cockburn, 1994), or knowledge about user needs (Shah and Tripsas, 2007). Since innovation entails the combination of different knowledge components and their recombination in new ways (Ahuja and Morris Lampert, 2001), core resources form the basis for firms to innovate and introduce new products to the market (Nerkar and Roberts, 2004; Katila and Ahuja, 2002). Complementary capabilities are "those [capabilities] that are required to profit from core knowledge" (Helfat and Lieberman, 2002: 732), and might comprise complementary technologies (Henderson and Clark, 1990), and manufacturing, distribution, and service systems (Mitchell, 1991).

Research on employee entrepreneurship suggests that employees serve as a conduit for knowledge spillovers across firms (Bahoo-Torodi, 2024). For example, it is argued that employees turned entrepreneurs in the same industry embody considerable resources in the form of the organizational routines (e.g. Feldman et al., 2019), technological know-how (e.g. Franco and Filson, 2006), and market-related knowledge (e.g. Chatterji, 2009) developed by incumbent firms active in the industry. Hence, inside–industry spinouts inherit both core technical resources and complementary capabilities such as operational and non-technical knowledge related to markets and services which are generic in the sense that they require little or no modification to allow their wide use within the focal industry. All these resources have been found to shape the performance of inside–industry spinouts (Agarwal et al., 2004; Dahl and Sorenson, 2014; Phillips, 2002).

Outside–industry spinouts also benefit from resources derived from their founders' previous employment experience outside the focal industry. The main driver of entry by academic-founded startups is to incubate and commercialize a university invention (Feldman et al., 2002; Jensen and Thursby, 2001; Rothaermel and Thursby, 2005; Shane, 2004). Accordingly, scientific knowledge that can be leveraged to act as an input for the focal industry's products is at the core of all academic spinouts (Agarwal and Shah, 2014). However, academic founders often lack the knowledge required to realize market applications for their scientific invention or the skills required to commercialize the invention at scale in the market (Clarysse et al., 2011; Roberts, 1991; Shane, 2004). Therefore, complementary capabilities are often conspicuously lacking in academic spinouts (Agarwal and Shah, 2014).

Spinouts originating from a supplier industry benefit from deep knowledge about the core components and key technologies required as inputs in the downstream industry (Adams et al., 2019; Alcacer and Oxley, 2014; Fontana et al., 2016). As they may interact with buyers, supplier industry spinouts may further benefit from understanding how key technologies are incorporated and integrated in downstream product markets (Adams et al., 2019).

Spinouts originating from user industries benefit from deep and contextual knowledge about how upstream products are used in downstream production and services (Shah and Tripsas, 2007; Shermon and Moeen, 2022). They also inherit extensive market knowledge related to their downstream industry origins, including insights into the effectiveness of the distribution and communication channels and regulation in the specific market (Adams et al., 2016). Therefore, user industry spinouts enter the focal industry with knowledge concerning the shortcomings of the existing products and unmet user needs (Smith and Shah, 2013). Overall, both supplier and user industry spinouts have access to core resources (i.e. knowledge about key technologies and user demand) and complementary capabilities such as operational, marketing, and distribution knowledge. However, unlike inside–industry spinouts, supplier and user industry spinout complementary capabilities tend to be specific and requiring tailoring and adjustment to become relevant for and applicable in the focal industry.

The last category of startup entrants includes startups with no pre-entry experience related to the focal industry. This category includes startups launched by individuals whose employment backgrounds are not related and complementary to the focal industry or who may come from unemployment (Cattani et al., 2024). Given the inherent differences between the resources required to survive and succeed in the focal industry versus those derived from unrelated contexts, these startups have limited initial stocks of core resources and complementary capabilities related to the target industry. Specifically, while these startups do not have access to any relevant core resources, some of them may hold complementary capabilities that are specific to their original industry sector. Table 1 summarizes the resource endowments of different types of startups.

## 3. Hypotheses development

Empirical research on the relationship between pre-entry experience and firms' innovation and long-term performance underscores the importance of the *match* between the firm's resources and capabilities and its environment (Chen et al., 2012; Klepper and Simons, 2000; Sosa, 2009; Eggers et al., 2020). In particular, prior work suggests that new entrants that possess related pre-entry experience are better positioned to overcome the liability of newness (Stinchcombe, 1965) and reduce the uncertainties related to the new environment (Klepper and Simons, 2000). Moreover, entrants with related pre-entry experience have better access to and can effectively accumulate resources that enable them to compete in dynamic environments (Dierickx and Cool, 1989; Moeen, 2017). Research on the effect of pre-entry experience on startup performance tends to focus on startups that remain in the same industry as the founder's most recent employer (e.g. Agarwal et al., 2004). We extend this stream of work by considering how founders' prior employment experience in vertically related knowledge contexts affects the performance of the startups. Specifically, we investigate the survival and successful exit chances of inside– and outside–industry spinouts in nascent industries in line with the argument that startup entrants play an important role in the emergence and subsequent evolution of a new industry (Agarwal et al., 2002; Gort and Klepper, 1982). Indeed, as noted by Winter (1984), the nascent stage of an industry can be

**Table 1**
Resources and Capabilities Held by Different Startups.

| | | *Core Resources* | *Complementary Capabilities* | *Reference* |
|---|---|---|---|---|
| Inside–industry spinouts | | Technological and market knowledge | Generic manufacturing, marketing, and service | Agarwal et al. (2004); Chatterji (2009); Klepper and Sleeper (2005) |
| Outside–industry Spinouts | Academic spinouts | Scientific knowledge | NA | Agarwal and Shah (2014); Clarysse et al. (2011); Shane (2004) |
| | Supplier Industry Spinouts | Knowledge of components and technologies | Specific manufacturing, marketing, and service | Adams et al. (2019); Alcacer and Oxley (2014); Fontana et al. (2016) |
| | User Industry Spinouts | Knowledge of products and user needs | Specific manufacturing, marketing, and service | Adams et al. (2016); Shah and Tripsas (2007); Shermon and Moeen (2022) |
| Other Startups | | NA | Specific manufacturing, marketing, and service | Cattani et al. (2024); Helfat and Lieberman (2002) |

characterized by an "entrepreneurial regime" during which entry rates are higher for startups compared to other types of entrants.

Our framework links the startup's pre-entry experience to its post-entry experience acquired through learning-by-doing from its operations (Balasubramanian, 2011; Jovanovic and Lach, 1989). We suggest that startup entrants with pre-entry experience in the focal industry as well as those originating from vertically related knowledge contexts possess core resources that can be leveraged to reduce uncertainties concerning the technology and demand, and therefore, they have lower risks of failure compared to other startups. Additionally, given that startup pre-entry experience works to augment post-entry experience by shaping the startup's longevity and the initial stock of resources, we would also suggest that conditional on surviving the early years, these startup types experience more effective post-entry learning which increases their chances of successful exits compared to other startups.

In section 3.1, we start by examining how the resources held by inside– and outside–industry spinouts condition their chances of survival and successful exit in a nascent industry. Next, we explicitly consider the heterogeneity among outside–industry spinouts and explore the specific types of pre-entry experience and resource endowments underlying their performance advantage. Note that the reference category for our analysis is startups with no related (or complementary) pre-entry experience in the target industry which allows us to evaluate the performance of inside– and outside–industry spinouts.

### 3.1. Pre-entry experience–performance relationship in nascent industries

It is acknowledged that nascent industries or industries that have not achieved their sales takeoff milestone (Moeen et al., 2020) differ from established sectors with respect to their current stock of industry-specific knowledge (Agarwal et al., 2025; Gort and Klepper, 1982; Klepper, 1996; Moeen, 2017), degree of technological uncertainty (Anderson and Tushman, 1990) and knowledge of customers' needs and preferences (von Hippel, 1986).

During the early stages of an industry emergence, experimentation with different technologies is common since at this point it is unclear which technologies will become obsolete and which will become dominant (Mitchell, 1991; Schilling, 1998; Utterback and Abernathy, 1975). Entrants may also test different product designs to try to cater to possibly not well defined user needs and preferences (Agarwal and Tripsas, 2008). For example, in the laser industry and prior to the introduction of diode (semiconductor) pumps for solid-state lasers, a wide range of materials was used as the laser medium, resulting in laser light of varying wavelengths for different applications (Bhaskarabhatla and Klepper, 2014; Klepper and Sleeper, 2005). Similarly, the typesetter industry initially used different generations of technology including hot metal, analog and digital CRT phototypesetters, and laser imagesetters (Tripsas, 1997). The core resources to develop these technologies might have been present in the focal industry but might also have originated from a related external knowledge context (Cooper and Schendel, 1976; Furr, 2019; Gort and Klepper, 1982; Tushman & Anderson, 1986). Indeed, in industries that begin with a technology breakthrough, access to scientific and technical knowledge developed in upstream knowledge contexts such as academic institutions or supplier industries provides an opportunity for new entrants to leverage this knowledge in order to achieve an innovation in the focal industry (Eggers, 2014; Haefliger et al., 2010; Moeen and Agarwal, 2017).

Likewise, in industries whose development is triggered by unmet user needs, even superficial knowledge about customer preferences can facilitate the introduction of new product variants that satisfy a certain group of customers (Adams et al., 2016; Baldwin et al., 2006; Shah and Tripsas, 2007). It follows then that startups with access to internal (e.g. Agarwal et al., 2004; Ganco and Agarwal, 2009) or related external sources of core knowledge (e.g. Gort and Klepper, 1982; Scherer, 1982) are better able to resolve uncertainties by generating new knowledge at the "technology-demand nexus" (Moeen et al., 2020). This in turn increases their chances of survival compared to other startups (Costa and Baptista, 2023). Empirical research on multiple industries supports this claim. For example, Klepper and Simons (2000) show that television (TV) set producers with pre-entry experience outside the TV industry (i.e. radios) survived longer, and achieved higher rates of innovation and market share compared to other entrants.[3] The study by Adams et al. (2016) shows that firms founded by entrepreneurs previously employed in a downstream industry that used semiconductors as components in its final products were more likely to survive in market-specific product categories than other startups. The above discussion leads to our first hypothesis:

**HYPOTHESIS 1**. *In a nascent industry, both inside– and outside–industry spinouts have lower risks of failure compared to other startups.*

Much of the academic literature on the pre-entry experience—firm performance relationship focuses on survival as a desirable outcome for new entrants (e.g. Agarwal and Gort, 1996; Klepper and Simons, 2000). However, as noted by Arora and Nandkumar (2011: 1844), "survival merely keeps alive the option of trying for a cash-out" and we need to know more about how the startup's pre-entry experience influences its chances of successful exit from the industry. Consistent with the entrepreneurship literature which considers financial harvest as the most desirable exit strategy for entrepreneurs and investors (Åstebro and Winter, 2012; DeTienne et al., 2015), we add to the literature by distinguishing between two potential outcomes for a startup: exit due to failure (i.e. bankruptcy or liquidation) and successful exit (i.e. acquisition or IPO).

We propose that the likelihood of successful exit is shaped by both pre-entry experience and post-entry learning during startup operations (Balasubramanian, 2011; Chen et al., 2017). While pre-entry experience enables startups to reduce technological and demand uncertainties, post-entry experience provides opportunities to reconfigure resources

[3] Although the study by Klepper and Simons (2000) focuses on diversifying entrants with experience of producing radios prior to entering the TV industry, in their conclusion, the authors raise the intriguing possibility that founders' experiences might play a similar role in the case of startup entrants.

and adapt to evolving conditions in the new environment. The efficacy of post-entry learning, however, will be determined by the longevity of the startup (Agarwal and Gort, 1996; Jovanovic and Lach, 1989; Levitt and March, 1988) and the stock of resources available to it at the time of establishment (Fontana and Nesta, 2010). It follows that conditional on survival, startups with substantial relevant pre-entry experience will be better positioned to gain more effective post-entry experience which in turn, will increase their likelihood of achieving a successful exit. This is for two reasons. First, startups with larger stocks of resources related to the focal industry will be better able to accumulate additional resources that complement or incrementally improve the existing ones due to the ability and efficiency in amassing interconnected resources (Dierickx and Cool, 1989). Second, during employment in the same industry or a related context, startup founders acquire core resources and complementary capabilities and also learn how to identify and integrate additional resources. Replicating these practices allows the startup to accumulate new resources related to the existing ones more rapidly (Moeen, 2017). Overall, compared to other startups, startups with pre-entry experience in the focal or a vertically related context will not only survive longer but also will be more successful at accumulating additional resources which will make them a more attractive acquisition target or increase the likelihood of an IPO (Adams et al., 2022). We therefore hypothesize that:

**HYPOTHESIS 2**. *Conditional on survival, both inside– and outside–industry spinouts have higher chances of successful exit compared to other startups.*

### 3.2. Heterogeneity among outside–industry spinouts

So far, we have discussed the link between pre-entry experience and the performance outcomes for inside– and outside–industry spinouts in nascent industries. We now examine the heterogeneity among outside–industry spinouts. As summarized in Table 1, there is a rich heterogeneity in the resources inherited by outside–industry spinouts. Therefore, the degree to which their pre-entry experience is relevant for reducing technological and demand uncertainties will vary depending on the specific context from which they originate. Technological uncertainties can be due to limited knowledge about technical components and their connecting architecture (Choudhury et al., 2020; Moeen et al., 2020) which might require entrants to experiment with different technical components and explore alternative linkages (Agarwal et al., 2017). This suggests that access to integrating knowledge will be important for the successful transformation of technological knowledge into a viable commercial product (Helfat and Raubitschek, 2000; Moeen, 2017). In Section 2, we discussed how both academic spinouts and supplier industry spinouts inherit the respective core resources of scientific and technical knowledge developed in adjacent upstream contexts. However, unlike academic spinouts that possess limited complementary manufacturing and marketing capabilities, supplier industry spinouts acquire the experience from the supplier side of supplier-user relationships. This means that supplier industry spinouts enter the focal industry with specific capabilities including knowledge of how upstream technologies are integrated into downstream products (Adams et al., 2019). Thus, the resources and capabilities held by supplier industry spinouts are better suited to experimentation aimed at resolving technological uncertainties and surviving in a nascent industry (Agarwal et al., 2017).

Demand uncertainty is derived in part from scant knowledge about customer preferences (Moeen et al., 2020). To reduce this uncertainty, industry entrants can shape customers' perceptions and assess demand conditions through prototype testing and feedback from the user community (Agarwal et al., 2017). Accordingly, access to knowledge about unfulfilled user demand is critical in the early stages of an industry. Since user industry spinouts originate from the downstream context, they gain experience from the user side of supplier-user relationships, thereby acquiring knowledge of existing product shortcomings and unfulfilled user needs (Shah and Tripsas, 2007; Shermon and Moeen, 2022). User industry spinout founders may embody other important resources such as knowledge about regulation and links to distributors in their previous downstream market (Adams et al., 2024). However, in contrast to established industries where user preferences are clear-cut, in emerging contexts such as nascent industries, user preferences are less well defined due to their limited product usage experience (Christensen and Bower, 1996; Moeen et al., 2020). Additionally, while technical knowledge inherited by supplier industry spinouts is often codified and transferable to other contexts, the core knowledge inherited by user industry spinouts is tacit and more contextualized and specific, especially in the case of extremely segmented downstream markets (Klepper and Sleeper, 2005; Bhaskarabhatla and Klepper, 2014; Adams et al., 2016). Overall, the above discussion would suggest that in nascent industries, both academic spinouts and user industry spinouts are in a less advantageous position compared to supplier industry spinouts. Therefore, we hypothesize that:

**HYPOTHESIS 3**. *Among outside–industry spinouts, supplier industry spinouts have a lower risk of exit by failure compared to other startups.*

We argue also that conditional on the resolution of uncertainties and on surviving the early years, all types of outside–industry spinouts are more likely to achieve a successful exit compared to other startups. This is based on their core resources, specific complementary capabilities, or a combination of both, which provide outside–industry spinouts with access to additional resources that complement those they possessed at the time of founding. Moreover, as discussed earlier, due to the efficiencies brought about by amassing similar resources (Dierickx and Cool, 1989; Moeen, 2017), the outside–industry spinout's initial stock of resources enables it to accumulate additional resources more efficiently during its production activities in the industry. By learning through operations, this type of startup can adapt its resources to evolving industry conditions, thereby strengthening its competitive advantage and improving its acquisition or IPO prospects compared with other startups. Therefore, we hypothesize that:

**HYPOTHESIS 4**. *Conditional on survival, academic, supplier industry, and user industry spinouts all have a higher chance of successful exit compared to other startups.*

## 4. Methodology

### 4.1. Research context: The U.S. artificial intelligence industry

We test our hypotheses using data from the U.S. AI industry, which in recent years has attracted the attention of both academics and practitioners due to the increased entry and commercial activities of diverse actors including startups. At the time of writing, debate over whether AI is a general-purpose technology (e.g. Goldfarb et al., 2023), an industry (e.g. Goldfarb and Trefler, 2019), or even an ecosystem (e.g. Hannigan et al., 2022) is on-going. While this debate has no implications for our theorizing, in this paper we consider AI to be a *broad industry* centered on "making intelligent machines, especially intelligent computer programs", and where competition is defined mostly by the possession of technological capabilities rather than supply of products and services with similar characteristics (McCarthy, 2004: 2).

In general, nascent industries follow a period of incubation prior to the first instance of product commercialization, a quasi-monopoly period prior to firm takeoff, and a third stage prior to sales takeoff (Moeen et al., 2020). The literature suggests that the emergence of a nascent industry can be triggered by recognition of an unmet need or a scientific discovery made in a university or corporate R&D unit (Agarwal et al., 2025). For example, the emergence of the agricultural biotechnology (Moeen and Agarwal, 2017), nanotechnology (Rothaermel and Thursby, 2007), and panel displays (Eggers, 2014) industries was linked to scientific discoveries by academic and industry scientists. The origins of AI go back to the 1950s when there was significant academic interest in the possibility of creating a machine able to simulate human intelligence. However, this initial enthusiasm was followed by so-called *AI winters* in the 1970s and 1980s when funding dried up as the early promises of AI failed to materialize, leading to skepticism about the feasibility of achieving true machine intelligence. Despite setbacks, AI experienced a resurgence in the 1990s due to advances in learning algorithms, growing availability of labeled digital data, and improving computational resources (Lee, 2018).

Since during the period of our analysis AI was an archetypical example of a nascent industry, its boundaries are unclear. However, based on emerging patterns of AI applications, the AI industry can be understood as consisting of three main fields: machine learning, symbolic systems, and robotics (for detailed descriptions of these areas see Cockburn et al., 2018). From a value-chain perspective, we have two broad categories of suppliers in this industry: academic institutions and upstream supplier industries (Jacobides et al., 2021). The upstream supplier industries comprise three sectors (see **Fig. 2**). The semiconductor industry includes hardware developers which design and manufacture processors and specialized AI chips; the software industry which includes firms that create AI algorithms and models; and the computer industry which includes data and cloud storage providers enabling large-scale data provision and storage solutions. AI-powered products or services are targeted to a wide range of AI-enabled industries, including retail, healthcare, manufacturing, finance, transportation, advertising, and education. These are downstream sectors where knowledge about user needs can serve as a cornerstone for creating a startup in the AI industry.

### 4.2. Data and sample

To identify the population of AI startups, we triangulated data from multiple sources. We began by obtaining the entire list of AI startups from Crunchbase including information on firm founders, firm financings, and firm exit events (Roche et al., 2020; Ter Wal et al., 2016). Crunchbase collects data from monthly portfolio updates submitted by global investment firms, community contributors such as executives, entrepreneurs, and investors, learning algorithms that validate the accuracy of user-generated data, and manual data gathering by its in-house data team. This last category includes information on unlisted failed early-stage startups. Thus, Crunchbase provides a more comprehensive coverage of startups than other data sources (Conti et al., 2025).

To identify AI startups, we searched on "artificial intelligence" as the industry group assigned by Crunchbase. For three reasons, we restricted our search to U.S. based startups founded between 1980 and 2014. First, this period coincides with the historical evolution of AI, from its early emergence to its resurgence in the 1990s when a range of different actors began exploring practical applications of AI in various markets.[4] Second, this period covers the 2010s which saw firm takeoff based on advancements in computational power, availability of large datasets, and rise and the widespread adoption of deep learning for various tasks. Third, this period ends in 2014 just before the industry's sales began to take off.[5] This search identified 1599 startups.

Crunchbase defines the AI industry group as a collection of sectors that includes "companies that concern themselves with the simulation of human intelligence in machines".[6] To validate Crunchbase's industry assignments, we reviewed startup descriptions to ensure alignment with our definition of AI, and to ensure that AI was their primary area of activity. Subsequently, we excluded 44 startups which only incorporated AI in their operations in some other industry. Next, we hand-collected data on the career histories of all founders listed on Crunchbase through a search on LinkedIn. In the case of incomplete career histories or no information on founder in LinkedIn, we searched on other data platforms such as CB Insights, or searched the Internet for personal CVs. Finally, we gathered information related to the startup's ownership history using the above-mentioned sources to control for the presence of any formal relationships between the startup and incumbent firm in the focal or other industry at the time of founding. This yielded a sample of 1223 startups.

Crunchbase's coverage of startups has been found to be more accurate in recent years (Block and Sandner, 2009; Roche et al., 2020). For example, Chattopadhyay et al. (2025) use Crunchbase to collect the list of AI startups founded after 2002. Given that our focus in this paper is on the early stages of the industry life cycle, we next searched for AI startups not listed in Crunchbase, particularly those founded prior to 2002. Specifically, we used patent data and applicant information to identify these startups. First, we performed keyword searches in titles and abstracts and considered technology classes to extract all AI-related patents with priority application dates between 1980 and 2001. This identified 2671 patents. Second, we consolidated applicant names and excluded patents assigned to individual inventors, universities, and public research organizations. Third, we manually-checked the remaining assignees and collected information on their origin, founding date, and primary line of business. This identified 26 additional AI startups not listed on Crunchbase.

Using patent data to identify early-stage startups has some shortcomings. For example, not all startups produce patentable knowledge while some might choose strategically to not use patents to protect their inventions (Mihm et al., 2015). To try to mitigate these limitations, we reviewed the proceedings of the International Joint Conference on Artificial Intelligence (IJCAI) - the oldest established AI conference. First held in 1969, this conference is organized every two years to showcase a broad range of AI research including machine learning, robotics, natural language processing, and computer vision. We collected the names of paper authors from the first conference up to 2001 and selected those affiliated to a company. We excluded industry incumbents, diversifying entrants, and new firms launched through sponsorship by an incumbent firm, which identified six additional startups that matched our definition of AI.

We merged all of our data which resulted in a database of 1255 startups launched in the U.S. AI industry in the period 1980 to 2014. Fig. 3 depicts patterns of entry by different startup types over the period of analysis. Entry was initially slow but accelerated in the early to mid-2000s and especially after 2010 with the rise of private clouds and commercial deep learning developments (Agrawal et al., 2016). This pattern is consistent with the shift in the late 2000s toward application-oriented learning research described by Cockburn et al. (2018). Entry peaks at the end of our period of analysis and before industry sales takeoff.

### 4.3. Measures

#### 4.3.1. Dependent variable

Startups' performance is measured in two ways. First, using

[4] As already mentioned, pre-1980, the development of AI was mostly confined to academic research. The earliest major AI startups such as Teknowledge, Exsys Inc., and IntelliGenetics were founded at the beginning of the 1980s (Nilsson, 2009). Thus, we do not expect this left truncation to introduce specific bias in our analysis.

[5] The literature on industry evolution defines the sales takeoff milestone as the point of industry transition from nascency to the growth phase (e.g. Moeen et al., 2020). In our analysis, we consider AI industry nascency ending in 2014 with global AI revenue rising from $6.3 bn. in 2014 to $126 bn. in 2015, with $49 bn. generated in North America (Statista, 2016).

[6] Sophie Chitsaz, "What Industries are included in Crunchbase?" Updated January 2024 available at **https://support.crunchbase.com/hc/en-us/articles/360043146954-What-Industries-are-included-in-Crunchbase**.

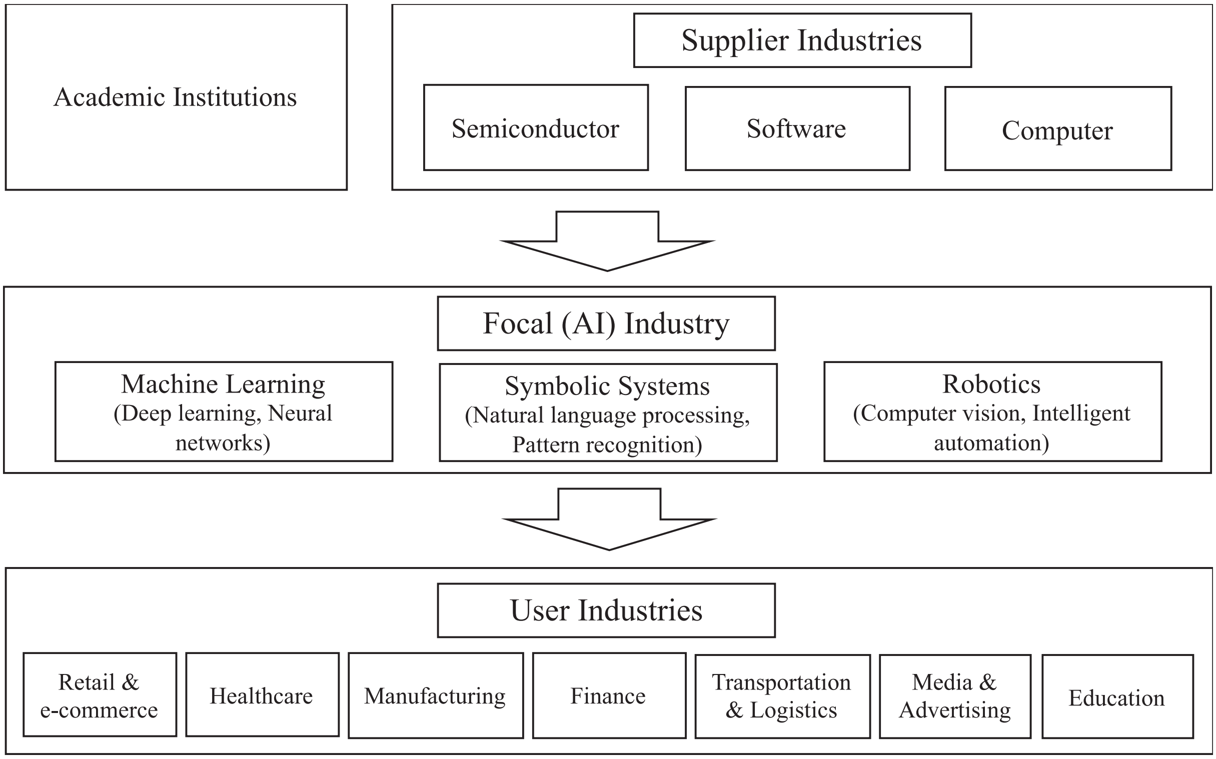


**Fig. 2.** AI Vertical Chain.

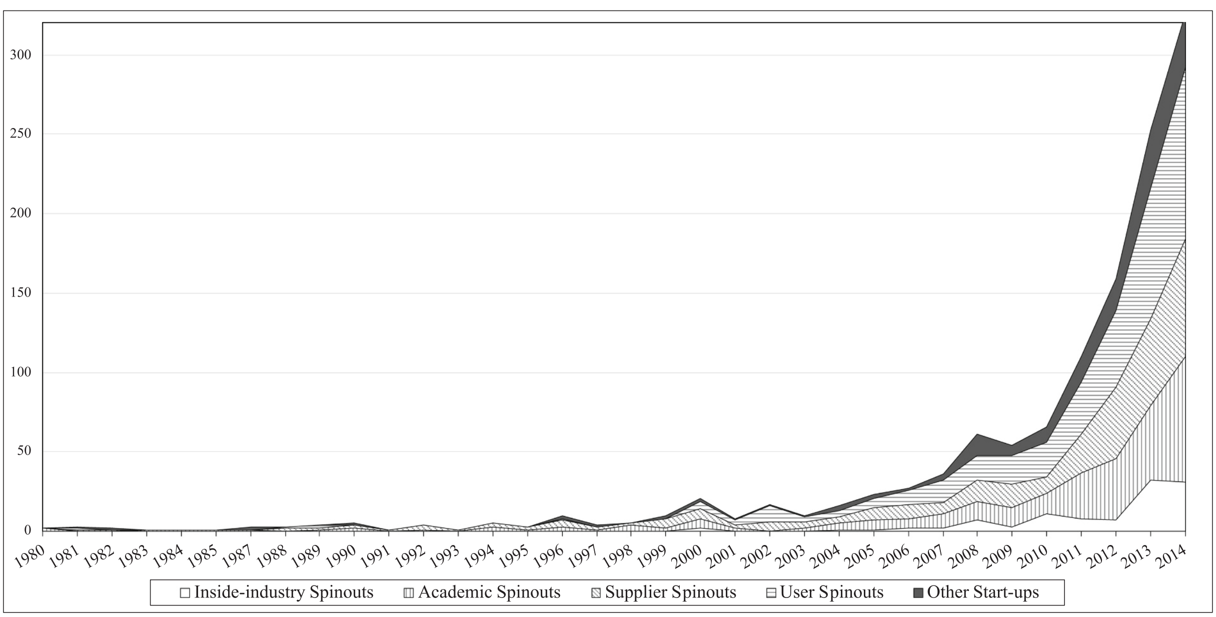


**Fig. 3.** Pattern of Entry by Startup Type (1980–2014).

information collected from Crunchbase, we created the binary variable *failure* which is a relevant measure of startup performance (e.g. Agarwal et al., 2004; Phillips, 2002). Since Crunchbase reported only 3 % of the startups in our sample as 'closed', we refined this measure using additional data sources. We chose a two-step approach: first, we cross-checked startups listed as active on Crunchbase against data from CB Insights and updated our list of failed startups accordingly, second, we examined the official websites of the remaining startups. Following prior research, we considered existence of an operating website to be a conservative proxy for an active startup (Lee and Kim, 2024). If the website did not load or the domain appeared to be available for sale, we used the Wayback Machine Internet Archive to estimate failure time, based on the last available snapshot of the site. This approach increased the failure rate to 8.3 %. The variable *failure* takes the value 1 for startups that failed and 0 for those that survived the entire period of our observation. Specifically, given that performance may take time to be revealed, we tracked startups from their establishment until either the end of 2020 or their closure, whichever came first. We then created the binary variable *success* which takes the value 1 for startups that exited the industry successfully and 0 for those that remained active. Following

Arora and Nandkumar (2011), we considered a successful closure to be either a favorable acquisition or an IPO, whichever came first. By combining these variables, we constructed a categorical dependent variable which takes the value of 1 if the startup failed and exited the industry via dissolution, 2 if the startup was acquired or achieved an IPO, and 0 if it survived until the end of our period of observation.

### 4.3.2. Independent variable

Using information on founder's career history and consistent with our taxonomy of startup entrants, we classified the startups in our sample as inside–industry spinouts, outside–industry spinouts, or other startups. Specifically, startups were classified as *inside–industry spinouts* if the founder was previously employed in an incumbent firm active in the focal AI industry (Agarwal et al., 2004). The *outside–industry spinout* category includes *academic spinouts* (i.e. startups founded by a faculty member, a university staff member, or a researcher) (Roberts, 1991), *supplier industry spinouts* (i.e. startups founded by a former employee of an incumbent firm operating in one of the upstream supplier industries) (Adams et al., 2019), and *user industry spinouts* (i.e. startups founded by a former employee of an incumbent firm operating in one of the downstream user industries) (Adams et al., 2016).[7] The remaining entrants in our sample are categorized as *other startups* which includes startups founded by previously unemployed individuals or individuals from an unrelated sector such as construction, agriculture, defense, personal care, etc..

The construction of the variable for startup type was straightforward in the case of startups with sole founders which includes 46.5 % of the startups in the sample. For startups founded by an entrepreneurial team, we classified the startup based on the largest proportion of founders from the same context. For example, for a startup with three founders, if two had been employed in a university and one was an ex-employee of an incumbent firm in a related supplier industry, we classified the startup as an academic spinout. In the case of equal numbers of founders from the same context, we considered their roles and positions in their previous employment and classified the startup based on founder with the most involvement in the development or application of AI. As summarized in Table 2, 107 of the sample startups are inside–industry spinouts, 987 are outside–industry spinouts, and 161 are classed as other startups. Of the 987 outside–industry spinouts, 290 are academic spinouts, 311 are supplier industry spinouts, and 386 are user industry spinouts.

**Table 2**
Startup Type and Mode of Exit.

| | *Survived* | *Failed* | *Acquired or Went Public* | *Total* |
|---|---|---|---|---|
| Inside–industry Spinouts | 87 | 5 | 15 | 107 (8.53 %) |
| Outside–industry Spinouts | 725 | 75 | 187 | 987 (78.65 %) |
| Academic Spinouts | 209 | 23 | 58 | 290 (23.11 %) |
| Supplier Industry Spinouts | 224 | 19 | 68 | 311 (24.78 %) |
| User Industry Spinouts | 292 | 33 | 61 | 386 (30.76 %) |
| Other Startups | 130 | 24 | 7 | 161 (12.83 %) |
| Total | 942 | 104 | 209 | 1255 |

### 4.3.3. Control variables

We included three sets of variables to control for other factors that might affect startup survival and likelihood of successful closure. First, following prior research (e.g. Adams et al., 2016; Cao and Posen, 2023; Roche et al., 2020), we included several variables to control for effect of founding team characteristics including *founding team size,* lead founder's *tenure* and *hierarchical position* with the previous employer, and a dummy variable for the presence of *serial entrepreneur.* We included the variable *experience variety* to capture founding team's mix of pre-entry experience operationalized using the *Blau index*, calculated as $1 - \sum p_i^2$, where $p$ is the proportion of founders from the same context (Criaco et al., 2022; Hashai and Zahra, 2022; Honoré, 2022). Second, we included three variables to control for effect of startup's resources including *number of patents granted,* the *number of trademarks registered,* and the *total amount of funding* in $ million. Third, as already discussed, AI encompasses several fields of application that need to be controlled for to properly examine the competitive dynamics among startups. We included *application field* and *founding year* fixed effects to capture these aspects. Specifically, to assign each startup to its primary field of AI application, we consulted the business descriptions of the startups on Crunchbase.

## 5. Estimation strategy and results

Table 3 presents the descriptive statistics and correlation coefficients for our variables. We observe that 104 startups (8.3 % of the sample) failed, and 209 startups (16.7 % of the sample) successfully exited the industry. In our sample, average founding team size is less than 2. Before launching their startup, the lead founders on average had worked for 4.7 years with the most recent employer: 58 % had a senior position and 39 % were serial entrepreneurs. Experience variety was 0 for 56 % of the startups, indicating that all founding team members had been employed in the same context. Average number of patents granted to the startups in our sample was 8.7, and average number of trademarks registered was 2 (the median for both variables is 0). Finally, the average amount of funding raised by the sample startups was $22.9 million.

Tables 4 and 5 report the results of the discrete-time competing risks model which jointly estimates different exit outcomes (Jenkins, 2005). We parameterized the baseline hazard using a time-varying covariate, log(time). We hypothesized that compared to other startups, both inside– and outside–industry spinouts have lower risks of failure (H1) and higher likelihood of successful exit (H2). Table 4 model 1 includes only the main variable of interest, which is a categorical variable for startup type. Models 2 and 3 include the control variables and fixed effects. The coefficient of inside–industry spinouts is negative and significant in the left column of Model 3 ($\beta = -1.22$, $p < .05$), suggesting that the relative risk of failure is 71 % lower for inside–industry spinouts compared to the reference category of other startups. Also, the coefficient of outside–industry spinouts is negative and significant ($\beta = -0.52$, $p < .05$), suggesting that for outside–industry spinouts the relative risk of failure is 40 % lower compared to other startups. In the right-hand column of Model 3, the coefficient of inside–industry spinouts is positive and significant ($\beta = 1.25$, $p < .01$), indicating a 249 % higher likelihood of successful exit compared to the reference category. The coefficient of outside–industry spinouts is also positive and significant ($\beta = 1.53$, $p < .01$), indicating that they are 4.6 times more likely to experience a successful exit (rather than just survival) compared to other startups. We conducted a Wald test of the joint null hypothesis that the coefficients of inside– and outside–industry spinouts are both zero. The test statistic in the failure equation is statistically significant ($\chi^2(2) = 6.79$, $p < .05$), indicating that both inside– and outside–industry

[7] When classifying startup entrants, we focused on the core area of activity of founder's most recent employer. For example, if the AI startup had been launched by a former employee in a downstream industry firm that had incorporated AI in its operations (e.g. Tesla Motors), this was considered an outside–industry spinout, specifically a user industry spinout. AI startups with origins in the upstream computer or software industries were classified as outside–industry spinouts, specifically supplier industry spinouts.

**Table 3**
Descriptive Statistics and Correlation Coefficients.

| VARIABLES | Mean | Std. Dev. | Min | Max | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Failure | 0.08 | 0.28 | 0 | 1 | 1.00 | | | | | | | | | | | | |
| 2. Success | 0.17 | 0.37 | 0 | 1 | −0.13 | 1.00 | | | | | | | | | | | |
| 3. Inside–industry Spinouts | 0.09 | 0.28 | 0 | 1 | −0.04 | −0.02 | 1.00 | | | | | | | | | | |
| 4. Outside–industry Spinouts | 0.79 | 0.41 | 0 | 1 | −0.05 | 0.12 | −0.59 | 1.00 | | | | | | | | | |
| 5. Other Startups | 0.13 | 0.33 | 0 | 1 | 0.09 | −0.13 | −0.12 | −0.74 | 1.00 | | | | | | | | |
| 6. Founding Team Size | 1.85 | 1.01 | 1 | 7 | −0.05 | 0.08 | −0.01 | 0.01 | −0.01 | 1.00 | | | | | | | |
| 7. Founder Tenure | 4.73 | 4.18 | 0 | 36 | −0.02 | 0.00 | −0.04 | 0.02 | 0.01 | −0.05 | 1.00 | | | | | | |
| 8. Founder Position | 0.58 | 0.49 | 0 | 1 | 0.00 | 0.02 | 0.08 | −0.05 | −0.01 | 0.00 | 0.18 | 1.00 | | | | | |
| 9. Serial Entrepreneur | 0.39 | 0.49 | 0 | 1 | 0.02 | 0.01 | 0.07 | 0.03 | −0.10 | 0.06 | 0.06 | 0.32 | 1.00 | | | | |
| 10. Experience Variety | 0.23 | 0.27 | 0 | 0.86 | −0.01 | 0.01 | −0.01 | 0.01 | −0.01 | 0.74 | −0.10 | −0.05 | 0.07 | 1.00 | | | |
| 11. N. Patent | 8.69 | 134.34 | 0 | 4005 | −0.02 | 0.10 | −0.02 | 0.03 | −0.02 | 0.02 | 0.03 | −0.01 | −0.03 | −0.04 | 1.00 | | |
| 12. N. Trademark | 2.04 | 9.01 | 0 | 245 | −0.04 | 0.12 | −0.02 | 0.03 | −0.02 | 0.03 | 0.07 | 0.01 | −0.04 | −0.04 | 0.86 | 1.00 | |
| 13. Total Funding | 22.94 | 132.38 | 0 | 4025 | −0.04 | 0.05 | −0.02 | 0.05 | −0.04 | 0.09 | 0.03 | −0.03 | −0.04 | 0.01 | 0.73 | 0.72 | 1.00 |

N. Observations = 1255.

spinouts have a lower risk of failure relative to other startups. In the success equation, the test statistic is also significant ($\chi^2(2) = 15.36$, $p < .01$), indicating that inside– and outside–industry spinouts combined are associated with a higher chance of successful exit. Overall, the results support hypotheses 1 and 2.

The results for the controls suggest that a larger founding team size is associated weakly with a lower risk of failure ($\beta = -0.31$, $p < .1$) and a higher likelihood of successful closure ($\beta = 0.27$, $p < .01$). These results are consistent with the work that underscores the importance of founding team's human capital for startups, and the role of the individual founders as conduits of knowledge from incumbents to new firms (Agarwal et al., **2016**). The coefficient of experience variety in founding team is not significant. In an alternative specification, we operationalized this variable as number of distinct contexts in which founders were previously employed. The results indicate that startups launched by individuals transitioning from different contexts are more likely to fail which is indirect confirmation of the importance of shared experience within founding teams as highlighted in other studies (Honoré, **2022**). These results are available upon request. Further, the positive coefficient of duration dependence (i.e. logarithm of time) in the right-hand column of Model 3 suggests that longer established startups have a relatively higher chance of successful exit, supporting our theoretical arguments about the effect of post-entry experience on startup performance. In section 6, we explore this relationship in more detail.

Table 5 model 1 includes the independent variable that distinguishes between different types of outside–industry spinouts; models 2 and 3 include the control variables and fixed effects. We hypothesized that compared to other startups, spinouts originating from upstream supplier industries have a lower risk of failure (H3), and that all outside–industry spinout types have a higher likelihood of successful exit (H4). The coefficient of supplier industry spinouts is negative and significant in the left column of Model 3 ($\beta = -0.78$, $p < .05$), suggesting that the relative risk of failure for this category of outside–industry spinouts is 54 % lower compared to other startups which supports hypothesis 3. Also in the right-hand column of Model 3, the coefficients of all types of outside–industry spinouts are positive and significant, suggesting that academic spinouts, supplier industry spinouts, and user industry spinouts are respectively 5.1 times, 4.9 times, and 3.9 times more likely to experience a successful exit compared to other startups. A Wald test of the joint null hypothesis that the coefficients of all types of outside–industry spinouts are zero is statistically significant in the success equation ($\chi^2(3) = 16.53$, $p < .01$) which supports hypothesis 4.

## 6. Additional analyses

We ran several additional analyses to validate our findings. First, we suggested above that the performance of startups in nascent industries is linked to both their pre-entry experience and post-entry experience accumulated during operations. In particular, we argued that startups with pre-entry experience in the focal industry or related contexts along the value chain hold the resources needed to reduce the technological and demand uncertainties pervasive in nascent industries, and therefore, have increased chances of survival compared to other startups. We argued also that since the ability to learn from post-entry experience is a function of startup longevity and initial stock of resources, startups with related pre-entry experience will be more likely to achieve a successful exit compared to other startups. Supporting our argument related to the role of post-entry experience, in section 5, we showed that the baseline hazard rises with the length of survival time, suggesting that longer lived startups have relatively higher likelihoods of successful closure. Here, we examine how startup pre- and post-entry experience shapes performance in a nascent industry in more depth. Specifically, we test whether, compared to other startups, inside– and outside–industry spinouts exhibit a higher likelihood of successful closure as they continue in operation for longer. Appendix table A1 reports the results.

The coefficient of the interaction between inside–industry spinouts

**Table 4**
Competing Risks Model of Failure and Success for Hypotheses 1&2.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| VARIABLES | Failure | Success | Failure | Success | Failure | Success |
| Inside–industry Spinouts | −0.955* | 1.449*** | −1.025** | 1.419*** | −1.221** | 1.250*** |
| | (0.497) | (0.472) | (0.512) | (0.473) | (0.524) | (0.478) |
| Outside–industry Spinouts | −0.587** | 1.585*** | −0.515** | 1.578*** | −0.517** | 1.525*** |
| | (0.242) | (0.399) | (0.246) | (0.399) | (0.251) | (0.398) |
| Founding Team Size | | | −0.314* | 0.270*** | −0.311* | 0.271*** |
| | | | (0.180) | (0.094) | (0.188) | (0.096) |
| Founder Tenure | | | −0.016 | −0.013 | −0.012 | −0.013 |
| | | | (0.023) | (0.015) | (0.023) | (0.016) |
| Founder Position | | | 0.019 | 0.052 | 0.028 | 0.070 |
| | | | (0.233) | (0.159) | (0.237) | (0.162) |
| Serial Entrepreneur | | | 0.298 | 0.099 | 0.312 | 0.062 |
| | | | (0.240) | (0.160) | (0.242) | (0.162) |
| Experience Variety | | | 1.404** | 0.111 | 0.840 | −0.186 |
| | | | (0.623) | (0.395) | (0.632) | (0.407) |
| Number of Patents | | | −0.001 | 0.002*** | 0.003 | 0.002*** |
| | | | (0.025) | (0.001) | (0.006) | (0.001) |
| Number of Trademarks | | | −0.087* | −0.000 | −0.066 | 0.004 |
| | | | (0.049) | (0.011) | (0.053) | (0.012) |
| Total Funding | | | −0.024 | −0.001*** | −0.025 | −0.001*** |
| | | | (0.017) | (0.000) | (0.018) | (0.000) |
| log(time) | 0.187** | 0.449*** | 0.269*** | 0.527*** | 0.719*** | 0.759*** |
| | (0.088) | (0.084) | (0.101) | (0.090) | (0.158) | (0.119) |
| Constant | −4.416*** | −6.122*** | −4.108*** | −6.777*** | −6.348*** | −7.590*** |
| | (0.250) | (0.436) | (0.408) | (0.490) | (1.177) | (0.807) |
| Application Field Fixed Effect | NO | | NO | | YES | |
| Founding Year Fixed Effect | NO | | NO | | YES | |
| Observations [a] | 10,924 (1255) | | 10,924 (1255) | | 10,924 (1255) | |
| Log pseudolikelihood | −1589 | | −1556 | | −1520 | |
| Wald Chi2 | 52.02*** | | 363.0*** | | 737.3*** | |
| Pseudo R2 | 0.0189 | | 0.0392 | | 0.0614 | |

Note: Standard errors are clustered at the firm level. Reference category is other startups.
[a] The number of firms is in parentheses.
* Significant at 10 %.
** significant at 5 %.
*** significant at 1 %.

and startup age (i.e. the time since founding) is positive and significant, suggesting that for inside–industry spinouts, each additional year of survival is associated with a 0.33 percentage point increase in the predicted probability of successful closure compared to other startups. Given the well-known complexities involved in testing and interpreting interaction terms in nonlinear models (Wiersema and Bowen, 2009), we also calculated the true interaction effect using the procedure suggested by Ai and Norton (2003). In our model, the true interaction effect—measured as the difference in marginal effects of age between the two categories—is approximately 0.004 and is significant (z-statistic = 1.74, p < .1) which supports our theoretical arguments. The coefficients of the interaction term between different categories of outside–industry spinouts and age are also positive and significant, indicating that compared to other startups, a one-year increase in startup age is associated with a 0.19 percentage point increase in the predicted probability of successful exit for academic spinouts, a 0.20 percentage point increase for supplier industry spinouts, and 0.16 percentage point increase for user industry spinouts. The calculated true interaction effects further support the significance of these interaction terms.

We also checked whether the performance differences among startups persist across different AI fields. To perform this test, we split the sample into three groups based on startup's primary field of application. The sample is dominated by machine learning startups (73 %), with 13 % in the field of symbolic systems, and 14 % in robotics. The results are reported in Appendix table A2. In model 1, which relates to the field of machine learning, the signs and significance levels of the coefficients are in line with our main findings; compared to startups with no pre-entry AI-related experience, inside–industry spinouts and supplier industry spinouts have lower risks of failure, while inside– and all outside–industry spinout types have higher chances of successful exit. In model 2 (symbolic systems), all spinout types except supplier industry spinouts have lower risks of failure but not significantly higher chances of successful exit compared to other startups. In Model 3 (robotics), we observe no significant difference in the failure risk across different startup types and, compared to other startup entrants, only academic spinouts exhibit a higher likelihood of successful exit. In our view, the non-significant coefficients of the variables of interest in the symbolic systems and robotics fields might be due to small sample size which might result in higher standard errors and reduced statistical power.

We also explored whether startups vary in modes of successful exit. We created a four-level dependent variable (failed, acquired, went public, survived) and re-estimated the models using the detailed startup entrant classification. Appendix table A3 presents the results which show that inside– and outside–industry spinouts are more likely to exit the industry through acquisition rather than an IPO: none of the inside–industry spinouts in our sample exited via an IPO. This suggests that, rather than affecting the likelihood of going public (possibly due to the nascency of the industry), pre-entry experience in the focal industry or vertically related knowledge contexts provides the startup with the resources and capabilities that facilitate the development of complementary technologies or products and make the startup an attractive acquisition target for incumbents or late entrants.

## 7. Robustness checks

We conducted two additional tests to check the robustness of our results. First, we controlled for sensitivity of our results to sample construction and the measurement of the failure variable. As already discussed, the accuracy of Crunchbase data is greater for more recently

**Table 5**
Competing Risks Model of Failure and Success for Hypotheses 3&4.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| VARIABLES | Failure | Success | Failure | Success | Failure | Success |
| Inside–industry Spinouts | −0.953* | 1.447*** | −1.036** | 1.406*** | −1.223** | 1.237*** |
| | (0.497) | (0.472) | (0.512) | (0.473) | (0.524) | (0.477) |
| Academic Spinouts | −0.534* | 1.646*** | −0.281 | 1.673*** | −0.410 | 1.628*** |
| | (0.300) | (0.414) | (0.317) | (0.420) | (0.323) | (0.422) |
| Supplier Industry Spinouts | −0.870*** | 1.647*** | −0.849*** | 1.631*** | −0.780** | 1.599*** |
| | (0.315) | (0.411) | (0.325) | (0.410) | (0.325) | (0.411) |
| User Industry Spinouts | −0.419 | 1.468*** | −0.435 | 1.440*** | −0.411 | 1.371*** |
| | (0.276) | (0.414) | (0.280) | (0.415) | (0.287) | (0.411) |
| Founding Team Size | | | −0.310* | 0.266*** | −0.300 | 0.266*** |
| | | | (0.177) | (0.094) | (0.186) | (0.095) |
| Founder Tenure | | | −0.016 | −0.017 | −0.011 | −0.017 |
| | | | (0.023) | (0.015) | (0.023) | (0.016) |
| Founder Position | | | 0.111 | 0.116 | 0.063 | 0.141 |
| | | | (0.263) | (0.176) | (0.266) | (0.179) |
| Serial Entrepreneur | | | 0.289 | 0.110 | 0.306 | 0.069 |
| | | | (0.235) | (0.159) | (0.241) | (0.161) |
| Experience Variety | | | 1.380** | 0.119 | 0.805 | −0.185 |
| | | | (0.613) | (0.394) | (0.628) | (0.407) |
| Number of Patents | | | −0.003 | 0.002*** | 0.003 | 0.002*** |
| | | | (0.024) | (0.001) | (0.011) | (0.001) |
| Number of Trademarks | | | −0.091* | −0.001 | −0.072 | 0.004 |
| | | | (0.049) | (0.011) | (0.053) | (0.012) |
| Total Funding | | | −0.025 | −0.001*** | −0.025 | −0.001*** |
| | | | (0.017) | (0.000) | (0.018) | (0.000) |
| log(time) | 0.197** | 0.443*** | 0.287*** | 0.522*** | 0.719*** | 0.761*** |
| | (0.089) | (0.084) | (0.103) | (0.090) | (0.157) | (0.119) |
| Constant | −4.433*** | −6.109*** | −4.181*** | −6.786*** | −6.368*** | −7.582*** |
| | (0.252) | (0.436) | (0.413) | (0.491) | (1.180) | (0.787) |
| Application Field Fixed Effect | NO | | NO | | YES | |
| Founding Year Fixed Effect | NO | | NO | | YES | |
| Observations [a] | 10,924 (1255) | | 10,924 (1255) | | 10,924 (1255) | |
| Log pseudolikelihood | −1587 | | −1553 | | −1518 | |
| Wald Chi2 | 56.78*** | | 371.4*** | | 703.0*** | |
| Pseudo R2 | 0.0201 | | 0.0408 | | 0.0626 | |

Note: Standard errors are clustered at the firm level. Reference category is other startups.
[a] The number of firms is in parentheses.
* Significant at 10 %.
** significant at 5 %.
*** significant at 1 %.

founded startups. To test whether our results hold for the sample with more reliable coverage, we reran the analysis on startups founded after 2002 (Chattopadhyay et al., 2025). We also relied on information reported on Crunchbase to measure startup failure. Appendix table A4 shows that compared to other startups, inside–industry spinouts and supplier industry spinouts have a lower risk of failure and inside– and outside–industry spinouts have a higher chance of successful exit which is consistent with the main findings.

Second, we explored whether the choice of the estimation method might have affected our results. We began by employing a standard discrete-time proportional hazard model (complementary log-log) using different specifications of the baseline hazard function: piece-wise constant, polynomial, and log(time). Appendix table A5 models 1 to 3 present the results which are largely consistent with the main findings. Next, while we added several control variables at the individual, founding team, and firm levels to account for other factors that might affect startup performance, there may be some systematic differences across startups that are not directly observable. In order to take account of unobserved heterogeneity (i.e. frailty), we employed both complementary log-logistic and logistic as the link function, and estimated random effects regressions with normally distributed error terms. *sigma_u* reports the standard deviation of the heterogeneity variance, and *rho* is the ratio of the heterogeneity variance to 1 plus the heterogeneity variance. Since the null hypothesis that rho is zero is rejected at the 10 % level (the reported LR frailty test) for the outcome category of failure, the results suggest that frailty is important in our data. The larger estimated coefficients suggest that the coefficients in the reference model are likely to be underestimates of the *true* value. However, the direction and significance level of the coefficients of the variables of interest are similar to those in the reference model (see **Table 5**) which support the main findings.

## 8. Discussion and conclusion

In this study, we examined how the pre-entry experience of startup entrants to a nascent industry shapes their likelihood of failure and successful exit. We advanced hypotheses grounded in the premise that the startup overall performance is linked to its pre-entry experience which influences the stock of resources available to the startup at the time of establishment. Extending prior literature that emphasizes the performance advantages of inside-industry spinouts derived from founders' previous employment in the focal industry, we argue that experience in a vertically related knowledge context also provides founders and their startups with core resources that can be leveraged to reduce the uncertainties typical of nascent industries and to increase the startups' chances of survival. We argued also that both inside– and outside–industry spinouts achieve more effective post-entry learning which increases their chances of successful exit compared to other startups. Our analysis of data from the nascent AI industry in the U.S. supports our hypotheses.

### *8.1. Theoretical contributions*

This study contributes to two literature streams. First, it adds to the strategy literature by theorizing and showing that pre-entry experience can condition the chances of startup survival and successful closure in the case of startups that cross industry boundaries. While the focus of prior literature has been mainly on startups launched by founders with experience in the same industry, some recent studies suggest that startups can originate in other knowledge contexts including academic institutions and both upstream and downstream industries related to a focal industry along the value chain (Adams et al., 2024; Cattani et al., 2024). We contribute to this literature by providing evidence that startup pre-entry experience in a vertically related context can condition its survival prospects in the focal industry. Indeed, the analysis in this paper suggests that in the nascent AI industry, the risks of failure are similar for both inside– and outside–industry spinouts. We show also that both inside– and outside–industry spinouts exhibit higher rates of successful exit compared to other startups. In this regard, our results reconcile the literature on employee entrepreneurship which emphasizes the performance advantages of inside–industry spinouts (e.g. Agarwal et al., 2004), with a more recent strand of work which identifies the conditions that influence the better performance of outside–industry spinouts (e.g. Adams et al., 2016; Costa and Baptista, 2023).

This study also adds to our understanding of the pre-entry experience–performance relationship in the context of a nascent industry. Prior work suggests that the performance of entrants is determined by the degree to which their resources and capabilities match the resources required for successful operation (e.g. Klepper and Simons, 2000; Sosa, 2009). However, compared with established industries, nascent industries exhibit a lower stock of industry-specific knowledge which makes the resources required for effective operation and competition largely unclear (Anderson and Tushman, 1990; Bayus and Agarwal, 2007; Ganco and Agarwal, 2009). By underlining the importance of the entrant's ability to resolve uncertainties related to technology and market demand, this study provides a more nuanced understanding of the determinants of startup entrants survival and exit chances in a nascent industry.

Second, we add to the body of research on industry evolution. The literature emphasizes the roles played by diverse actors in the emergence and evolution of a new industry (e.g. Agarwal et al., 2025). Startups contribute to the growth of an emerging industry by building knowledge through sense-making, experimentation, and active investment in different technologies and variants of existing products (Agarwal et al., 2017; Moeen et al., 2020). In this study, we suggest that startups originating from vertically related contexts are not only relevant actors in the nascent industries, but they are a heterogeneous category of entrants, therefore bringing distinct core resources and complementary capabilities that influence the evolution of the industry's knowledge base and in turn, shape its subsequent structure. Our findings show that the best-performing category of outside–industry spinouts in terms of survival is supplier industry spinouts. Through the prior employment experience of their founders in related upstream industries, supplier industry spinouts get access to knowledge of core components and key technologies that they can leverage to reduce uncertainty related to technology and the whole industry context through innovative, entrepreneurial, and production activities. Therefore, this study underscores the important role played by this category of startups in shaping market structure and the dynamic patterns of industrial change in a new industry.

### *8.2. Limitation and policy implications*

This study has some limitations which provide opportunities for future research. First, in examining the effect of pre-entry experience on spinout performance, we focused on the most recent employment experience of the founding team. While this is in line with work on employee and academic entrepreneurship (e.g. Adams et al., 2016; Agarwal and Shah, 2014; Roche et al., 2020), prospective founders often work at multiple firms before embarking on entrepreneurship, gaining diverse career experiences which might influence the performance of the startups they establish (Åstebro et al., 2011; Burton et al., 2002; Chen and Thompson, 2016). Research shows that the effect of previous employment experiences tends to decay over time (Burt, 2000) which makes the founder's most recent employment experience more relevant in terms of the resources they bring to the startup (Agarwal et al., 2004). We hope, however, that our work will encourage further investigation of how founders' pre-entry experience across their entire careers affects the performance of the startups they eventually establish.

Second, although we introduced several controls to capture other factors that may affect startup performance, the nature of our data limits our ability to draw definitive conclusions about the causal effect of founder's prior employment experience on the performance of their startup in a nascent industry. Future research could exploit experimental and quasi-experimental methods to address identification issues and strengthen causal inferences.

Third, our empirical setting (a technology-oriented industry with a pervasive effect across a wide range of sectors) might limit the generalizability of our findings. However, we believe that the results of our analysis of a specific nascent industry can be generalized to other emerging industries with features common to the AI industry. High-tech industries such as semiconductors, packaged software, and telecoms equipment have strong links to universities and upstream or downstream sectors. Empirical studies suggest that in these industries, academic, supplier industry, and user industry spinouts are indeed relevant (Adams et al., 2024). Future research could investigate the extent to which our results hold for these industries or in other sectors that are not necessarily technology intensive.

The heterogeneity in startup entrants' pre-entry experience has important implications for policy. We highlighted the importance of universities and industry incumbents operating in vertically related upstream and downstream industries as hotbeds for entrepreneurship. Given the systematic differences across these knowledge contexts, our results suggest the need for more targeted policies to promote innovation and entrepreneurship in these contexts. These policies could include but should not be limited to support for commercialization of university generated inventions and early-stage funding for startup founders with prior experience relevant to the focal industry. In line with previous work (Clarysse et al., 2011; Roche et al., 2020), our findings highlight the absence of complementary capabilities as a critical factor for the survival of academic spinouts. Our paper should be informative for universities, governments, and policymakers involved in formulating policies to support academic entrepreneurs, and particularly those launching startups in emerging sectors. These interventions could include programs that would facilitate links between experienced professionals in the focal industry and academic entrepreneurs such as startup incubators, mentorship schemes, or advisory networks.

## CRediT authorship contribution statement

**Aliasghar Bahoo-Torodi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Roberto Fontana:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Franco Malerba:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

**Table A1**
Additional Analysis (Interaction between Startup Type and Age).

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| VARIABLES | Failure | Success | Failure | Success | Failure | Success |
| Inside–industry Spinouts | −1.204** | 1.307*** | −2.129*** | 0.005 | −2.198*** | −0.040 |
| | (0.499) | (0.476) | (0.651) | (0.667) | (0.667) | (0.689) |
| Academic Spinouts | −0.621** | 1.595*** | −0.465 | 0.769 | −0.408 | 0.889* |
| | (0.306) | (0.417) | (0.391) | (0.509) | (0.416) | (0.526) |
| Supplier Industry Spinouts | −0.835*** | 1.623*** | −0.777* | 0.846* | −0.765* | 0.792 |
| | (0.311) | (0.417) | (0.416) | (0.499) | (0.420) | (0.506) |
| User Industry Spinouts | −0.431 | 1.405*** | −0.544 | 0.537 | −0.640* | 0.548 |
| | (0.279) | (0.414) | (0.350) | (0.502) | (0.352) | (0.513) |
| Startup Age | 0.071** | 0.076*** | 0.069 | −0.054 | 0.060 | −0.043 |
| | (0.031) | (0.017) | (0.043) | (0.061) | (0.043) | (0.064) |
| Inside–industry Spinouts × Age | | | 0.165** | 0.215** | 0.172** | 0.216** |
| | | | (0.078) | (0.086) | (0.078) | (0.090) |
| Academic Spinouts × Age | | | −0.028 | 0.131** | −0.002 | 0.125* |
| | | | (0.051) | (0.063) | (0.053) | (0.066) |
| Supplier Industry Spinouts × Age | | | −0.010 | 0.125** | −0.004 | 0.132** |
| | | | (0.050) | (0.062) | (0.052) | (0.065) |
| User Industry Spinouts × Age | | | 0.021 | 0.139** | 0.039 | 0.134** |
| | | | (0.041) | (0.063) | (0.044) | (0.066) |
| Founding Team Size | | | | | −0.309* | 0.260*** |
| | | | | | (0.185) | (0.094) |
| Founder Tenure | | | | | −0.012 | −0.018 |
| | | | | | (0.022) | (0.017) |
| Founder Position | | | | | 0.080 | 0.168 |
| | | | | | (0.266) | (0.181) |
| Serial Entrepreneur | | | | | 0.313 | 0.077 |
| | | | | | (0.237) | (0.160) |
| Experience Variety | | | | | 0.802 | −0.188 |
| | | | | | (0.620) | (0.402) |
| Number of Patents | | | | | 0.003 | 0.002*** |
| | | | | | (0.006) | (0.001) |
| Number of Trademarks | | | | | −0.073 | 0.005 |
| | | | | | (0.053) | (0.012) |
| Total Funding | | | | | −0.025 | −0.001*** |
| | | | | | (0.018) | (0.000) |
| Constant | −6.576*** | −6.601*** | −6.569*** | −5.711*** | −5.718*** | −6.386*** |
| | (1.528) | (0.864) | (1.743) | (0.995) | (1.733) | (1.057) |
| Observations [a] | 10,924 (1255) | | 10,924 (1255) | | 10,924 (1255) | |
| Log pseudolikelihood | −1562 | | −1559 | | −1532 | |
| Wald Chi2 | 108.7*** | | 124.6*** | | 714.0*** | |
| Pseudo R2 | 0.0356 | | 0.0376 | | 0.0541 | |

Note: Standard errors are clustered at the firm level. Reference category is other startups.
All models include application field and founding year fixed effects.

[a] The number of firms is in parentheses.
* Significant at 10 %.
** significant at 5 %.
*** significant at 1 %.

**Table A2**
Additional Analysis (Competing Risks Model by Application Field).

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Application Field: Machine Learning | | Application Field: Symbolic Systems | | Application Field: Robotics | |
| VARIABLES | Failure | Success | Failure | Success | Failure | Success |
| Inside–industry Spinouts | −1.590** | 1.783*** | −15.208*** | −0.681 | 0.699 | 1.256 |
| | (0.778) | (0.606) | (0.684) | (1.404) | (0.731) | (0.987) |
| Academic Spinouts | −0.450 | 1.668*** | −1.178* | 1.591 | 0.443 | 1.626* |
| | (0.413) | (0.554) | (0.652) | (1.056) | (0.801) | (0.872) |
| Supplier Industry Spinouts | −1.588*** | 1.973*** | −1.009 | 0.547 | −0.358 | 0.658 |
| | (0.495) | (0.540) | (0.746) | (1.079) | (0.784) | (0.912) |
| User Industry Spinouts | −0.301 | 1.833*** | −2.031** | 0.313 | −1.332 | 0.206 |
| | (0.334) | (0.539) | (0.814) | (1.127) | (1.167) | (1.149) |
| Founding Team Size | −0.268 | 0.250** | −0.210 | 0.625*** | −0.430 | 0.187 |
| | (0.205) | (0.124) | (0.474) | (0.230) | (0.647) | (0.173) |
| Founder Tenure | −0.021 | −0.018 | 0.021 | 0.017 | −0.031 | −0.012 |
| | (0.031) | (0.021) | (0.056) | (0.034) | (0.052) | (0.045) |
| Founder Position | 0.141 | 0.024 | −0.150 | 0.145 | 0.653 | 0.103 |
| | (0.329) | (0.209) | (0.588) | (0.449) | (0.741) | (0.718) |
| Serial Entrepreneur | 0.527* | 0.039 | 0.314 | 0.075 | −0.978 | 1.087* |
| | (0.301) | (0.188) | (0.573) | (0.418) | (0.919) | (0.564) |
| Experience Variety | 1.719** | 0.429 | −0.247 | −1.447 | 0.643 | −0.699 |
| | (0.701) | (0.487) | (1.750) | (1.022) | (2.248) | (1.149) |
| Number of Patents | 0.004 | 0.001 | −0.130 | 0.005 | −0.095 | 0.004 |
| | (0.003) | (0.001) | (0.147) | (0.005) | (0.096) | (0.011) |
| Number of Trademarks | −0.092 | 0.008 | 0.026 | −0.068 | −0.045 | −0.015 |
| | (0.094) | (0.021) | (0.186) | (0.052) | (0.128) | (0.083) |
| Total Funding | −0.027 | −0.002* | −0.038 | −0.001 | −0.010 | −0.016* |
| | (0.023) | (0.001) | (0.025) | (0.003) | (0.014) | (0.009) |
| log(time) | 0.311** | 0.594*** | 0.211 | 0.698*** | 0.514** | 0.035 |
| | (0.139) | (0.108) | (0.226) | (0.192) | (0.248) | (0.303) |
| Constant | −4.571*** | −7.178*** | −2.499*** | −6.341*** | −4.414*** | −5.622*** |
| | (0.581) | (0.638) | (0.714) | (1.109) | (0.957) | (1.254) |
| Observations [a] | 7998 (917) | | 1379 (159) | | 1547 (179) | |
| Log pseudolikelihood | −1048 | | −270.8 | | −193.5 | |
| Wald Chi2 | 873.0*** | | 1558*** | | 77.51*** | |
| Pseudo R2 | 0.0519 | | 0.0854 | | 0.0739 | |

Note: Standard errors are clustered at the firm level. Reference category is other startups.
[a] The number of firms is in parentheses.
* Significant at 10 %.
** significant at 5 %.
*** significant at 1 %.

**Table A3**
Additional Analysis (Competing Risks Model of Failure, Acquisition, and IPO).

| | (1) | | | (2) | | | (3) | | | (4) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Failure | ACQ | IPO | Failure | ACQ | IPO | Failure | ACQ | IPO | Failure | ACQ | IPO |
| Inside–industry Spinouts | −1.213** | 1.386*** | −11.198*** | −1.221** | 1.387*** | −12.617*** | −1.209** | 1.382*** | −11.240*** | −1.222** | 1.377*** | −12.657*** |
| | (0.501) | (0.497) | (1.047) | (0.524) | (0.503) | (1.128) | (0.502) | (0.497) | (1.045) | (0.524) | (0.502) | (1.116) |
| Outside–industry Spinouts | −0.603** | 1.559*** | 1.179 | −0.516** | 1.610*** | 0.991 | | | | | | |
| | (0.247) | (0.422) | (1.104) | (0.251) | (0.422) | (1.220) | | | | | | |
| Academic Spinouts | | | | | | | −0.621** | 1.606*** | 1.256 | −0.409 | 1.688*** | 1.046 |
| | | | | | | | (0.309) | (0.440) | (1.115) | (0.323) | (0.445) | (1.325) |
| Supplier Industry Spinouts | | | | | | | −0.830*** | 1.630*** | 1.423 | −0.779** | 1.665*** | 1.389 |
| | | | | | | | (0.314) | (0.436) | (1.186) | (0.324) | (0.436) | (1.274) |
| User Industry Spinouts | | | | | | | −0.428 | 1.454*** | 0.688 | −0.410 | 1.493*** | 0.400 |
| | | | | | | | (0.282) | (0.436) | (1.192) | (0.287) | (0.437) | (1.261) |
| Founding Team Size | | | | −0.311* | 0.283*** | 0.067 | | | | −0.300 | 0.280*** | 0.094 |
| | | | | (0.188) | (0.101) | (0.402) | | | | (0.186) | (0.100) | (0.396) |
| Founder Tenure | | | | −0.012 | −0.022 | 0.053 | | | | −0.011 | −0.024 | 0.057 |
| | | | | (0.023) | (0.018) | (0.035) | | | | (0.023) | (0.019) | (0.038) |
| Founder Position | | | | 0.027 | −0.025 | 1.390* | | | | 0.062 | 0.031 | 1.410* |
| | | | | (0.237) | (0.165) | (0.810) | | | | (0.266) | (0.183) | (0.795) |
| Serial Entrepreneur | | | | 0.312 | 0.105 | −0.788 | | | | 0.305 | 0.110 | −0.841 |
| | | | | (0.242) | (0.168) | (0.665) | | | | (0.241) | (0.168) | (0.662) |
| Experience Variety | | | | 0.841 | −0.140 | −0.663 | | | | 0.806 | −0.140 | −0.818 |
| | | | | (0.632) | (0.424) | (2.020) | | | | (0.628) | (0.423) | (1.971) |
| Number of Patents | | | | 0.003 | 0.002 | 0.000 | | | | 0.003 | 0.002 | −0.000 |
| | | | | (0.005) | (0.001) | (0.001) | | | | (0.010) | (0.001) | (0.001) |
| Number of Trademarks | | | | −0.066 | −0.023 | 0.044 | | | | −0.073 | −0.023 | 0.047* |
| | | | | (0.054) | (0.022) | (0.029) | | | | (0.054) | (0.022) | (0.029) |
| Total Funding | | | | −0.025 | −0.002** | −0.002* | | | | −0.025 | −0.002** | −0.002* |
| | | | | (0.018) | (0.001) | (0.001) | | | | (0.018) | (0.001) | (0.001) |
| log(time) | 0.704*** | 0.849*** | −0.097 | 0.720*** | 0.862*** | 0.115 | 0.703*** | 0.850*** | −0.091 | 0.720*** | 0.863*** | 0.130 |
| | (0.156) | (0.130) | (0.187) | (0.158) | (0.131) | (0.232) | (0.156) | (0.130) | (0.188) | (0.157) | (0.131) | (0.235) |
| Constant | −6.992*** | −8.097*** | −5.486*** | −6.349*** | −8.336*** | −6.967*** | −6.998*** | −8.091*** | −5.487*** | −6.369*** | −8.327*** | −7.139*** |
| | (1.192) | (0.905) | (1.346) | (1.178) | (0.988) | (1.688) | (1.195) | (0.893) | (1.343) | (1.181) | (0.971) | (1.713) |
| Observations [a] | | 10,924 (1255) | | | 10,924 (1255) | | | 10,924 (1255) | | | 10,924 (1255) | |
| Log pseudolikelihood | | −1595 | | | −1559 | | | −1593 | | | −1556 | |
| Wald Chi2 | | 3019*** | | | 16404*** | | | 3079*** | | | 16236*** | |
| Pseudo R2 | | 0.0537 | | | 0.0751 | | | 0.0549 | | | 0.0766 | |

Note: Standard errors are clustered at the firm level. Reference category is other startups. All models include application field and founding year fixed effects.
[a] The number of firms is in parentheses.
[*] Significant at 10 %.
[**] significant at 5 %.
[***] significant at 1 %.

**Table A4**
Robustness Test (Competing Risks Model for Startups Founded After 2002).

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Failure | Success | Failure | Success | Failure | Success | Failure | Success |
| Inside–industry Spinouts | −1.873* | 0.955** | −2.074* | 0.940** | −1.880* | 0.955** | −2.071* | 0.938** |
| | (1.072) | (0.475) | (1.067) | (0.478) | (1.073) | (0.475) | (1.068) | (0.478) |
| Outside–industry Spinouts | −0.910** | 1.132*** | −0.901** | 1.193*** | | | | |
| | (0.420) | (0.389) | (0.431) | (0.387) | | | | |
| Academic Spinouts | | | | | −1.138* | 1.100*** | −0.977 | 1.187*** |
| | | | | | (0.599) | (0.417) | (0.681) | (0.425) |
| Supplier Industry Spinouts | | | | | −1.147** | 1.314*** | −1.220** | 1.384*** |
| | | | | | (0.573) | (0.408) | (0.586) | (0.404) |
| User Industry Spinouts | | | | | −0.648 | 0.999** | −0.681 | 1.035** |
| | | | | | (0.461) | (0.406) | (0.463) | (0.404) |
| Founding Team Size | | | −0.032 | 0.281** | | | −0.020 | 0.271** |
| | | | (0.228) | (0.113) | | | (0.232) | (0.113) |
| Founder Tenure | | | 0.015 | −0.047** | | | 0.020 | −0.052** |
| | | | (0.044) | (0.023) | | | (0.043) | (0.023) |
| Founder Position | | | −0.228 | 0.031 | | | −0.300 | 0.055 |
| | | | (0.432) | (0.191) | | | (0.500) | (0.210) |
| Serial Entrepreneur | | | 0.915** | 0.092 | | | 0.907** | 0.090 |
| | | | (0.427) | (0.188) | | | (0.415) | (0.187) |
| Experience Variety | | | 0.183 | −0.248 | | | 0.137 | −0.224 |
| | | | (0.971) | (0.458) | | | (0.982) | (0.459) |
| Number of Patents | | | −0.589** | −0.011 | | | −0.594** | −0.012 |
| | | | (0.280) | (0.012) | | | (0.284) | (0.012) |
| Number of Trademarks | | | 0.060 | 0.029 | | | 0.055 | 0.030 |
| | | | (0.120) | (0.019) | | | (0.121) | (0.018) |
| Total Funding | | | −0.004 | −0.002** | | | −0.004 | −0.002** |
| | | | (0.013) | (0.001) | | | (0.013) | (0.001) |
| log(time) | 0.582** | 0.697*** | 0.606** | 0.709*** | 0.581** | 0.699*** | 0.605** | 0.711*** |
| | (0.281) | (0.138) | (0.280) | (0.138) | (0.282) | (0.138) | (0.278) | (0.139) |
| Constant | −18.562*** | −6.669*** | −18.476*** | −6.939*** | −19.542*** | −6.693*** | −20.492*** | −6.961*** |
| | (0.715) | (0.618) | (1.116) | (0.653) | (0.724) | (0.622) | (1.032) | (0.656) |
| Observations [a] | 9044 (1141) | | 9044 (1141) | | 9044 (1141) | | 9044 (1141) | |
| Log pseudolikelihood | −922.1 | | −906.7 | | −920.3 | | −904.8 | |
| Wald Chi2 | 1932*** | | 1390*** | | 2372*** | | 3113*** | |
| Pseudo R2 | 0.0356 | | 0.0518 | | 0.0375 | | 0.0537 | |

Note: Standard errors are clustered at the firm level. Reference category is other startups.
All models include application field and founding year fixed effects.
[a] The number of firms is in parentheses.
* Significant at 10 %.
** significant at 5 %.
*** significant at 1 %.

**Table A5**
Robustness Test (Discrete-time Proportional Hazard Model with Alternative Specifications of Baseline and Incorporating Unobserved Heterogeneity).

| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Failure | Success | Failure | Success | Failure | Success | Failure | Success | Failure | Success | Failure | Success |
| Inside–industry Spinouts | −1.231** | 1.225*** | −1.244** | 1.234*** | −1.225** | 1.242*** | −2.135** | 1.361*** | −1.236** | 1.254*** | −2.356** | 1.383*** |
| | (0.523) | (0.464) | (0.521) | (0.463) | (0.525) | (0.465) | (0.845) | (0.520) | (0.527) | (0.469) | (1.034) | (0.532) |
| Academic Spinouts | −0.460 | 1.596*** | −0.470 | 1.581*** | −0.429 | 1.623*** | −0.720 | 1.779*** | −0.433 | 1.636*** | −0.801 | 1.810*** |
| | (0.318) | (0.412) | (0.316) | (0.410) | (0.321) | (0.413) | (0.545) | (0.482) | (0.324) | (0.415) | (0.621) | (0.497) |
| Supplier Industry Spinouts | −0.804** | 1.581*** | −0.823*** | 1.554*** | −0.793** | 1.600*** | −1.450** | 1.740*** | −0.802** | 1.611*** | −1.603** | 1.770*** |
| | (0.320) | (0.401) | (0.318) | (0.400) | (0.322) | (0.403) | (0.570) | (0.467) | (0.324) | (0.405) | (0.706) | (0.481) |
| User Industry Spinouts | −0.435 | 1.356*** | −0.454 | 1.335*** | −0.424 | 1.369*** | −0.753 | 1.499*** | −0.428 | 1.379*** | −0.840 | 1.523*** |
| | (0.281) | (0.400) | (0.279) | (0.399) | (0.283) | (0.401) | (0.506) | (0.460) | (0.286) | (0.403) | (0.585) | (0.472) |
| Founding Team Size | −0.305* | 0.265*** | −0.316* | 0.266*** | −0.304* | 0.265*** | −0.451 | 0.320*** | −0.306* | 0.269*** | −0.496 | 0.328** |
| | (0.182) | (0.093) | (0.183) | (0.092) | (0.183) | (0.093) | (0.309) | (0.124) | (0.184) | (0.095) | (0.351) | (0.129) |
| Founder Tenure | −0.010 | −0.016 | −0.013 | −0.018 | −0.010 | −0.016 | −0.025 | −0.021 | −0.010 | −0.017 | −0.028 | −0.021 |
| | (0.022) | (0.016) | (0.022) | (0.017) | (0.022) | (0.017) | (0.044) | (0.022) | (0.022) | (0.017) | (0.049) | (0.022) |
| Founder Position | 0.043 | 0.131 | 0.053 | 0.134 | 0.058 | 0.139 | 0.074 | 0.159 | 0.060 | 0.141 | 0.085 | 0.162 |
| | (0.267) | (0.179) | (0.263) | (0.178) | (0.265) | (0.180) | (0.398) | (0.200) | (0.266) | (0.181) | (0.444) | (0.205) |
| Serial Entrepreneur | 0.291 | 0.052 | 0.297 | 0.043 | 0.300 | 0.065 | 0.612 | 0.088 | 0.304 | 0.066 | 0.677 | 0.089 |
| | (0.238) | (0.160) | (0.236) | (0.159) | (0.239) | (0.161) | (0.375) | (0.179) | (0.240) | (0.162) | (0.437) | (0.184) |
| Experience Variety | 0.818 | −0.178 | 0.806 | −0.232 | 0.800 | −0.186 | 1.231 | −0.272 | 0.811 | −0.192 | 1.355 | −0.283 |
| | (0.619) | (0.394) | (0.618) | (0.390) | (0.620) | (0.395) | (1.058) | (0.451) | (0.624) | (0.401) | (1.192) | (0.463) |
| Number of Patents | 0.001 | 0.002** | 0.001 | 0.001* | 0.002 | 0.002** | 0.005 | 0.002* | 0.003 | 0.002** | 0.005 | 0.002* |
| | (0.024) | (0.001) | (0.022) | (0.001) | (0.011) | (0.001) | (0.024) | (0.001) | (0.010) | (0.001) | (0.028) | (0.001) |
| Number of Trademarks | −0.072 | 0.004 | −0.068 | 0.006 | −0.072 | 0.004 | −0.131 | 0.008 | −0.072 | 0.004 | −0.143 | 0.008 |
| | (0.052) | (0.013) | (0.050) | (0.012) | (0.053) | (0.013) | (0.095) | (0.015) | (0.053) | (0.013) | (0.106) | (0.016) |
| Total Funding | −0.025 | −0.001*** | −0.025 | −0.001** | −0.025 | −0.001*** | −0.034*** | −0.002** | −0.025 | −0.001*** | −0.037** | −0.002** |
| | (0.018) | (0.000) | (0.019) | (0.000) | (0.018) | (0.000) | (0.013) | (0.001) | (0.018) | (0.000) | (0.015) | (0.001) |
| log(time) | | | | | 0.699*** | 0.747*** | 1.831*** | 0.962*** | 0.706*** | 0.754*** | 2.021*** | 0.983*** |
| | | | | | (0.155) | (0.118) | (0.376) | (0.310) | (0.157) | (0.119) | (0.658) | (0.322) |
| Constant | −5.683*** | −7.114*** | −16.078*** | −18.593*** | −6.321*** | −7.558*** | −10.326*** | −8.372*** | −6.328*** | −7.582*** | −10.974*** | −8.462*** |
| | (0.982) | (0.705) | (0.553) | (0.612) | (1.059) | (0.728) | (2.296) | (1.424) | (1.066) | (0.733) | (3.108) | (1.486) |
| Link Function | C log-log | | C log-log | | C log-log | | C log-log | | Logistic | | Logistic | |
| Baseline Hazard Function | Polynomial | | Piece-wise constant | | Logarithmic | | Logarithmic | | Logarithmic | | Logarithmic | |
| Frailty Term Distribution | – | | – | | – | | Normal | | – | | Normal | |
| Log-likelihood | −538.1 | −980.0 | −549.3 | −998.3 | −540.4 | −979.9 | −538.6 | −979.5 | −540.3 | −980.0 | −538.6 | −979.4 |
| Chi2 | 153.2*** | 113.4*** | 67.74*** | 1104*** | 83.88*** | 111.7*** | 38.95*** | 34.93** | 82.48*** | 108.8*** | 19.14 | 32.72** |
| Sigma_u | | | | | | | 2.85 | 1.07 | | | 3.17 | 1.10 |
| Rho | | | | | | | 0.83 | 0.41 | | | 0.75 | 0.27 |
| LR test for frailty (rho = 0) | | | | | | | 3.51** | 0.94 | | | 3.41** | 1.12 |

Note: Robust standard errors in parentheses, except for models 4 and 6. Reference category is other startups.
All models include application field and founding year fixed effects.

* Significant at 10 %.

** significant at 5 %.

*** significant at 1 %.

## Data availability

Data will be made available on request.

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