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Pre-entry experience, knowledge inheritance, and entrepreneurial resource mobilization

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Abstract We study the conditions under which founders' pre-entry experience in the industry affects the prospects of new ventures mobilizing financial resources. Drawing on signaling theory, we theorize that the signal value of pre-entry experience is contingent on the extent to which new ventures leverage such experience as well as the environmental context in which they operate. Specifically, we argue that knowledge linkages to founders' former employer increase the clarity of the pre-entry experience signal. We further posit that this clarified pre-entry experience signal is more valuable in competitive environments. We investigate these effects by focusing on the time to first VC funding for startups in the US semiconductor industry. We show that (1) knowledge linkages to the founders' previous employer accentuate the effect of pre-entry experience by further

shortening the time to VC funding and (2) this shortening in time is more significant when the industry clustering is high.

Plain English Summary When does pre-entry experience matter more for technology entrepreneurs? Pre-entry experience is considered a key success factor for technology entrepreneurs. In this study, we uncover the conditions under which pre-entry experience can support the founders' efforts to overcome resource bottlenecks in their quest to commercialize their ideas. We find that pre-entry experience remedies the information gap prospective investors encounter, especially when startups use knowledge from the founder's former employer, thus enabling founders to attract financial resources faster than others. Building on the previous employer's knowledge is even more impactful in accelerating the influx of financial capital when startups face stiff competition for resources. Our findings imply that researchers must further unpack the nuances associated with the influence of founders' pre-entry experience on startups' success. For practitioners, our findings suggest that founders can reap the benefits of their experiences by more deeply engaging with their experience in observable ways.

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1 Introduction

Financial resource mobilization is a central concern for new ventures (Kotha & George, 2012; Plummer et al., 2016; Shane & Cable, 2002). In the quest for financial resources, new ventures encounter an arduous path because their meager credentials present prospective investors with uncertainty and information asymmetry (Amit et al., 1990). New ventures can assuage investors' concerns through their observable attributes and actions that function as quality signals (Stuart et al., 1999). Prominent among such attributes that can serve as a signal is the pre-entry experience of founders at existing firms in the industry (Chatterji, 2009; Ko & McKelvie, 2018).

The signal value of pre-entry experience can point to a newborn venture's industry-specific knowledge and skills, features hard to observe for outsiders (Ko & McKelvie, 2018), but comes with inherent limits. It is limited because investors' concerns center not on the initial stock of knowledge and skills founders pass on to the new venture per se but on the new venture's capacity to learn and build on those endowments, which determines commercial success ultimately (Dencker & Gruber, 2015). Whereas such theoretical bounds on the signal value of pre-entry experience indicate the significance of contingencies, prior research has paid little attention to the factors that shape the signaling effects of pre-entry experience. This lack of attention is a crucial gap from the standpoint of signaling theory as well as that of pre-entry experience literature. Recent signaling research suggests a contingent view of signaling (Bapna, 2019; Kotha et al., 2018; Vanacker et al., 2020) and calls for a deeper examination of the context in which signals are sent (Connelly et al., 2011). Similarly, a summative account of pre-entry experience research by Cao and Posen (2023) reveals a paucity of studies on when and how pre-entry experience matters for new ventures and advocates delving into the conditions that modify the effects of pre-entry experience.

To address the gap outlined above, we investigate the conditions influencing the effect of pre-entry experience on new ventures' financial resource mobilization. The starting point of our investigation is that new ventures with pre-entry experience in the

industry enjoy a signaling advantage when mobilizing financial resources. Building on this baseline, we formulate two research questions. In the first question, we draw on the notion of inherited knowledge (Huber, 1991; Klepper & Sleeper, 2005) to consider the knowledge characteristics of the new ventures with pre-entry experience and ask: to what extent does drawing on the previous employer's knowledge affect the signaling value of pre-entry experience? In the second question, we consider the tendency of entrepreneurial activity to cluster spatially (Buenstorf & Klepper, 2010; Delgado et al., 2010; Klepper, 2011). Focusing on geographic clustering as an essential feature of the environmental context in which the signal is transmitted, we ask how this contingent effect varies further with the geographic clustering of the focal industry.

To answer these research questions, we develop a theoretical framework grounded in signaling theory. In this framework, we concentrate on the notion of signal clarity: the extent to which a signal can be read quickly and with minimal error, allowing fewer alternative interpretations (Heil & Roberson, 1991). We first argue that the clarity of the pre-entry experience signal is enhanced when new ventures draw on the previous employers' knowledge, thereby indicating the ability to learn from their pre-entry experience. We then elaborate on this clarifying effect by considering the resource competition in the environment. Specifically, we argue that the clarifying effect from drawing on knowledge from the former employer is more valuable in a dense cluster where many rivals are vying to attract investor attention.

We tested our predictions using data on new ventures in the US semiconductor industry between 1997 and 2014. Our sample consists of 731 new ventures founded between 1997 and 2009, and we track their activity until 2014. We collected detailed information about all the new ventures in the industry and the founders' employment histories to track pre-entry experience. We document two major findings. We show that new ventures with pre-entry experience that build more on their former employers' knowledge reach the first round of VC funding faster. Doing so enables new ventures with pre-entry experience to enjoy on average up to 30% reduction in time to the first round of VC funding relative to other new ventures with pre-entry experience that do not. Furthermore, we find that such knowledge

linkages are more impactful for those new ventures endowed with pre-entry experience and located in areas with high levels of industry clustering.

This study makes the following contributions. It extends the entrepreneurship literature on pre-entry experience (Agarwal et al., 2004; Argyres & Mostafa, 2016; Cao & Posen, 2023; Dencker & Gruber, 2015; Helfat & Lieberman, 2002; Klepper, 2001; Rocha & Brymer, 2024) by casting light on contingencies that modify the effects of pre-entry experience. These contingencies linked to venture-level and environment-level factors enrich the theoretical framework explaining the intuitively compelling pre-entry experience effects. In fleshing out these nuances, the study sharpens our understanding of the mechanisms that underpin pre-entry experience effects and answers the call to go beyond *whether* pre-entry experience matters to *under what conditions* it matters (Cao & Posen, 2023). Furthermore, it complements prior work on pre-entry experience effects that mainly focused on product market implications (Fern et al., 2012; Gruber et al., 2012). In this regard, it explicates how and under what conditions pre-entry experience serves as a signal in resolving information asymmetries in factor markets.

We also contribute to the literature on signaling in business and entrepreneurship by probing the contingent nature of signals (Connelly et al., 2011; Heil & Robertson, 1991). Recent scholarship has sought to advance signaling theory by incorporating interactions of signals among themselves and with the environment (Bapna, 2019; Plummer et al., 2016; Vanacker et al., 2020). Whereas the former has attracted much attention, the latter aspect remains understudied (Connelly et al., 2011). Our findings suggest that signal clarity can be enhanced depending on conditions that strengthen the signal itself and by the characteristics of the environment in which the signaling occurs. In particular, it reveals that the value of a signal is contingent on the competition in the environment. In examining these contingencies for the effects of the pre-entry experience signal, we also complement the entrepreneurship research that examines how new ventures can signal their potential and capabilities amidst early-stage uncertainty (Colombo et al., 2019; Courtney et al., 2017; Kotha et al., 2018).

2 Theoretical background and hypotheses

2.1 Signaling and resource mobilization by new ventures

New ventures face resource constraints in their nascent stages (Stinchcombe, 1965; Stuart et al., 1999). In these stages, new ventures lack track records to facilitate quality assessment, and their business outlook is uncertain. These informational deficiencies make it difficult to mobilize financial resources from factor markets (Hsu & Ziedonis, 2013; Shane & Cable, 2002). Asymmetrically informed about a new venture's capabilities and prospects, resource providers may be reluctant to commit their scarce resources or do so only at a discount that is unfavorable to the new venture (Akerlof, 1970; Nicholson et al., 2005). Although new ventures might want to reveal information regarding their quality and prospects, they encounter credibility problems because they have a limited track record and may be naturally inclined to disclose only favorable information and to misrepresent capabilities that are difficult to verify or articulate (Ozmel et al., 2013; Shane & Cable, 2002). Nonetheless, the inherent information asymmetry problems need not prevent financial resource mobilization by new ventures (Gompers & Lerner, 2001).

Signaling theory provides a parsimonious framework to understand how new ventures can tackle these problems (Colombo et al., 2019; Spence, 1973). The challenge new ventures face is to convey information about their unobserved quality to prospective financial resource providers (Shane & Stuart, 2002). They can do so through attributes and actions that are observable and that are associated with the unobserved quality (Heil & Robertson, 1991; Stuart et al., 1999). Also called signals, these attributes and actions can help new ventures distinguish themselves in factor markets to the extent that others find it unprofitable to emulate the same attributes and actions (Connelly et al., 2011).

Investors' assessment can benefit from any information founders know privately. It is that private information founders hold that is at the center of the problem of information asymmetry (Hirshleifer & Riley, 1979). Founders can attract investments if they can reduce the information asymmetry investors face. However, several concerns arise: (a) founders may find it arduous to convey such private information

credibly; (b) founders may put themselves at risk of appropriation by disclosing such information; (c) founders may have genuine incentives to misrepresent their private information (Anton & Yao, 1994; Gans & Stern, 2003). The fundamental insight from signaling theory is that informed founders can take actions that can alter prospective investors' beliefs about the uncertainty associated with a new venture.

Whether signals resolve information asymmetry with prospective resource providers is contingent on the signal characteristics and the environment in which signals are transmitted and processed (Connelly et al., 2011; Heil & Robertson, 1991). The signals that new ventures send can differ in their clarity (Connelly et al., 2011; Heil & Robertson, 1991; Kotha et al., 2018; Vanacker et al., 2020). Additionally, signal clarity depends on the environment where the signaling occurs, particularly the level of noise or distortion present (Connelly et al., 2011). These theoretical considerations highlight the value of examining the contingent nature of signals and how the environment shapes their impact on new venture resource mobilization.

Signaling theory is particularly helpful in understanding resource assembly in technology-intensive sectors. Information asymmetries are notably severe in these sectors, wherein new ventures mostly possess intangible assets and hard-to-assess capabilities (Gans & Stern, 2003; Hsu, 2007). In addition, new ventures in these sectors may still be going through trial and error to develop their technology, learn about potential markets, and establish external linkages with suppliers and complementors (Shepherd et al., 2000). New technology ventures must carry out this process of experimentation and adaptation armed with limited information of their own (Ozcan & Eisenhardt, 2009) and rely on the knowledge and skills founders endow them at birth (Helfat & Lieberman, 2002; Klepper & Sleeper, 2005). Because pre-entry experience provides valuable knowledge and skills (Agarwal et al., 2004; Dencker et al., 2008), it serves as an essential quality signal for investors when deciding whether to commit resources to a new venture (Beckman et al., 2007; Ko & McKelvie, 2018).

2.2 Pre-entry experience

Founders with experience working in the industry endow their new ventures with pre-entry experience

at birth (Agarwal et al., 2004; Klepper, 2001). Generally regarded as an asset, pre-entry experience bestows on new ventures knowledge and social connections, which assist in exploiting product market opportunities and growing the venture (Dencker et al., 2008; Fern et al., 2012; Klepper & Sleeper, 2005). Because assets can offer multiple services in different markets (Hsu & Ziedonis, 2013), pre-entry experience can perform a dual role as an asset and a signal in factor markets. Pre-entry experience can serve as an asset to the extent that it bestows social capital, thus encouraging investments from outsiders (Shane & Stuart, 2002). Pre-entry experience also confers signaling benefits on new ventures, enabling them to mitigate the information asymmetry of potential resource providers. Because we contemplate pre-entry experience at industry incumbents, it is reasonable to expect that the signaling function of pre-entry experience will dominate because the social capital associated with prior experience at incumbents may not necessarily carry to venture capital networks (Ferrary & Granovetter, 2009; Hochberg et al., 2007).

In its signal role, pre-entry experience can reduce information asymmetry with potential resource providers for several reasons. Endowed with pre-entry experience, new ventures are more likely to assure potential investors about their ability to discover unserved or under-served markets, keep abreast with technological developments, understand competition, and navigate industry norms and procedures—abilities that can only be acquired through employment in an industry (Agarwal et al., 2004; Chatterji, 2009; Ganco, 2013; Gruber et al., 2012). Also, new ventures with pre-entry experience will be able to signal to others a strong command of their business (Dencker & Gruber, 2015) and connectivity with important stakeholders (Bruderl et al., 1992; Certo, 2003; Gimeno et al., 1997). Pre-entry experience can thus serve as a quality signal, reducing information asymmetry with resource providers and accelerating resource acquisition.

Accelerated resource acquisition early on provides several strategic and organizational benefits for a new venture in innovative sectors (Colombo et al., 2019; C. Lee et al., 2001). Specifically, speed in securing the initial influx of VC money quickly eases early cash flow pressures and facilitates experimentation and preparation for the scale-up phase (Hsu, 2007). Also, receiving VC funding early on can help a new

venture exploit resource-rich market niches, develop and commercialize the technology, hire valuable human capital sooner (Chatterji, 2009; C. Lee et al., 2001), and gain external visibility (Stuart et al., 1999). We expect pre-entry experience to have a positive relationship with the speed with which a new venture secures the first round of VC funding. We thus formulate the following baseline expectation:

Baseline hypothesis: New ventures with pre-entry experience will secure the first round of venture capital funding faster than new ventures without such experience.

Although signaling theory provides the basis for the intuition behind the baseline, probing the contingencies will deepen the theoretical grounding and clarify the conditions under which new ventures can leverage pre-entry experience. The contingencies naturally follow from the context in which new ventures operate. In the context of technology-intensive sectors, a key success factor is the new ventures' capacity to learn (Agarwal et al., 2004; Dencker et al., 2009; Fern et al., 2012), yet such capacity is opaque to prospective resource providers. These sectors also exhibit significant agglomeration that engenders competition for resources (Klepper, 2010; McCann & Folta, 2011), which exacerbates the information asymmetry problem inherent in new ventures. From a signaling theory standpoint, these conditions correspond to an increase in noise not only in the pre-entry experience signal but also in the environment in which that signal is processed. Under these conditions, a signal's clarity is crucial for investors to arrive at utility-enhancing decisions (e.g., Hirschleifer & Riley, 1979; Heil & Roberson, 1991). In the hypotheses below, we argue that new ventures with pre-entry experience conveying their capacity to learn from their pre-entry experience augment the clarity of the pre-entry experience signal. And signaling such capacity is likely to have a stronger impact in environments with heightened competition for resources. Focusing on these factors enables us to explicate the contingent nature of the pre-entry experience signal.

To clarify the contingent nature of pre-entry experience, we draw on ideas from the research on industry evolution that identifies employee entrepreneurship and agglomeration as crucial factors driving the process (Buenstorf & Klepper, 2010; Klepper, 2009, 2011). A key idea in this line of work is that

employees with pre-entry experience in the industry tend to locate their new ventures near their erstwhile employers to benefit from that experience through knowledge spillovers and labor market pooling (Carias et al., 2023; Rosenthal & Strange, 2004). Two notions at the heart of this literature and the phenomenon of employee entrepreneurship are *knowledge inheritance* (i.e., the knowledge that founders acquire during their employment at the former employer) and *clustering* (Klepper & Sleeper, 2005).

2.3 The contingent effect of knowledge linkages

Notwithstanding its potential signaling benefits, pre-entry experience is an attribute fixed at birth (Agarwal et al., 2004). While it can shift the evaluations of prospective resource providers in a direction favorable to the new venture (Ko & McKelvie, 2018), it remains weakly informative of the fluid internal conditions of a new venture. What may still concern prospective resource providers is whether new ventures are able to make use of their initial stock of knowledge and skills to navigate an uncertain environment. This is a crucial concern for at least two reasons: experience does not always translate to learning and leveraging experience comes with challenges (Herriott et al., 1985). Facing these concerns, prospective resource providers may find value in additional information that augments the clarity of the pre-entry experience signal.

We argue that by drawing on and extending the former employers' technical knowledge, new ventures with pre-entry experience can more credibly signal their capacity to leverage their pre-entry experience and learn from it. Such knowledge linkages are obtained through purposeful and costly actions *after* funding, thereby revealing private information about the new ventures' capacity to learn from and build on the prior employers' knowledge. Specifically, the founders' familiarity with the former employers' technical knowledge ensures that they understand not only an invention's novelty and utility but also its technical context and potential applications (Dencker & Gruber, 2015; Fern et al., 2012; Ganco, 2013). This affords outside resource providers more confidence in the new venture's technical knowledge and capacity to learn. Also, by drawing on and extending the former employers' technical knowledge, new ventures endowed with pre-entry experience can credibly

show their ability to manage, maintain, and recombine knowledge (Danneels, 2002). In sum, knowledge linkages, i.e., the degree to which new ventures draw on founders' former employers' knowledge, are likely to enhance the clarity of pre-entry experience signal by conveying information about the new venture's ability to learn and leverage capabilities in the early stages. Therefore, we predict that:

Hypothesis 1 (H1): New ventures with pre-entry experience with greater knowledge linkages to founders' former employers secure the first round of venture capital funding faster.

2.4 The contingent effect of industry clustering

So far, we have built on the signal characteristics of pre-entry experience and explicated the amplifying effect of knowledge linkages to former employers on speeding up financial resource mobilization. However, apart from signal characteristics, what also affects the extent to which signaling reduces information asymmetries is the signaling environment (Connelly et al., 2011). The signaling environment can dilute the clarity of a signal and reduce its reliability in differentiating high-quality new ventures (Lee et al., 2011; Lester et al., 2006). One condition that clutters the signaling environment and impedes signal reliability is high competition in the environment (Connelly et al., 2011). For instance, when many new ventures vie for attention, potential resource providers may not find pre-entry experience by itself to be sufficiently informative and would look out for extra clues to increase their chances of picking a high-quality venture. Below, we argue that knowledge linkages to former employers are more likely to augment the signaling value of pre-entry experience when the competition for resources is high.

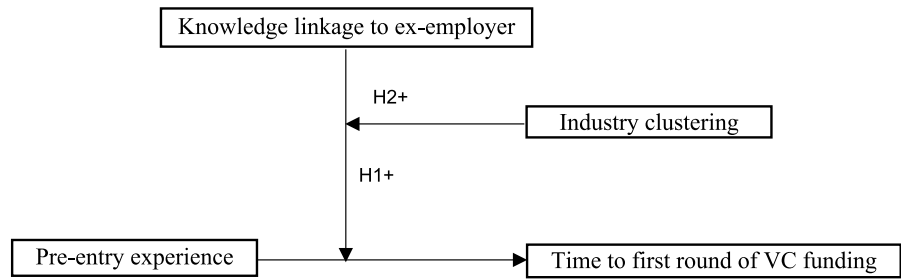
A key condition affecting a new venture's pathways to resource access is its location (Rosenthal & Strange, 2004; Stuart & Sorenson, 2003). In many sectors, entrepreneurial activity tends to exhibit spatial variation; i.e., some regions serve as hotbeds of vigorous entrepreneurial entry and competition, while others remain barren (Delgado et al., 2010; Dunford, 2006). These differences arise from local conditions that support increasing returns to scale (Carlton, 1983; Krugman, 1991). Such

agglomeration economies derive from the co-location of numerous firms that use similar intermediate goods, demand common skills, draw on overlapping knowledge bases, and facilitate dense social networks (Audretsch & Feldman, 2004; Duranton & Puga, 2004). The same agglomeration economies also promote entrepreneurial entry (Pe'er et al., 2008; Pe'er & Keil, 2013). Locations with high industry clustering generously supply the human capital and knowledge spillovers on which entrepreneurship in technology-intensive industries thrives (Qian et al., 2013). It should not come as a surprise, then, that such locations tend to generate new ventures with pre-entry experience at a high rate (Baltzopoulos et al., 2016).

With a high concentration of new ventures as well as incumbents, areas with high industry clustering may not necessarily work in new ventures' favor during the resource mobilization process (Baum & Haveman, 1997; Pe'er & Keil, 2013). Such areas may erode the signaling value of pre-entry experience that new ventures enjoy because of the congestion arising from many rivals battling for resource providers' attention. Such congestion creates a noisy signaling environment for new ventures with pre-entry experience, precluding prospective resource providers from adequately distinguishing quality among the many ventures. In this regard, new ventures with pre-entry experience located in highly clustered areas may find additional information complementing pre-entry experience more valuable than new ventures with pre-entry experience located in other areas do. Specifically, new ventures with pre-entry experience hailing from areas with high industry clustering may find the amplifying effect of knowledge linkages particularly valuable in distinguishing themselves from similar nearby firms. By contrast, new ventures with pre-entry experience located in areas with low clustering do not face a cluttered signaling environment that renders their pre-entry experience signal ineffective. In sum, knowledge linkages more strongly enhance the clarity of pre-entry experience when new ventures with pre-entry experience are located in areas with high industry clustering. We thus propose hypothesis 2 below. Figure 1 presents our conceptual framework.

Hypothesis 2 (H2): The effects predicted in Hypothesis 1 are stronger when the industry clustering is higher.

Fig. 1 Conceptual framework of the proposed interactions of knowledge linkages and industry clustering on the relationship between pre-entry experience and the time to first round of VC funding



3 Methods

3.1 Data

The context of the study is the US semiconductor industry, which serves our purpose well for several reasons. First, since its inception in the 1950s, the industry has been a hotbed of entrepreneurial activity, especially sparking entry by founders with experience working at existing firms (Brittain & Freeman, 1986; Sporck, 2001). Second, this industry relies on intensive technological innovation, which allows us to observe the relationship with the former employers' knowledge base (Ganco, 2013; Macher et al., 1998). Because semiconductor firms have a high propensity to patent, knowledge linkages among firms can be tracked through the paper trail left by patents (Hall & Ziedonis, 2001; Jaffe et al., 1993).

We assembled our dataset from several archival sources. Our main list of new ventures in the semiconductor industry comes from the Pinestream Consulting Group. Pinestream has been keeping a trail of all new entrants in the semiconductor industry since 1997, documenting their essential attributes such as founding dates, location, and activities, as well as founders' and early employees' names and previous employers (Adams et al., 2016). We verified and augmented data from Pinestream with data from other sources such as ThomsonOne's VentureXpert, Dow Jones' Venture Source, Crunchbase, and company websites (and archived websites using www.archive.org). To identify pre-entry experience, we cross-validated and enriched the founders' and early employees' employment histories by referring to LinkedIn profile pages (details follow in the next section). For the dependent variable, we relied on VentureXpert, Venture Source, and Crunchbase to assemble the new ventures' VC funding histories. For our explanatory variables, we obtained patent and citation histories of

firms from the US Patent and Trademark Office's PatentsView database (www.patentsview.org) and data on the geography of industry activity from the US Bureau of Labor Statistics (www.bls.gov). Finally, we tracked alliance activity using the Strategic Alliance database of the Securities Data Company (SDC) and government grants using Small Business Innovation Research data (www.sbir.gov).

3.2 Sample construction

To construct our sample, we applied the following screens to the list of new entrants from Pinestream. Because we are interested in independent entrepreneurial ventures, we excluded subsidiaries, joint ventures, consortia, management buyouts, corporate spinoffs, business combinations, and incumbent-incubated ventures (Agarwal et al., 2004; Helfat & Lieberman, 2002). Also, only new ventures with at least one patent filed in the observation period entered the final sample. The reason is that the semiconductor industry shifted to a business model focused on designing and marketing chips while outsourcing production, a change that made patent-protected intellectual property essential to generating revenues (Hall & Ziedonis, 2001). This screen also allows us to track knowledge linkages using patent data. These steps yielded a final sample of 731 new ventures founded between 1997 and 2009, and we tracked their activity until 2014.

Our analysis aims to evaluate the contingent effect of knowledge linkages to founders' prior employers on the relationship between pre-entry experience and time to VC funding. Estimating these effects necessitates accounting for the following plausible subgroup combinations: (1) a new venture with pre-entry experience at former employer E and showing a knowledge linkage to that former employer E; (2) a new venture with

pre-entry experience at former employer E but not showing a knowledge linkage to former employer E; (3) a new venture without pre-entry experience and showing a knowledge linkage to former employer E (where E is a former employer for other new ventures with pre-entry experience); (4) a new venture without pre-entry experience but not showing knowledge linkages to former employer E (where E is a former employer for other new ventures with pre-entry experience). Among these four subgroups, the last two subgroups are normally absent in a sample in which knowledge linkages are tracked for new ventures with pre-entry experience. However, the analysis of a sample with groups (1) and (2) only could result in overestimating the effects of interest. To address this concern, we drew inspiration from the synthetic controls approach to include the missing subgroups (Abadie et al., 2010). The synthetic control subgroups consist of new ventures with no pre-entry experience that are randomly assigned to the former employers of new ventures with pre-entry experience. These new ventures may or may not show knowledge linkages to the synthetically matched “former employer” E, but the founding team has no prior working experience at that firm. Even though the founding team does not have any prior working experience at the synthetically matched “former employer,” it is plausible that the new venture builds on the knowledge of the “former employer” assigned to it. This construction allows us to disentangle the effect of knowledge inheritance from the former employer from the effect of merely building on an incumbent’s knowledge.

Our unit of analysis is the new venture–month. To build our panel, we traced the founding and exit dates—whether by failure, acquisition, or IPO—for all firms in our sample. When a firm experiences an exit event in the sample period, it drops out of the analysis sample in the month of the event and thereafter. We used the new ventures’ age in months as the time unit because we are interested in modeling the time to the first VC funding event as a function of the time since venture formation. We used months as the time unit to better satisfy the econometric assumptions of continuous survival models (Cox & Oakes, 1984). The resulting dataset for regression analysis consists of 81,381 new venture–month observations.

3.3 Measures

3.3.1 Dependent variable

Our dependent variable is the time it takes for a new venture to receive the first round of VC funding. We measure this time as the age of the venture in months, calculated from the founding date to the date when the first round of VC funding is secured. We use a dummy variable labeled *First VC event* to mark the month a venture received its first round of VC funding. Given our interest in estimating the time for this first VC funding event, we employ event history analysis to test our predictions. In this analysis, we use the venture’s age in months as the time unit to model the occurrence of the *First VC event* as a function of time since founding.

3.3.2 Independent variables

Following prior work, we measured our first explanatory variable, *Pre-entry experience*, as a dummy variable that equals one if one of the founders worked for an existing firm in the semiconductor industry the year before founding the new venture and zero otherwise (Agarwal et al., 2004; Argyres & Mostafa, 2016; Kim & Steensma, 2017). To identify new ventures with pre-entry experience and their former employers, we constructed the founders’ employment histories using information on employment from LinkedIn. We manually tracked the LinkedIn profiles of the founders in our sample using their first and last names and the name of the new venture. Inspecting the founders’ LinkedIn profiles, we identified their prior employer the year before founding the new venture. We used the industry in which the founders were last employed to classify the new ventures into two groups, i.e., new ventures with pre-entry experience and new ventures without pre-entry experience. We identified 517 new ventures with pre-entry experience and 214 new ventures without pre-entry experience. The group without pre-entry experience contained new ventures whose founders lacked experience in the focal industry, such as coming from universities (staff and students), research institutes, and consultancies.

Our second explanatory variable, *Knowledge linkage (proportion)*, measures how much new ventures with pre-entry experience draw on former employers’ technical knowledge. We built on the widely

acknowledged method of using patent citations to study a firm's use of other organizations' knowledge (Almeida & Kogut, 1997, 1999). We analyzed backward citations of the new venture's patents to track whether the patented technology drew on former employers' patented knowledge. We calculate *Knowledge linkage (proportion)* as the ratio between the number of citations to the former employer and the total number of citations.¹ In robustness analysis, we consider the number of citations labeled as *Knowledge linkage (count)*.

Our final explanatory variable, *Local industry density*, is measured using the location quotient of semiconductor industry establishments. Location quotient captures the degree to which a region disproportionately harbors an industry. It is calculated as the ratio of the share of semiconductor industry establishments within the county where the new venture is located to the share of the semiconductor industry establishments nationwide (Delgado et al., 2014; Pe'er & Vertinsky, 2008). To facilitate the interpretation of the results for Hypothesis 2, which involves moderation of a previous interaction (as stated in Hypothesis 1), we use a split-sample approach based on *Local industry density* as described below.

3.3.3 Control variables

We included several new venture and industry-level variables plausibly linked to the outcome of interest. We controlled for the new ventures' knowledge stock in case a venture with a larger knowledge base received funding faster (Hsu & Ziedonis, 2013; Marx et al., 2014). For this purpose, we included *Patent stock*, measured as the sum of the number of patent applications filed each month using a five-year moving sum (inverse hyperbolic sine transformed for skewness). Because the former employers' quality may affect a new venture's capabilities and its probability of receiving funding (Klepper & Sleeper, 2005), we controlled for *Ex-employer's knowledge value* measured as the five-year moving sum of the

number of the citations received (inverse hyperbolic sine transformed).²

Because receiving inputs from other actors may affect the new venture's propensity to secure initial VC funding, we controlled for whether a new venture has formed an alliance prior to receiving the first VC funding (Stuart et al., 1999) and whether a new venture has received support from the SBIR program. Accordingly, we included *Alliance formed*, a dummy variable that takes the value of one once a venture has formed its first alliance (and remains one for all subsequent months) and zero otherwise. We also included *SBIR funded*, a dummy variable that takes the value of one if a new venture has received SBIR funding before the first round of VC funding and zero otherwise.

The geographic characteristics of the industry may influence both the formation of new ventures and the probability of receiving VC funding (Glaeser et al., 1992; Stuart & Sorenson, 2003). We controlled for *Location industry diversity* measured as one minus the Herfindahl-Hirshman Index calculated using the employment distribution across industries within the county where the new venture is located. We also controlled for the *Urban scale*, measured as the employment level per square mile within the county where the new venture is located. In addition, we included *California*, a dummy variable that takes the value of one if a new venture is located in semiconductor hotspot California and zero otherwise.

Geographic and technological distance from the former employer can influence whether a new venture with pre-entry experience draws on knowledge from the former employer (Audretsch & Feldman, 2004) and its propensity to secure initial VC funding. To account for this, we controlled for *Co-location with ex-employer*, a dummy variable that equals one if a former employer's location lies within a 50-mile radius from the focal new venture with pre-entry experience and zero otherwise. We calculated the distance using Vincenty's ellipsoid method (Chatterji et al., 2016). We also included *Tech distance to ex-employer* measured as the angular separation between

¹ We calculated *Knowledge linkage (proportion)* with reference to the actual former employer for new ventures with pre-entry experience and the assigned former employer for the synthetic control group.

² We calculated *Ex-employer's knowledge value* for the actual former employer for new ventures with pre-entry experience and for the assigned former employer for the synthetic control group.

the patent classes of a new venture with pre-entry experience and those of the former employer (Benner & Waldfoegel, 2008).³ Finally, we incorporated year fixed effects in all models to control for unobserved period effects.

3.4 Estimation method

We used event history analysis to test our predictions. Because we are interested in estimating a new venture's time to first VC funding, we used an accelerated failure time (AFT) class of models (Cox & Oakes, 1984). AFT models allow for various parametric forms for the baseline survival distribution. We found the log-normal distribution to be the most suitable parameterization of the baseline survival distribution (Cleves et al., 2016). The log-normal distribution assumes that the instantaneous likelihood of the event happening bears a non-monotonic relationship with time that increases in the beginning and decreases at the end of the period. We model the time to the event of interest as the age of the new venture in months. All errors are clustered at the new venture level.

Because AFT models estimate the effects of covariates on acceleration or deceleration of the time to event, we interpret a significant negative coefficient as experiencing the outcome of interest earlier and a positive coefficient as experiencing the outcome of interest later (Box-Steffensmeier & Jones, 2004). This connects directly with our hypotheses, formulated in terms of time to the event. Accordingly, a significant negative coefficient implies a faster time to VC funding, while a significant positive coefficient indicates a longer time to VC funding.

4 Results

Table 1 reports summary statistics at the unit of analysis level: venture-month. This data structure tracks time-varying covariates. At the venture level, 572 firms in our sample (80%) secured at least one round of VC funding. Also, 517 firms (70%) have

pre-entry experience, while 214 (30%) firms lack pre-entry experience. We also cross-tabulated the *Pre-entry experience* and the *First VC event* variables to understand the variance that the new ventures with and without pre-entry experience show with respect to whether they secured first-time VC funding. Pearson's chi-squared statistic shows statistically significant differences (Pearson's $\chi^2(1) = 175.85$; $p = 0.000$) between the groups (i.e., new ventures with and without pre-entry experience and securing or not first-time VC funding). Further, 476 firms (67%) are located in *California*. In addition, of the 517 firms with pre-entry experience, 147 (28%) co-locate with their former employers. Table 2 shows the key clusters aggregated at the county level in our sample. Turning to the time-varying covariates, the value of *Knowledge linkage (proportion)* ranges from 0 to 92%. New ventures in our sample have, on average, 3.83 patents and are located in areas with varying levels of *Local industry density*.

Table 3 presents our main results for time to the first round of VC funding using AFT models with a log-normal distribution. We begin with estimates from the model with controls only in column 1. Column 2 introduces the baseline effect of *Pre-entry experience*. To test the contingent effect proposed in the first hypothesis, column 3 introduces the interaction between *Pre-entry experience* and *Knowledge linkage (proportion)*. To test the impact of *Local industry density* (Hypothesis 2), we split the sample based on the strength of *Local industry density*. Finally, we report estimates from the seemingly unrelated estimation models analyzing these two sub-samples in column 4 and column 5. All models include a full set of year fixed effects and cluster standard errors at the new venture level (731 new ventures). Recall that AFT models directly capture the time of the event instead of the hazard of the event. Accordingly, a significant negative coefficient suggests a decrease in time to the first VC funding round, and a significant positive coefficient suggests an increase in time to VC funding.

We begin the discussion with the baseline hypothesis. This baseline hypothesis predicts that new ventures endowed with *Pre-entry experience* to secure VC funding faster than other new ventures. This expectation is supported by the negative and significant coefficient of *Pre-entry experience* in column 2 ($p < 0.001$). All else equal, having pre-entry

³ As with the other measures related to former employers, *Tech distance to ex-employer* is calculated with reference to the actual former employer for the new ventures with pre-entry experience to the assigned former employer for the synthetic control group.

Table 1 Descriptive statistics and correlations table

Variables	Mean	S.D	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
1 First VC event	0.01	0.11	0.00	1.00	1																
2 Pre-entry experience	0.23	0.42	0.00	1.00	0.05	1															
3 Knowledge linkage (proportion)	0.02	0.04	0.00	0.92	-0.02	-0.07	1														
4 Knowledge linkage (level)	0.35	0.63	0.00	4.72	-0.02	-0.08	0.64	1													
5 Local industry density (estabs)	2.19	1.09	0.00	3.45	0.02	0.07	0.05	0.07	1												
6 Local industry density (emplmt) ^a	2.12	1.31	0.00	4.14	0.02	0.10	0.05	0.07	0.96	1											
7 Patent stock	1.41	1.14	0.00	5.97	-0.04	-0.07	0.12	0.43	0.03	0.03	1										
8 Ex-employer's knowledge value	9.54	5.83	0.00	19.11	-0.03	-0.35	0.30	0.42	0.02	0.01	0.15	1									
9 Alliance formed	0.06	0.24	0.00	1.00	-0.03	-0.10	-0.01	0.14	-0.05	-0.05	0.06	0.10	1								
10 Location industry diversity	0.98	0.02	0.78	0.99	0.01	0.05	-0.05	0.02	0.17	0.14	0.07	0.06	0.01	1							
11 Urban scale	6.39	1.15	2.29	9.40	0.00	-0.05	0.00	0.05	-0.09	-0.09	0.20	0.05	-0.20	0.21	1						
12 Co-location with ex-employer	0.12	0.33	0.00	1.00	0.02	0.23	-0.01	-0.04	0.17	0.18	0.00	-0.21	-0.08	0.03	0.08	1					
13 Tech distance to ex-employer	0.16	0.27	0.00	1.00	-0.03	0.04	0.30	0.42	0.10	0.09	0.33	0.22	0.12	0.04	0.01	0.07	1				
14 California	0.65	0.48	0.00	1.00	0.00	0.06	0.04	0.05	0.61	0.56	0.11	0.01	-0.18	0.17	0.16	0.19	0.05	1			
15 SBIR funded	0.05	0.22	0.00	1.00	0.00	0.03	-0.04	-0.04	-0.10	-0.11	0.04	-0.09	-0.04	0.03	-0.13	-0.03	-0.03	-0.03	-0.09	1	
16 Startup age	45.17	33.35	1.00	120.00	-0.07	-0.09	0.17	0.27	-0.01	0.02	0.49	0.14	0.16	-0.02	0.00	-0.03	0.32	0.05	0.15	0.15	1

Notes: $N = 81,381$ (firm-month). Coefficients with absolute values greater than 0.01 are significant at $p < 0.05$
^aMeasures of clustering based on establishments and based on employment are included in separate analyses (Tables 2 and 3, respectively)

Table 2 Key semiconductor clusters (county level) in our sample

County	State	Establishments	Employment
Santa Clara County	CA	557	54,045
Orange County	CA	275	15,364
Los Angeles County	CA	245	11,415
San Diego County	CA	148	7285
Alameda County	CA	138	8582
Middlesex County	MA	127	10,887
Dallas County	TX	127	22,006
Maricopa County	AZ	125	28,307
Travis County	TX	71	15,900
Washington County	OR	70	19,859

Note. Establishment and employment levels are averaged over the sample period

experience accelerates the time to first VC funding by 55.8% relative to the average time it takes to secure the first round of VC funding.⁴ This result corroborates the beneficial effects of pre-entry experience (Chatterji, 2009; Ko & McKelvie, 2018).

Given the baseline pre-entry experience effect, we now turn to our main hypotheses about the contingencies. The contingency we advance in Hypothesis 1 is knowledge linkages to the former employer. Hypothesis 1 states that knowledge linkages to the former employer strengthen the effect of pre-entry experience, enabling new ventures with pre-entry experience to secure VC funding faster. To estimate this effect, we interact *Pre-entry experience* with *Knowledge linkage (proportion)* in the model shown in column 3. A negative sign for this interaction term indicates that new ventures with pre-entry experience that draw on former employers' knowledge secure the first round of VC funding faster. Consistent with our prediction, the interaction term is negative and significant ($p=0.005$). Because of the non-linear nature of the model, the magnitude of the effect varies with *Knowledge linkage (proportion)*.⁵ So,

⁴ We compute the economic significance as $1-\exp(\beta_x\delta_x)$ where β_x is the coefficient estimate for the independent variable x and δ_x is unit change of covariate x . For *Pre-entry experience*, this calculation is $1-\exp(-0.817)=0.558$, indicating a 55.8% faster average time to first VC funding.

⁵ In our model, let X_1 and X_2 be the pre-entry experience and knowledge linkage and Z be the vector of controls, then the log-normal AFT model can be written as:

$$\log T = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 * X_2 + Z\delta + \epsilon \quad \text{where}$$

it is helpful to examine this effect graphically. The plot shown in Fig. 2 traces the incremental impact of knowledge linkages to former employers over the theoretical range of the variable (i.e., 0 to 1). The Y-axis shows the gain in time to VC funding for a new venture with pre-entry experience. To illustrate the interpretation of this plot, consider a new venture with pre-entry experience with knowledge linkages to its former employer measured at 10%, at which the expected gain in time to first VC funding is about 35%. This means that a new venture with pre-entry experience drawing 10% of the knowledge underpinning its technologies from the founder's former employer is likely to see a 35% decrease in the time to VC funding compared to a new venture with pre-entry experience not showing such knowledge linkages.

In Hypothesis 2, we propose that the contingent effect of knowledge linkages to former employers (H1) is more influential for new ventures with pre-entry experience located in areas where industry clustering is high. To simplify the estimation and interpretation of these effects in a non-linear accelerated failure time model, we conduct sub-sample analyses by splitting the sample at the mean of the *Local industry density* variable (Penner-Hahn & Shaver, 2005; Shaver, 2007). We estimate separate models for both sub-samples and compare the coefficients of *Knowledge linkage (proportion)* across both models using the joint robust covariance matrix.⁶

Moving on to the results of the sub-sample analyses, columns 4 and 5 show the coefficient estimates for the sub-samples in which industry clustering is low and high, respectively. The coefficient of the interaction between *Pre-entry experience* and *Knowledge linkage (proportion)* is negative and significant in both column 4 ($p=0.029$) and column 5 ($p=0.001$). Although the sign of these coefficients

Footnote 5 (continued)
 $\epsilon \sim N(0, \sigma^2)$.

$$\Rightarrow E[T|X_1, X_2, Z] = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 * X_2 + Z\delta + \sigma^2}$$

Using this expectation function, the time ratio and the relative gain in time to VC event can be written as:

$$\text{Time ratio} = \frac{E[T|X_1=1, X_2=c, Z=\bar{Z}]}{E[T|X_1=1, X_2=0, Z=\bar{Z}]} = \frac{e^{\beta_0 + \beta_1 + \beta_2 * c + \beta_{12} * c + Z\delta + \sigma^2}}{e^{\beta_0 + \beta_1 + Z\delta + \sigma^2}}$$

$$\text{Relative gain in time to VC event} = 1 - e^{-\beta_{12} * c + \beta_{12} * c}$$

⁶ We use the *suest* command in Stata 17.

Table 3 Accelerated failure time models of the conditions under which pre-entry experience affects the time to first VC funding. Knowledge linkage is measured using the proportion of citations to the former employer

Variables	Controls	Baseline	Knowledge linkage	Clustering	
				Low	High
Pre-entry experience (<i>expected sign: -</i>)		-0.817 (0.251) [0.001]	-0.740 (0.250) [0.003]	-0.961 (0.257) [0.000]	-0.631 (0.343) [0.066]
Pre-entry experience × knowledge linkage (proportion) (<i>H1 / H2: expected sign: -</i>)			-10.943 (3.890) [0.005]	-6.552 (3.003) [0.029]	-23.790 (7.492) [0.001]
Knowledge linkage (proportion)			6.637 (3.334) [0.047]	4.366 (2.541) [0.086]	13.540 (5.889) [0.022]
Local industry density (estabs)	-0.463 (0.173) [0.007]	-0.452 (0.172) [0.009]	-0.453 (0.172) [0.008]	-0.109 (0.204) [0.594]	-0.570 (0.688) [0.407]
Patent stock	-0.031 (0.148) [0.833]	-0.054 (0.146) [0.711]	-0.056 (0.144) [0.695]	-0.116 (0.147) [0.431]	0.204 (0.201) [0.309]
Ex-employer's knowledge value	0.053 (0.016) [0.001]	0.035 (0.012) [0.003]	0.031 (0.013) [0.013]	0.052 (0.014) [0.000]	0.016 (0.016) [0.315]
Alliance formed	2.998 (0.718) [0.000]	2.822 (0.687) [0.000]	2.830 (0.684) [0.000]	2.523 (0.631) [0.000]	2.666 (1.705) [0.118]
Location industry diversity	-8.309 (11.700) [0.478]	-5.414 (11.584) [0.640]	-4.808 (11.191) [0.667]	-15.634 (8.231) [0.058]	-280.381 (268.255) [0.296]
Urban scale	-0.013 (0.129) [0.921]	-0.032 (0.126) [0.801]	-0.032 (0.125) [0.800]	0.095 (0.097) [0.331]	2.516 (1.867) [0.178]
Co-location with ex-employer's	-0.371 (0.150) [0.014]	-0.187 (0.130) [0.151]	-0.179 (0.130) [0.169]	-0.509 (0.229) [0.027]	-0.092 (0.157) [0.558]
Tech distance to ex-employer's	0.612 (0.412) [0.138]	0.894 (0.397) [0.024]	0.900 (0.397) [0.023]	0.494 (0.441) [0.263]	1.322 (0.527) [0.012]
California	0.583 (0.363) [0.108]	0.610 (0.341) [0.074]	0.596 (0.342) [0.081]	0.781 (0.319) [0.014]	-1.949 (0.985) [0.048]
SBIR funded	-1.269 (0.801) [0.113]	-1.216 (0.803) [0.130]	-1.180 (0.793) [0.137]	-0.606 (0.718) [0.398]	-1.454 (1.283) [0.257]
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	13.033 (10.995) [0.236]	10.712 (10.889) [0.325]	10.095 (10.493) [0.336]	18.555 (7.827) [0.018]	266.293 (253.534) [0.294]

Table 3 (continued)

Variables	<i>Controls</i>	<i>Baseline</i>	<i>Knowledge linkage</i>	<i>Clustering</i>	
				<i>Low</i>	<i>High</i>
Sigma (log)	0.543 (0.067) [0.000]	0.525 (0.069) [0.000]	0.519 (0.067) [0.000]	0.350 (0.086) [0.000]	0.524 (0.065) [0.000]
Observations	81,381	81,381	81,381	46,488	34,893

Note: Clustered robust standard errors in parentheses (Clusters = 731). *P*-values in square brackets

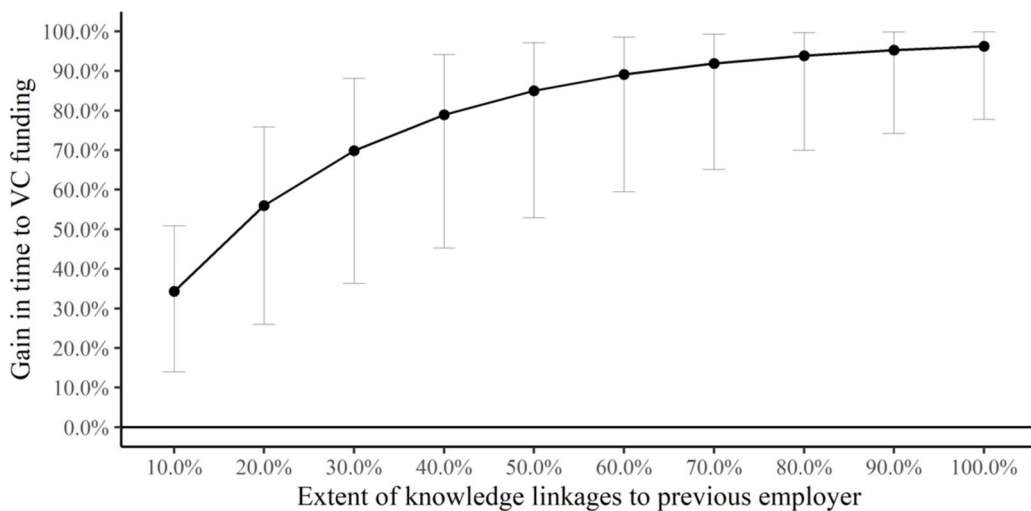


Fig. 2 The effect of the extent of knowledge linkages to former employer on time to first VC funding for new ventures with pre-entry experience (H1). Note: Error bars show the 95% confidence interval

indicates that knowledge linkages amplify pre-entry experience effects in locations with low and high clustering, testing Hypothesis 2 requires a comparison of these two coefficients. Specifically, Hypothesis 2 not only predicts a negative sign for the interaction term in the high clustering sub-sample but also expects the coefficient to exceed that for the low clustering sub-sample in magnitude. Testing the difference, we find that the coefficient in the high clustering sub-sample is statistically different in magnitude from that in the low clustering sub-sample ($\chi^2(1) = 4.58$; $p = 0.03$).

To demonstrate the magnitude of the clustering effects, we turn to the graphical analysis shown in Fig. 3. Panel A shows how the contingent effect of knowledge linkage to former employers varies with a low and high degree of industry clustering. For illustration, consider a new venture with pre-entry

experience with 10% *Knowledge linkage (proportion)* situated in a location with high industry clustering. This new venture with pre-entry experience is likely to see a 60% decrease in the time to the first round of VC funding compared to a proximate new venture with pre-entry experience without knowledge linkages to its former employer. This 60% advantage reduces to 20% for a new venture with pre-entry experience with 10% *Knowledge linkage (proportion)* but situated in a location with low industry clustering. The gap between the plots in Panel A is depicted in Panel B. The plot in Panel B indicates the differential gain in time to the first round of VC funding arising from knowledge linkages to former employers. This plot reveals that when rivalry in resource assembly is intense because of industry clustering, possessing even low to moderate knowledge linkages to former

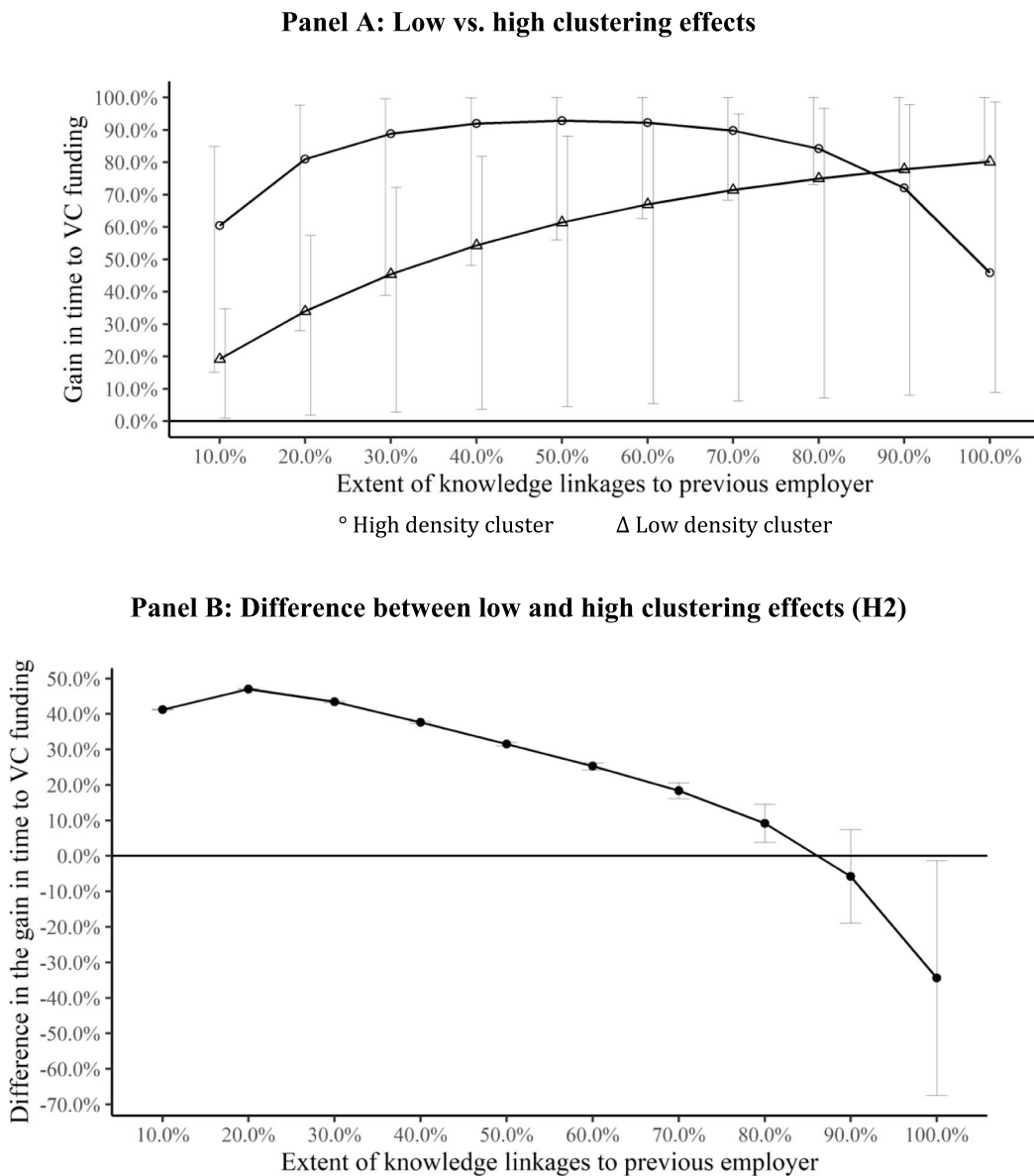


Fig. 3 The impact of clustering on the effect of the extent of knowledge linkages to former employer on time to first VC funding for new ventures with pre-entry experience. Note: Error bars show the 95% confidence interval

employers results in significant gains in the time to the first round of VC funding for new ventures with pre-entry experience.

Taken together, these results illuminate essential contingencies shaping the effects of pre-entry experience. They inform us about the value of building on pre-entry experience and the importance of considering the geographic clustering of the industry. In doing so, they explicate how and under what conditions

pre-entry experience enables financial resource mobilization.

4.1 Additional analyses

We conduct several additional analyses to check the robustness of our results. First, we probed the sensitivity of our results to alternative ways of measuring our core explanatory variables. In the main analysis,

we measure knowledge linkages to former employers as the ratio of the number of backward citations to former employers to the total number of backward citations. An alternative to this measure is using the absolute number of backward citations to former employers. As the estimates reported in Table 4 show, our results remain consistent and robust to this alternative way of measuring knowledge linkages. For our second hypothesis, we measure industry clustering using the number of industry establishments. In Table 5, we report estimates using the employment scale of the region as an alternative measure for clustering (Baptista & Swann, 1998). Our results remain unaltered with this alternative measure as well.

Another source of sensitivity concerns the assumptions underlying our modeling approach and the specifications we employ. AFT models require us to assume a parametric form for the baseline survival distribution. A non-monotonic duration dependence can be modeled using log-logistic, log-normal, and generalized gamma distributions. Although we report results from the log-normal model because of their superior fit based on information criteria, in other analyses, we obtain qualitatively similar results across distributional assumptions.⁷

Also, we verified whether the test for the second hypothesis is sensitive to the split-sample approach we employed. Instead of splitting the sample, we introduced a three-way interaction term and found the results consistent with those reported above. Overall, these additional analyses indicate the robustness of the effects across the different measures, model assumptions, and specifications.

Finally, in unreported analyses, we performed additional tests that account for the heterogeneity among venture capital firms (results available upon request). In particular, we compiled data on the reputation index of VCs (Lee et al., 2011) and conducted a new set of analyses that use the logarithmic transformation of the reputation index as the dependent variable and estimate random effects panel regressions. To remain consistent with our main analyses, we perform this analysis for the first round of VC investment. These results are consistent with our main results. As with the main models, *Pre-entry experience* has

a positive effect on the reputation index of the VC (*coef.* = 0.713; *p* = 0.031); the positive effect of *Pre-entry experience* becomes accentuated when the new venture utilizes knowledge from the former employer (*coef.* = 1.365; *p* = 0.096); that effect of *Knowledge linkage* to the former employer is especially strong for new ventures located in denser industry clusters (*coef.* = 3.595; *p* = 0.050).

The results of this study provide a deeper understanding of how and when pre-entry experience reduces information asymmetry about new ventures in factor markets. Prior literature has focused on whether pre-entry experience matters for new ventures in securing financing from venture capitalists (Beckman et al., 2007; Chatterji, 2009; Ko & McKelvie, 2018). Rooted in signaling arguments, extant findings in this literature show that pre-entry experience signals quality and helps attract VC funding. These accounts of pre-entry experience effects, however, leave us with an incomplete understanding of the signaling effects of pre-entry experience because they ignore the contingencies that shape these effects.

The signaling effects of pre-entry experience can be impacted by two considerations: “What additional information is the new venture relaying to enhance the clarity of pre-entry experience signal?” and “How does the environment where the new venture operates influence the processing of the signal?” (Connelly et al., 2011). These considerations are also related to Cao & Posen’s (2023) framework, underscoring the attributes of pre-entry experience as well as that of the context as contingencies. The new venture’s attributes may act as additional information interacting with the pre-entry experience signal to enhance or distort the clarity of the pre-entry experience signal (e.g., Bapna, 2019). The contextual attributes may play a part in altering the clarity of the signal because of noise in the environment (e.g., Connelly et al., 2011).

We pay attention to knowledge linkages between a new venture with pre-entry experience and its former employer as a crucial contingency shaping the effects of pre-entry experience. We also examine how the interaction between knowledge linkages and pre-entry experience unfolds in a signaling environment where industry clustering causes cluttering and weakens the pre-entry experience signal. Our findings suggest that these two contingencies shape the effects of pre-entry experience in resolving information asymmetries for

⁷ Results of these analyses and the analyses reported in the next paragraph are available on request.

Table 4 Accelerated failure time models of the conditions under which pre-entry experience affects the time to first VC funding. Knowledge linkage is measured using the number of citations to the former employer

Variables	<i>Knowledge linkage</i>	<i>Clustering</i>	
		<i>Low</i>	<i>High</i>
Pre-entry experience	−0.710 (0.250) [0.004]	−0.960 (0.257) [0.000]	−0.558 (0.344) [0.105]
Pre-entry experience × knowledge linkage (level)	−0.732 (0.328) [0.026]	−0.204 (0.255) [0.424]	−1.757 (0.470) [0.000]
Knowledge linkage (level)	0.319 (0.211) [0.130]	−0.123 (0.161) [0.443]	1.179 (0.329) [0.000]
Local industry density (estabs)	−0.442 (0.171) [0.010]	−0.099 (0.206) [0.632]	−0.566 (0.679) [0.404]
Patent stock	−0.051 (0.141) [0.716]	−0.072 (0.153) [0.635]	0.168 (0.191) [0.380]
Ex-employer's knowledge value	0.030 (0.012) [0.014]	0.057 (0.014) [0.000]	0.007 (0.015) [0.640]
Alliance formed	2.754 (0.689) [0.000]	2.486 (0.639) [0.000]	2.559 (1.694) [0.131]
Location industry diversity	−4.677 (11.511) [0.685]	−16.331 (8.517) [0.055]	−282.242 (263.934) [0.285]
Urban scale	−0.035 (0.126) [0.781]	0.097 (0.098) [0.318]	2.610 (1.826) [0.153]
Co-location with ex-employer	−0.178 (0.130) [0.171]	−0.532 (0.227) [0.019]	−0.064 (0.155) [0.680]
Tech distance to ex-employer	0.997 (0.399) [0.012]	0.717 (0.462) [0.121]	1.239 (0.496) [0.013]
California	0.592 (0.341) [0.083]	0.776 (0.319) [0.015]	−1.942 (0.965) [0.044]
SBIR funded	−1.177 (0.791) [0.137]	−0.625 (0.716) [0.383]	−1.395 (1.248) [0.264]
Year fixed effects	Yes	Yes	Yes
Constant	9.940 (10.820) [0.358]	19.182 (8.109) [0.018]	267.436 (249.526) [0.284]

Table 4 (Continued)

Variables	<i>Knowledge linkage</i>	<i>Clustering</i>	
		<i>Low</i>	<i>High</i>
Sigma (log)	0.516 (0.066) [0.000]	0.348 (0.085) [0.000]	0.509 (0.064) [0.000]
Observations	81,381	46,488	34,893

Note: Clustered robust standard errors in parentheses (Clusters = 731). *P*-values in square brackets

prospective resource providers. Knowledge linkages to former employers enhance the clarity of the pre-entry experience signal for new ventures, enabling them to secure their first round of VC funding faster. The reason for such enhancement is that knowledge linkages convey that a new venture with pre-entry experience can learn from its pre-entry experience. Extending this reasoning to the contingencies arising from the environment, a key implication is that the augmented pre-entry experience signal tends to be more valuable when the noise in the environment can distort that signal. With increased competition due to many rivals also possessing pre-entry experience, the amplification of the pre-entry experience signal by knowledge linkages becomes more valuable when new ventures with pre-entry experience are located in areas with high industry clustering.

This study provides important implications for the theory and practice of entrepreneurship. The pre-entry experience literature has revealed a robust main effect on the economic performance of startups (Adams et al., 2016; Agarwal et al., 2004; Argyres & Mostafa, 2016; Cao & Posen, 2023; Klepper & Sleeper, 2005). What is yet to be revealed are the contextual factors that shape these effects as well as the theoretical underpinnings of such interactions (Cao & Posen, 2023). Our paper takes a step in this direction by expanding on knowledge linkages to the former employer as an essential contingent factor for understanding when and why the genealogy of startups matters. In addition, our paper adds a new way of looking at regional industry clustering in the context of new ventures with pre-entry experience by considering the competitive effects on resource mobilization (Buenstorf & Klepper, 2010; Klepper, 2010; Vedula & Kim, 2019). Our study demonstrates that conditions conducive to entry also cause crowding, calling

for the boosting of quality signals (Baptista & Swann, 1998; Shaver & Flyer, 2000). In the main, our study aligns very closely with Cao & Posen's (2023) observation that the effects of pre-entry experience are "intuitively compelling" and yet "nuanced." We thus answer Cao & Posen's (2023) call to shift the focus of pre-entry experience research from whether pre-entry experience benefits startups to elaborating on the conditions under which it matters.

Our study also adds to the literature on signaling theory by attending to the contingent nature of signaling (e.g., Bapna, 2019; Kotha et al., 2018; Vanacker et al., 2020). The signaling literature has shifted from examining the effects of individual signals to probing interactions among signals and with the signaling environment (Lee et al., 2011; Plummer et al., 2016). We incorporate these emerging ideas in our investigation into when and how new ventures endowed with pre-entry experience can better discern themselves in factor markets. In addition to highlighting the signal interaction between pre-entry experience and knowledge linkages, we shed light on the importance of competition in the external environment, which has been an understudied aspect of signaling contingencies (Connelly et al., 2011). In this regard, our study also underscores the significance of the regional concentration of an industry as a factor to consider in understanding signaling effects.

Notwithstanding the light it casts on the contingent effects of pre-entry experience on new venture resource assembly, our study also has limitations that present avenues for future research. Whereas the semiconductor industry offers a suitable context for examining our research question, the high rates of new ventures with pre-entry experience (Brittain & Freeman, 1986; Sporck, 2001) and a high propensity to file patents (Hall & Ziedonis, 2001) do not

Table 5 Accelerated failure time models of the conditions under which pre-entry experience affects the time to first VC funding. In the first two columns, we use *Knowledge linkage (proportion)*, and in the last two columns, we use *Knowledge linkage (level)*

Variables	<i>Knowledge linkage (proportion)</i>	<i>Clustering</i>		<i>Knowledge linkage (level)</i>	<i>Clustering</i>	
		<i>Weak</i>	<i>Strong</i>		<i>Weak</i>	<i>Strong</i>
Pre-entry experience	-0.701 (0.258) [0.007]	-0.883 (0.244) [0.000]	-0.556 (0.350) [0.112]	-0.673 (0.257) [0.009]	-0.882 (0.243) [0.000]	-0.486 (0.353) [0.169]
Pre-entry experience × knowledge linkage	-10.891 (3.902) [0.005]	-4.876 (2.656) [0.066]	-27.897 (7.779) [0.000]	-0.731 (0.328) [0.026]	-0.153 (0.232) [0.509]	-1.945 (0.457) [0.000]
Knowledge linkage	6.611 (3.348) [0.048]	2.841 (2.233) [0.203]	16.489 (6.045) [0.006]	0.317 (0.212) [0.135]	-0.182 (0.152) [0.233]	1.289 (0.317) [0.000]
Local industry density(emplmt)	-0.329 (0.138) [0.017]	-0.030 (0.138) [0.829]	3.983 (1.988) [0.045]	-0.320 (0.137) [0.020]	-0.022 (0.138) [0.873]	4.274 (1.907) [0.025]
Patent stock	-0.055 (0.144) [0.700]	-0.131 (0.133) [0.323]	0.363 (0.201) [0.071]	-0.050 (0.141) [0.723]	-0.086 (0.138) [0.536]	0.322 (0.192) [0.093]
Ex-employer's knowledge value	0.030 (0.013) [0.016]	0.057 (0.014) [0.000]	-0.002 (0.015) [0.895]	0.029 (0.012) [0.017]	0.061 (0.014) [0.000]	-0.011 (0.013) [0.426]
Alliance formed	2.825 (0.695) [0.000]	2.446 (0.621) [0.000]	2.561 (1.812) [0.157]	2.751 (0.699) [0.000]	2.418 (0.627) [0.000]	2.421 (1.797) [0.178]
Location industry diversity	-4.825 (11.271) [0.669]	-16.637 (8.337) [0.046]	115.814 (296.290) [0.696]	-4.735 (11.602) [0.683]	-17.180 (8.520) [0.044]	158.438 (285.807) [0.579]
Urban scale	-0.018 (0.124) [0.885]	0.081 (0.097) [0.408]	-0.022 (0.505) [0.965]	-0.021 (0.124) [0.866]	0.083 (0.097) [0.393]	-0.052 (0.502) [0.918]
Co-location with ex-employer	-0.183 (0.131) [0.163]	-0.427 (0.216) [0.048]	-0.123 (0.157) [0.433]	-0.182 (0.131) [0.164]	-0.450 (0.213) [0.035]	-0.086 (0.154) [0.575]
Tech distance to ex-employer	0.873 (0.400) [0.029]	0.379 (0.423) [0.371]	1.257 (0.514) [0.015]	0.971 (0.401) [0.015]	0.598 (0.444) [0.179]	1.213 (0.483) [0.012]
California	0.418 (0.323) [0.195]	0.576 (0.296) [0.052]	-2.256 (1.157) [0.051]	0.416 (0.322) [0.196]	0.573 (0.295) [0.052]	-2.249 (1.137) [0.048]
SBIR funded	-1.322 (0.846) [0.118]	-0.670 (0.741) [0.365]	-1.683 (1.444) [0.244]	-1.317 (0.843) [0.118]	-0.684 (0.739) [0.354]	-1.623 (1.401) [0.247]
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	9.793 (10.598) [0.355]	19.596 (7.943) [0.014]	-119.845 (293.949) [0.683]	9.683 (10.934) [0.376]	20.073 (8.126) [0.014]	-162.363 (283.406) [0.567]

Table 5 (continued)

Variables	Knowledge linkage (proportion)	Clustering		Knowledge linkage (level)	Clustering	
		Weak	Strong		Weak	Strong
Sigma (log)	0.523 (0.068) [0.000]	0.335 (0.086) [0.000]	0.518 (0.066) [0.000]	0.520 (0.067) [0.000]	0.332 (0.086) [0.000]	0.501 (0.066) [0.000]
Observations	81,381	48,965	32,416	81,381	48,965	32,416

Note: Clustered robust standard errors in parentheses (Clusters = 731). *P*-values in square brackets

guarantee the generalizability of the results of this study, e.g., in sectors where the technology intensity is low to moderate. We would expect the predictors we theorized to be critical uncertainty-reducing signals in factor markets in other technology-intensive sectors with high innovation rates, such as the biotechnology, disc drive, and medical device industries. Further, the magnitude of these effects could differ in non-high-tech settings and may require adjusting the conceptualization of building on the former employers' knowledge in service industries. In this regard, service industries may be subject to a competitive environment in which industrial diversity can increase noise, necessitating alternative signals to bolster resource assembly.

4.2 Practical implications

The study shows that new ventures can benefit from showcasing not only their founders' prior experience in the industry but also their knowledge linkages to their former employers in building the new venture's technology. Many technology entrepreneurs face a Darwinian struggle to secure resources. In this regard, our findings reveal that leveraging knowledge linkages to the erstwhile employers of the founders affords new ventures one more advantage in the competition for resources. By leveraging knowledge from the founders' former employers, new ventures signal to external resource providers their ability to learn and build upon inherited knowledge, thereby enabling external resource providers to assess the venture's future potential better and more positively. This approach differs from traditional practices that may simply list prior experience without illustrating how that experience is leveraged in the new venture.

For external resource providers, the study suggests a more nuanced interpretation of founders' pre-entry experience. Resource providers should look beyond the mere presence of industry experience and assess how founding teams are utilizing their inherited knowledge from previous employers to drive innovation in their new ventures. Evaluating the extent to which founders draw on specific skills and technologies from their experience can provide deeper insights into the venture's capacity for learning and potential long-term success. Additionally, in industries characterized by high geographic clustering, where numerous startups vie for attention, considering these context contingencies can help resource providers identify ventures with future potential. This approach moves beyond the founder's credentials, encouraging investors to consider how founders use their prior experience in the new venture.

Data availability Data is available on request.

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