Practice makes perfect: Entrepreneurial-experience curves and venture performance

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A B S T R A C T

This study tackles the puzzle of why increasing entrepreneurial experience does not always lead to improved financial performance of new ventures. We propose an alternate framework demonstrating how experience translates into expertise by arguing that the positive experience–performance relationship only appears to expert entrepreneurs, while novice entrepreneurs may actually perform increasingly worse because of their inability to generalize their experiential knowledge accurately into new ventures. These negative performance implications can be alleviated if the level of contextual similarity between prior and current ventures is high. Using matched employee–employer data of an entire population of Swedish founder-managers between 1990 and 2007, we find a non-linear relationship between entrepreneurial experience and financial performance consistent with our framework. Moreover, the level of industry, geographic, and temporal similarities between prior and current ventures positively moderates this relationship. Our work provides both theoretical and practical implications for entrepreneurial experience—people can learn entrepreneurship and pursue it with greater success as long as they have multiple opportunities to gain experience, overcome barriers to learning, and build an entrepreneurial-experience curve.

1. Executive summary

Central to the entrepreneurship literature is the conventional wisdom that entrepreneurs and investors alike use experience as a vital clue for anticipating future performance—the level of financial success in new ventures. Extant literature suggests that entrepreneurs who have more experience found better-performing ventures, their experience enabling them to generalize knowledge from one setting and to apply it effectively to a new situation. However, according to learning studies, experience may not necessarily trigger increased performance if incorrect inferences are drawn from previous experiences. The objective of our study is to investigate these contrasting theoretical arguments in entrepreneurship.

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In this paper, we argue that entrepreneurs, despite their experience, may actually perform worse in subsequent ventures because of conditions that prevent learning from automatically occurring from one venture to the next. We refer to these conditions as *barriers to learning*, which we define as "obstacles encountered by entrepreneurs that prevent them from extracting appropriate knowledge from their prior venturing or from applying their existing knowledge appropriately to new ventures." Our study uses theories of experience curves and superstitious learning from the organizational learning literature to propose an alternate framework that demonstrates how the positive experience-performance relationship only appears to expert entrepreneurs, while less-experienced entrepreneurs may be unable to apply their experiential knowledge accurately and successfully to new ventures. While expert entrepreneurs have the necessary general awareness to make more effective connections and to place particular events into their proper contexts, entrepreneurs with lower levels of venture experience attempt to apply lessons learned from experiences they believe to be similar but in practice are inherently different.

To investigate the experience-performance relationship, we developed a set of predictions derived from the experience curve literature to show a number of barriers to learning based on content- and context-domain differences. We described our predictions specifically in terms of three context-domain differences between prior and current ventures: industry, geographic, and temporal. For each of these three context-domain characteristics, we predicted that, at low to moderate levels of experience, high context similarity weakens the negative direct relationship between experience and venture performance. At moderate to high levels of experience, we predicted that high context similarity strengthens the positive direct relationship between experience and venture performance.

We tested our theory by using matched employee–employer data of an entire population of Swedish founder-managers between 1990 and 2007. Consistent with our theoretical predictions, we found evidence to support our framework predicting why limited experience lowers performance while enhanced financial performance only occurs at substantial levels of experience. We observed that contextual similarities among prior and current ventures positively moderated the direct experience–performance relationship.

Our work provides both theoretical and practical implications for entrepreneurial experience—people can learn entrepreneurship and pursue it with greater success as long as they have multiple opportunities to gain experience, overcome barriers to learning, and build an entrepreneurial-experience curve. As such, this study provides new insights for the experience curve literature by challenging the assumption that repeated task experience generates automatic and consistent returns to performance. In demonstrating the contours of entrepreneurial-experience curves, we provide a corrective to mixed evidence reported in the literature regarding the experience–performance relationship. Just as critically for aspiring entrepreneurs, our work shows that extensive practice enables them to learn entrepreneurship and makes for the possibility of better performing ventures.

2. Introduction

Entrepreneurs and investors alike use experience as a vital clue for anticipating future performance—the level of financial success in new ventures. In its simplest form, entrepreneurial experience is past involvement in founding a business. Entrepreneurs tap into the knowledge gleaned from their prior ventures to formulate and execute their plans in new ventures. Investors, on the other hand, regularly tout a philosophy of "betting on the jockey rather than the horse" when evaluating potential entrepreneurs to back with their financial support. But for both parties, entrepreneurial experience serves as a proxy for expertise—an underlying ability to generalize knowledge from one setting and to apply it effectively to a new situation (Eisenhardt and Martin, 2000; Hayes, 1989). Thus, conventional wisdom dictates that entrepreneurs who have more experience would also found better-performing ventures, a relationship consistent with experience curve theory (Argote and Todorova, 2007).[3] Acceptance of this null argument depends on the validity of the assumption that learning from prior ventures is cumulative and automatic with each successive effort (Hayes and Clark, 1985; Yelle, 1979). However, we also know from learning studies that experience may not necessarily trigger increased performance if incorrect inferences are drawn from previous experiences, a theoretical concept known as superstitious learning (e.g., Levitt and March, 1988). In particular, infrequent events are more difficult to learn from due to the lack of repetitiveness or the time decay of learning (e.g., March et al., 1991; Parker, 2012).

The purpose of our study is to investigate these contrasting theoretical arguments in entrepreneurship. Despite their experience, entrepreneurs may actually perform worse in subsequent ventures because of conditions that prevent learning automatically occurring from one venture to the next (Bingham et al., 2007; Rerup, 2005; Shepherd, 2003). We refer to these conditions as *barriers to learning*, which we define as obstacles encountered by entrepreneurs that prevent them from extracting appropriate knowledge from their prior venturing or from applying their existing knowledge appropriately to new ventures. We develop arguments for why some experienced entrepreneurs are unable to overcome these barriers fully—and why they experience poorer entrepreneurial performance—by comparing experience curve and superstitious learning theories.

We investigate our research questions using a unique longitudinal dataset of new ventures in Swedish knowledge-intensive sectors from 1990 to 2007. This comprehensive, historical, and time-varying information about the owner-managers of these ventures allows us to examine carefully the experience-venture performance relationship. Our analyses reveal a non-linear relationship between these two facets of entrepreneurship, such that entrepreneurs actually perform progressively worse between low to moderate levels of experience and improve only at moderate to high levels of experience. The strength of this non-linear relationship varies depending on industry, geographic, and temporal similarities between the entrepreneurs' current and prior ventures.

[3] Initially introduced in psychology, the term has acquired a broader interpretation over time, and expressions such as "learning curve" and "progress curve" are often used interchangeably (Epple et al., 1991).

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Our study offers several contributions to the entrepreneurship literature. By applying experience curve theory to this literature, we provide a more comprehensive framework for understanding how entrepreneurial experience can be applied to new venturing efforts, why experience does not always lead to increased performance outcomes, and how it produces both positive- and negative-performance outcomes (e.g., Chandler, 1996; Eesley and Roberts, forthcoming; Gartner and Starr, 1999; Parker, 2012; Rerup, 2005; Shepherd et al., 2009; Ucbasaran et al., 2009). These insights have especially broad appeal to those studying *serial entrepreneurs*—individuals who found one venture and subsequently found at least one other venture. This population represents 15 to 25% of the total population of entrepreneurs, and these entrepreneurs are considered essential contributors to economic growth (MacMillan, 1986; Ucbasaran et al., 2008). By developing a new framework for assessing the level of experience and its similarity to current entrepreneurial efforts, we clarify the moderating conditions in which experience produces both positive- and negative-performance outcomes. Our approach resolves some of the inconclusive findings reported in prior studies addressing the relationships between experience and venture performance (Delmar and Shane, 2006; Ucbasaran et al., 2008). By using a carefully constructed longitudinal study design mitigating survival and success biases, our work broadens knowledge about the time-varying and non-linear aspects of learning and performance also reported in recent studies (Campbell, 2012; Parker, 2012). Accordingly, our study reveals the conditions in which entrepreneurs can learn to overcome barriers to "learning" entrepreneurship, leading to improved performance in the ventures they create. Only with *extensive* practice, entrepreneurs can actually learn how to launch and manage new ventures effectively as they eventually proceed upward along their entrepreneurial-experience curves.

3. Conceptual background

In the following sections, we define the key theoretical concepts we employ in our study: entrepreneurial experience and experience curves (MacMillan, 1986). We use these concepts to build our theoretical arguments regarding their relationships with venture performance.

3.1. Entrepreneurial experience and venture performance

We define *entrepreneurial experience* as past involvement in founding a business. Research on entrepreneurial performance suggests that financial success is partly dependent upon the entrepreneurs' expertise in effectively applying knowledge from prior ventures to current efforts (Aldrich and Yang, 2013; Baron and Ensley, 2006; Eesley and Roberts, forthcoming; Gompers et al., 2006; Politis, 2005; Shepherd et al., 2009). Yet without the ability to measure expertise directly, entrepreneurial experience is more generally used as a predictor of a venture's financial performance and has generally been argued to enhance such performance in positive ways (e.g., Delmar and Shane, 2004; Haynes, 2003; Stuart and Abetti, 1990). Animating this null argument is the mechanism that experienced entrepreneurs increasingly develop expertise in starting and running businesses with each venture, which in turn is reflected in successive venture performance improvements (Eesley and Roberts, forthcoming; MacMillan, 1986). But the accumulated empirical evidence to support an association between experience and a venture's financial performance remains inconclusive. Some studies reported no effects (e.g., Dencker et al., 2009; Oe and Mitsuhashi, in press; Ucbasaran et al., 2006; Westhead and Wright, 1998), while others showed non-linear effects (e.g., Delmar and Shane, 2006; Eesley and Roberts, forthcoming; Reuber and Fischer, 1994), while still others found even negative effects (Alsos and Carter, 2006; Tornikoski and Newbert, 2007).[4] Given these inconsistent findings, we argue that the relationship between entrepreneurial experience and venture performance is not necessarily straightforward. To help clarify this connection, we look to experience curve theory to generate our arguments for how these two facets of entrepreneurship are related.

3.2. Experience curves and serial entrepreneurship

Following psychology research, we define individual *experience curves* as "improvement in performing a given task as a function of cumulative experience" (Ellis, 1965; Harlow, 1949). Principles of experience curves (or learning curves) have been developed in studies across a number of contexts and at the levels of individuals, groups, organizations, and industries (Argote, 1999; Yelle, 1979). Research on experience curves typically measures learning in terms of quality, cost, and speed-related performance outcomes (Dutton and Thomas, 1984; Lapré et al., 2000). Experience curves represent the link between experience and performance over time from repeating a series of events, each of which represents an opportunity for learning (Yelle, 1979). They are explicitly longitudinal because learning from experience is an inherently iterative and dynamic process (March, 2010). This description of experience curves is also consistent with the definition of learning found in the organizational literature, in which it is described as a change in behavior or performance that occurs as a function of experience (Argote and Epple, 1990; Dutton and Thomas, 1984). From these principles, then, one could predict positive but diminishing returns to experience (Dutton and Thomas, 1984; Wright, 1936; Yelle, 1979).

[4] In our review of papers associating entrepreneurial experience with performance, we searched the Journal of Business Venturing, Entrepreneurship Theory and Practice, and Strategic Entrepreneurship Journal for papers with the following key words: entrepreneurial experience, start-up experience, serial entrepreneur, habitual entrepreneur, expert entrepreneur, repeat entrepreneur, and experienced entrepreneur. We then added all papers identified through Web of Science and Google Scholar, as well as papers cited in prior literature reviews (Delmar and Shane, 2006; Ucbasaran et al., 2008). Among the 22 empirical studies we identified measuring the effect of entrepreneurial experience on performance, 10 studies show insignificant or mixed effect, three studies report curvilinear effects (positive and negative effects; e.g., context or time dependent), seven report positive effects (many of which are cross-sectional and small-sample studies), and two studies report negative effects.

The empirical evidence, however, shows variations in the shape of experience curves across levels of analysis, as well as across task-content and contextual domains (Argote and Epple, 1990; Hayes and Clark, 1985). These variations point to a more complex connection between experience and performance. Although experience curve theory is based on multiple repetitions of the same task, improved performance depends on similarities between the repeated tasks. Thus, we argue that these similarities can be viewed in terms of the content domain of the task and the context domain in which it occurs. Following Barnett and Ceci (2002:621), we define the *content domain* as what can be learned from experience with a given task and the *context domain* as where and when learning is transferred from and to. Content-domain similarities occur when entrepreneurs repeat similar actions when launching their businesses, such as developing products, conducting market research, mobilizing resources, and carrying out other activities typically associated with business formation. Conversely, context-domain similarities arise when entrepreneurs launch new ventures in similar contexts, such as in the same industry or general location as their prior efforts.

But when the tasks in content and context domains are not similar in one or both dimensions, barriers to learning complicate the ability for individuals to apply knowledge effectively from prior efforts to their current endeavors. Entrepreneurs' encounters with learning barriers depend on their level of general experience in starting ventures (content-domain similarity) and also depend on the extent to which those experiences are similar to their current efforts (context-domain similarity). Our argument highlights why content-domain similarities from previous businesses do not necessarily produce better performance in new ventures. We attribute this learning barrier to incorrect inferences made by serial entrepreneurs from previous experiences (Levitt and March, 1988; March, 2010; Novick, 1988). Moreover, we contend that this experience-performance relationship varies depending on context-domain similarities between past experiences and current conditions (Argote, 1999; Lampel et al., 2009; March et al., 1991; Parker, 2012).

4. Theory and hypotheses

In the following sections, we first address the role of increased content-domain similarity of starting businesses to overcome learning barriers. This represents the direct-effect relationship in our theoretical model explaining how the level of prior entrepreneurial experience influences current venture performance (Section 3.1). We then address the role of increased context-domain similarity as a second means of overcoming learning barriers. At large, we treat these contextual similarities as moderators to the direct experience-performance relationship in our theoretical model (Sections 4.2–4.5).

4.1. Limited entrepreneurial experience as a barrier to learning

Experience curve theory predicts that, when current situations seem similar to previous experiences, behavior from previous situations will be generalized to the current situation (Pinder, 1984; Tripsas and Gavetti, 2000). Taken at face value, we would then expect serial entrepreneurs to benefit increasingly from what they learned from their prior ventures (content-domain similarity) given their awareness of what is required to build new ventures and their assumed desire to pursue this effort successfully. However, learning theory also predicts the following—if current conditions are unlike previous situations, generalizing from past experience can lead to unfavorable outcomes (Mazur, 1994). Specifically, studies of learning both at the individual (Kahneman et al., 1982) and firm levels (Barnett and Ceci, 2002; Kahneman et al., 1982; March, 2010) have revealed that transferring knowledge derived from prior experiences becomes more difficult when new content domains are complex, such as the challenges faced by entrepreneurs starting businesses.

To apply experience curve theory to serial entrepreneurship, we first assume experienced entrepreneurs who start new ventures will not approach them as completely new endeavors (MacMillan, 1986; Parker, 2006). However, each new venture will have its own set of unique challenges to overcome, weakening the assumption that content-domain similarity is integral to experience curve theory for predicting increasing performance. Thus, serial entrepreneurs still wrestle with a variety of fundamental issues that are different for each new venture: how to deliver value to customers, secure financial resources, and thwart competitors. Despite the apparent similarities of these business-formation requirements, serial entrepreneurs are likely to encounter enough differences in each new venture so that application of prior knowledge is not straightforward.

To reconcile these two conflicting views, we argue that entrepreneurial experience has a curvilinear influence on venture performance. This argument contains two parts. In the first part, we argue that novice entrepreneurs—those with low to moderate venture experience—will generalize their knowledge incorrectly to new ventures, resulting in a negative influence on venture performance. This occurs because of superstitious learning, a false sense of understanding of the current situation from prior experience (Levitt and March, 1988). Novice entrepreneurs attempt to apply lessons learned in content domains they believe are similar but in practice are inherently different.

This false sense of understanding arises from an impulse to generalize from a limited set of experiences without full awareness of a wider body of challenges and accompanying solutions (Simon, 1978). When multiple solutions exist for addressing a particular venture-related problem, novice entrepreneurs find it difficult to compare the feasibility of alternative solutions ex ante, because novel, intuitive insights cannot be judged a priori right or wrong (Crossan et al., 1999). Thus, they increasingly generalize mediocre solutions from the past and import them to superficially similar conditions in the present (Mazur, 1994; Novick, 1988).

This increasingly negative influence is most acute at moderate levels of experience because moderate experience leads entrepreneurs into competence traps where they perceive such similarities, but lack sufficient perspective to recognize the similarities are only superficial (Levitt and March, 1988; Zollo, 2009). With low or moderate experience, entrepreneurs may continue employing developed routines even when confronted with pressure against their use (Frese, 2009; Kim et al., 2009).

Consequently, this application of prior knowledge can negatively affect venture performance (Dencker et al., 2009). In fact, studies have shown that performance loss can occur when entrepreneurs draw inaccurate inferences from even just one prior event that is incorrectly perceived to be similar to the current effort (Haleblian and Finkelstein, 1999).

The negative influence of superstitious learning reverses when serial entrepreneurs exceed moderate levels of experience. These individuals we refer to as expert entrepreneurs. For the second part of our direct-effect argument, we posit that venture performance starts to improve only at higher levels because these serial entrepreneurs are better equipped to deduce differences between prior and current conditions; that is to say, they are more likely to draw more accurate inferences based on their knowledge from other ventures. As the content domain of entrepreneurship is complex, each new venture will require entrepreneurs to transfer knowledge across conceptually distant content domains (Barnett and Ceci, 2002; Gick and Holyoak, 1987). Each venture contains its own set of unique circumstances and start-up challenges (Beckman and Burton, 2008; Eisenhardt and Schoonhoven, 1990). Addressing these varied challenges requires them to have at least a moderate level of experience for the necessary perspective to make more accurate generalizations and to apply them successfully to their new ventures (Eesley and Roberts, forthcoming; Kim et al., 2009; Levitt and March, 1988).

Expert entrepreneurs are better able to transfer knowledge into new content domains (i.e., the new challenges associated with each new venture), even if they lack direct experience for dealing with these specific challenges. These highly experienced entrepreneurs have the necessary general awareness to make more effective connections (Brown et al., 1989) and to place particular events into their proper contexts (Mitchell et al., 2007). The development of new entrepreneurial routines also increases entrepreneurs' ability to go beyond existing routines (Frese, 2009). Expert entrepreneurs are additionally able to better resist the impulse to react solely on initial impressions—reactions referred to by scholars as anchoring biases (Kahneman et al., 1982; Wilson et al., 1996). As the real benefits from learning commonly attributed to entrepreneurial experience manifest with extensive experience (Kim et al., 2009; Ucbasaran et al., 2008), we expect experience to exhibit a non-linear relationship with venture performance.

Specifically, it declines at low to moderate levels of entrepreneurial experience, but turns positive for entrepreneurs with moderate to high levels of experience. Therefore, we predict:

Hypothesis 1. The level of entrepreneurial experience will exhibit a U-shaped relationship with venture performance. Specifically, *low to moderate levels of experience* have a direct *negative* relationship with venture performance while *moderate to high levels of experience* will have a direct *positive* relationship with venture performance.

4.2. Contextual similarities and barriers to learning

In addition to the venture-performance implications resulting from content-domain differences, we also argue that contextual-domain similarities play an important role in why some entrepreneurs perform better than others in subsequent ventures. Recall that we define context domain as where and when learning is transferred from and to (Barnett and Ceci, 2002:621). From the experience curve literature, we know context-domain similarities directly affect performance outcomes when transferring knowledge across contexts (Argote and Miron-Spektor, 2011; Lapré et al., 2000). Beyond this direct relationship, however, we posit that context-domain differences also moderate the strength of the experience–performance relationship we described in the previous section.

In the following sections, we begin with a general overview about our moderating predictions. Because our direct experience-performance relationship in H1 is curvilinear (depending on the level of experience), we introduce our moderation argument in two parts: (1) why context-domain differences attenuate the negative experience–performance relationship for low to moderately experienced entrepreneurs (enabling them to alleviate barriers to learning) and (2) why context-domain differences accentuate the positive experience–performance relationship for moderate to highly experienced entrepreneurs (enabling them to enhance the effects of learning). After providing the general moderation argument, we describe our predictions specifically in terms of three context-domain differences between prior and current ventures: industry, geographic, and temporal.

4.2.1. Contextual similarity as means to alleviate barriers to learning

In the first part of our moderation argument, we focus on novice entrepreneurs, those with low to moderate venture experience. Among these entrepreneurs, those with high similarities between their prior ventures and current efforts, however limited, most improve their accuracy of transferring knowledge from one context to another. We offer several reasons for this improvement. Superstitious learning theory predicts that applying knowledge from a similar situation reduces the need for adapting the knowledge into the current context (Levitt and March, 1988; Zollo, 2009). Entrepreneurs can immediately use the insights derived from their prior ventures and benefit from this expertise. Generalization in similar contexts reduces the negative effects of behavioral persistence (Mazur, 1994; Tripsas and Gavetti, 2000). Additionally, the benefits of contextual similarity enable entrepreneurs to alleviate the barriers to learning that exist with limited experience. When current and past experiences are similar, process knowledge improves through specialization (Zollo et al., 2002). Small deviations in context across ventures thus allow entrepreneurs to distinguish easily between higher-order and lower-order heuristics by elaborating on existing knowledge and, ultimately, by developing deeper understandings of causal relationships (Bingham et al., 2007). Although we still expect the negative direct relationship between the experience and venture performance to exist, similarities between prior and current ventures help to address those drawbacks associated with limited experience.

4.2.2. Contextual similarity as means to enhance learning

In the second part of our moderation argument, we switch the focus to expert entrepreneurs—those with moderate to high venture experience. Among these entrepreneurs, high similarity between prior ventures and current efforts further improves their ability to generalize knowledge from one context to another. In addition to the benefits we described in the previous section, we outline two additional advantages. First, high similarity reduces challenges posed by superstitious learning theory, such as transferring knowledge from conceptually distant domains (Barnett and Ceci, 2002; Gick and Holyoak, 1987). Expert entrepreneurs benefit more from this association because of their ability to apply, easily and accurately, their insights from past ventures to their current efforts (Bingham et al., 2007). Second, high similarity also enables individuals to respond more quickly to current efforts based on their previous experiences because they do not need to learn new concepts (Nye, 1979). With the broad perspective they gain from extensive experience, expert entrepreneurs stand to further benefit from their experience when starting similar ventures. In the following sections, we outline our moderation arguments more specifically in terms of three forms of contextual similarities: industry, geographic, and temporal.

4.3. Industry similarity and barriers to learning

Perhaps the most salient indicator of context-specific entrepreneurial experience identified in the literature is industry similarity (Delmar and Shane, 2006; Eesley and Roberts, forthcoming; Klepper, 2001). Industry similarity is the extent to which an entrepreneur's prior ventures are similar to their current venture in terms of the industry in which they operate. Serial entrepreneurs may be able to respond quicker to a given challenge than novice entrepreneurs (Ucbasaran et al., 2008), yet there is a risk that their responses draw on incorrect inferences because the given context has changed (Levitt and March, 1988). Applying this general rationale of our moderating argument specifically to industry similarity, we posit that, at low to moderate levels of entrepreneurial experience, the negative direct relationship with venture performance will weaken as industry similarity increases. Under these conditions, industry-experienced entrepreneurs benefit from employing relevant knowledge to similar industry conditions they face with their current ventures. With such similarities, the positive benefits of industry experience—such as identifying more entrepreneurial opportunities (Gruber et al., 2008), increasing venture survival and growth prospects (Cooper et al., 1994), and forecasting performance more accurately (Cassar, in press)—help to mitigate the negative outcomes associated with limited entrepreneurial experience.

The positive benefits associated with industry experience become even more evident at a high range of experience because of the ease with which entrepreneurs can accurately generalize from past venturing experiences in similar industries (Haunschild and Sullivan, 2002; Schilling et al., 2003). These benefits from industry-context similarities help entrepreneurs to overcome barriers to learning and to minimize the drawbacks associated with transferring knowledge into new contexts with limited experiences (Chandler, 1996; Gartner and Starr, 1999; Mazur, 1994). We also expect that at moderate to high levels of entrepreneurial experience, the positive direct relationship with venture performance will strengthen as industry similarity increases. For these reasons, we predict:

Hypothesis 2. Industry similarity moderates the curvilinear relationship between entrepreneurial experience and venture performance such that it *reduces* the direct negative effect of *low to moderate levels* of experience, while *strengthening* the direct relationship at *moderate to high levels* of experience.

4.4. Geographic similarity and barriers to learning

A second type of context similarity concerns the geographic proximity of an entrepreneur's current venture with their prior efforts. Geographic similarity is the extent to which an entrepreneur's prior ventures are located in close distance with their current venture. Again, we argue that at low to moderate levels of entrepreneurial experience, the negative direct relationship with venture performance will weaken as geographic similarity increases. Establishing new ventures within close proximity to previous ventures allows entrepreneurs to leverage a broader resource base and to profit from reputations established through previous entrepreneurial efforts (Mason and Harrison, 2006). These benefits help them to overcome the drawbacks that come with limited entrepreneurial experience and its consequences of superstitious learning (Levitt and March, 1988).

We also argue that at moderate to high levels of entrepreneurial experience, the positive direct relationship with venture performance will strengthen as geographic similarity increases. Entrepreneurs tend to engage in social networks with stakeholders primarily close to their base (Dahl and Sorenson, 2009). The locally bounded value of knowing who knows what and who knows whom becomes even more beneficial if new ventures are established in proximity to their previous ventures (Klepper, 2002; Stuart and Sorenson, 2003). Local experience yields knowledge about proximate patterns in demands, access to suppliers, regulations, and insights about social and economic trends. This knowledge is more applicable and easily transferred to new ventures started in the same region (Ingram and Baum, 1997; Pe'er et al., 2006). For these reasons, we expect:

Hypothesis 3. Geographic similarity moderates the curvilinear relationship between entrepreneurial experience and venture performance such that it *reduces* the direct negative effect of *low to moderate levels* of experience, while *strengthening* the direct relationship at *moderate to high levels* of experience.

4.5. Temporal similarity and barriers to learning

In addition to industry and geographic similarity, the time elapsed between entrepreneurial spells can impede learning from venture to venture as well. We define temporal similarity as the time elapsed between an entrepreneur's last venture and current venture. Similar to our previous two predictions, we argue that at low to moderate levels of entrepreneurial experience, the negative direct relationship with venture performance will weaken as temporal similarity increases. The value of experience from the prior venture is most valuable when the knowledge soon translates into a new effort because experiential knowledge depreciates over time unless that knowledge is put into action (Argote et al., 1990; Baum and Ingram, 1998; Benkard, 2000; Darr and Argote, 1995; Parker, 2012). By starting a new venture shortly after running a previous one, entrepreneurs are able to alleviate the disadvantages of limited experience by quickly putting their experiential knowledge into action. For example, knowledge of a market context is more relevant for subsequent ventures if it is applied quickly because markets are highly dynamic. Knowledge of yesterday's rules may not necessarily lead to future success (Gartner and Starr, 1999).

Temporal similarity will also have an enhancing effect on performance by expert entrepreneurs. Again, we expect that at moderate to high levels of entrepreneurial experience, the positive direct relationship with venture performance will strengthen as temporal similarity increases. By starting new ventures within short periods of time, entrepreneurs avoid the decline in their abilities and can go on to attribute sources of success correctly (Golden, 1997). This association strengthens the positive benefits of entrepreneurial experience on performance because of the more accurate inferences they can make from recent ventures (Levitt and March, 1988; Zollo, 2009). For these reasons, we predict:

Hypothesis 4. Temporal similarity moderates the curvilinear relationship between entrepreneurial experience and venture performance such that it *reduces* the direct negative effect of *low to moderate levels* of experience, while *strengthening* the direct relationship at *moderate to high levels* of experience.

5. Methods

5.1. Data

Investigating entrepreneurial learning at the individual level over time requires a study context with several features. We needed longitudinal data tracking ventures from their formation (Delmar and Shane, 2006). The data also had to follow serial entrepreneurs in ways that properly accounted for sample selection biases (Delmar and Shane, 2003; Hamilton and Nickerson, 2003). We additionally required a context in which entrepreneurial experience could be measured more comprehensively than a simple binary indicator of having any experience or not. Our study also needed an outcome measure that accurately reflected venture performance consistently across companies and industries (Delmar and Shane, 2006).

To fulfill these criteria and to accomplish our study objectives, we created a dataset with these features in mind. Our data came from two longitudinal sources maintained by Statistics Sweden—RAMS, which contains yearly data on all firms registered in Sweden, and LISA, which provides yearly data on all Swedish inhabitants from 1990 onwards.[5] We used RAMS to identify all Swedish privately owned firms started between 1990 and 2007. Because these data contain complete information on the entire population of Swedish firms, we were able to examine new ventures from their very inception, which we define as when a single owner-manager worked full time in the new business. We excluded sole proprietorships and partnerships to avoid part-time ventures for which entry and exit may be “a trivial decision” (Gimeno et al., 1997). To decrease industry heterogeneity, we also limited the sample to entrepreneurs in knowledge-intensive sectors (i.e., high-tech manufacturing and knowledge-intensive services). Knowledge-intensive industries constitute about 35% of all firms started in Sweden (Folta et al., 2010), and they include most rapidly growing industries (e.g., chemicals, medicine, telecom, finance, business services, information technology, education and research). To identify these sectors, we used the Eurostat and Organisation for Economic Co-operation and Development's (OECD) classification system, which is based on whether or not the industry's R&D intensity is higher than the mean of the overall economy (Götzfried, 2004). A full list of sectors included in our study sample is shown in Appendix 1.

To investigate how experiences of individual entrepreneurs affect their ventures, we required the entrepreneurs to hold discretion over the firm's future (Beckman and Burton, 2008). Thus, we analyzed only newly started ventures from their inception onward, those enterprises founded by founder-managers working full time in a new firm in which they held a majority ownership stake. After excluding 4058 firms (5.8% of the sample) where no individual entrepreneur held a majority stake, we formed an analytical sample of 65,390 genuinely new (de-novo) firms started by individual entrepreneurs as full-time ventures.[6]

We used LISA to form our individual-level experience variables based on venturing activities occurring from 1990 to 2007. Because the RAMS and LISA datasets can be linked together, we were able to construct detailed individual- and firm-level

[5] Additional details about these data can be found here: http://www.scb.se/Pages/List____257743.aspx.

[6] Exclusion of these team start-ups was theoretically motivated by our experience-curve framework's focus on learning at the individual level. They were methodologically necessary since we cannot compare the benefits of an individual entrepreneur's learning with that of two- or three-member entrepreneurial teams in any systematic way. A small number of cases (0.08% of the sample) were reported as owners with entrepreneurial earnings but not reported as “entrepreneurs” in the occupational data. After discussion with experts at Statistics Sweden, rather than omit these cases they were corrected by assigning people with “missing” employment information as entrepreneurs or non-entrepreneurs, based on them reporting entrepreneurial earnings or not.

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Table 1
Variable descriptive statistics.

Variable	Mean	St. dev.	Min	Max	VIF
Ln (entrepreneurial earnings)	12.89	5.60	0	16.13	1.19
Age	45.41	11.13	21	87	1.35
Female	0.56	0.50	0	1.00	1.05
Education	12.35	6.20	6	19	1.35
Management experience	0.46	0.55	0	2	1.10
Parents as entrepreneurs	0.34	2.09	0	8.00	1.00
Ln (capital)	10.35	40.20	0	190.44	1.01
Firm survival (lambda)	450.42	110.14	0	95.00	1.02
Ln (past performance as serial ent.)	6.33	3.73	0	21.4	2.34
Industry similarity	10.42	3.99	0	15,34	1.07
Geographic similarity	−240.81	160.87	−1010	0.00	1.28
Temporal similarity	−10.34	20.63	−15	0.00	3.83
# Ventures founded	0.39	0.77	0	5	5.32
# Ventures founded ^{2}	0.64	2.07	0	25	8.23

Note: N = 65,390 individuals.

measures that met the necessary longitudinal requirements for testing our study predictions. One advantage of this study design is that our sample includes every individual who has ever worked in these knowledge-intensive industries. As such, we have complete labor-market histories for each entrepreneur who has started a venture in these industries (i.e., a balanced panel design). These histories include data on entrepreneurial experience if the entrepreneur previously funded or co-funded one or several businesses outside these sectors. We provide information on our variables' descriptive statistics in Tables 1 and 2.

5.2. Dependent variables

5.2.1. Venture performance

We measured venture performance based on Hamilton's (2000) definition of entrepreneurial earnings—[revenues − expenses = money taken out + retained earnings]. To construct this variable, we combined firm-level performance data from the venture's annual reports (in RAMS) with individual-level tax records (from LISA). Because of the high skewness in the earnings variable, we log-transformed it, following a commonly used technique in the labor economics literature.

We used entrepreneurial earnings as our performance measure because of its comparability and meaningfulness across industries. Some performance measures are not equivalent from industry to industry (e.g., annual sales growth), whereas other measures may not be as meaningful in some industries (e.g., number of patents). Given our objectives of testing theory that is generalizable across industries, we argue that entrepreneurial earnings are an appropriate performance measure. Using such an indicator to measure performance also helps to disentangle the role of learning's effect on firm performance as opposed to firm survival because collecting performance data is difficult for discontinued ventures. In such studies, performance has either been ignored or measured indirectly as "financial leverage" (Bates, 1990) or as "money taken out of the business" (Gimeno et al., 1997). These are highly imperfect measures because entrepreneurs often choose to forego current benefits in preference of reinvesting money. Given our longitudinal dataset with complete coverage of an entire population of firms, we also avoid recall bias and sample-selection problems in our dependent variable.

Table 2
Correlation matrix.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Ln (Entrepreneurial earnings)													
2	Age	0.064												
3	Female	0.292	0.001											
4	Education	0.041	0.012	−0.016										
5	Management experience	0.084	0.160	0.123	0.138									
6	Parents as entrepreneurs	−0.006	−0.025	0.006	−0.002	−0.041								
7	Ln (capital)	0.083	0.017	0.102	0.013	0.122	−0.028							
8	Firm survival (lambda)	0.005	0.041	0.039	0.006	0.201	−0.160	0.265						
9	Ln (past performance as serial ent.)	0.055	0.043	0.123	0.032	−0.039	0.001	0.059	0.177					
10	Industry similarity	−0.083	−0.019	0.212	0.016	0.090	−0.003	0.042	0.128	0.052				
11	Geographic similarity	0.108	−0.045	0.362	0.011	0.089	−0.015	0.133	0.200	0.087	0.145			
12	Temporal similarity	−0.096	0.052	0.184	0.050	0.021	0.001	0.067	0.165	0.834	0.087	0.099		
13	# of ventures founded	0.140	0.033	0.141	0.022	0.006	0.004	0.047	0.127	0.757	0.110	−0.105	−0.477	
14	# of ventures founded ^{2}	−0.073	0.122	−0.029	−0.010	−0.062	0.005	0.010	−0.207	−0.073	−0.002	−0.002	0.296	0.916

Note: N = 65,390 individuals.

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5.3. Independent variables

5.3.1. Number of ventures founded

We used data from LISA on individuals' career histories to determine the number of prior entries into entrepreneurship during the 17 years of our study period. To consider them as prior entries, we used several criteria. We first determined all occasions when there was at least a one-year gap between an individual's spells of entrepreneurship. For entries in the same industry and geographic location, we implemented a more stringent criterion of a two-year gap between spells to eliminate situations when individuals closed and restarted the same firm. Among all entrepreneurs in the sample, 14,288 (21.9%) had one or more spells of prior venturing activity.

5.4. Interaction variables

We included three variables—industry, geographic, and temporal similarity—to test our moderating predictions. To form our three interaction variables, we multiplied our main predictor variable, the number of prior ventures, with each of these variables.

5.4.1. Industry similarity

To test our arguments in H2, we used data from RAMS on a prior venture's industry affiliation to measure industry similarity between all prior and current ventures. We adopted Lien and Klein's (2008) industry-similarity measure, which is based on distances of firm sales across SIC industry codes. We created this measure using information about the prior ventures' industry sectors (i), current industry sectors (j), and sales (s) with this formula:

$$\text{Similarity} = \frac{\sum d_{ij} s_j}{\sum s_j} \tag{1}$$

where

d_{ij} 2 if i and j are in the same 3-digit SIC codes
d_{ij} 1 if i and j are in different 3-digit, but the same 2 digit SIC codes
d_{ij} 0 if i and j are in different 2-digit SIC codes

5.4.2. Geographic similarity

We also used data from RAMS to determine the venture's most recent location so that we could measure geographical relatedness between prior and focal ventures among serial entrepreneurs for testing our arguments in H3. We used geographical coordinates (latitude and longitude) to measure the simple geographical distance (in kilometers) between the most recent and current venture of serial entrepreneurs. This variable ranged from 0 to 1010 km. Since we expect a lower distance to exhibit a positively moderating effect of serial entrepreneurship on entrepreneurial performance, we reverse coded this variable to test for a positive moderating effect.

5.4.3. Temporal similarity

To test our arguments of experiential knowledge depreciation in H4, we measured the gap in time between the start of the current venture spell and the end of the most recent prior spell (this value is zero for first-time entrepreneurs). This variable ranges from two years (the minimum cut-off threshold, as previously explained in the number of ventures founded variable) to a maximum of 15 years. We expect a shorter time gap between the most recent venturing activity and a focal venture will positively enhance the effect of serial entrepreneurship on performance. Hence, we also reverse coded this variable.

5.5. Control variables

We included several additional variables to account for alternate influences on our performance dependent variable. All time-varying variables were lagged one year to mitigate problems of endogeneity.

5.5.1. Age

All individuals living in Sweden receive a personal identification number based on their date of birth. This information was used to calculate the age (number of years) of the individual.

5.5.2. Gender

Prior research has shown male and female entrepreneurs have different performance goals (Shane, 2003). We therefore included a dummy variable coded 0 for men and 1 for women.

5.5.3. Education

We included the number of years of formal education, the most common operationalization of general human capital in the entrepreneurship literature (Brüderl et al., 1992). We formed this variable from education codes in LISA describing the length and type of an individual's highest education level (e.g., three-year high school, two years of college, four-year college degree).

5.5.4. Management experience

To control for managerial capabilities, we included a three-category variable (0 = no experience, 1 = some experience, and 2 = extensive experience) taken from the 1990 and 2000 censuses associated with the LISA data.

5.5.5. Parents were entrepreneurs

It is possible that growing up with entrepreneurial parents precipitates vicarious learning influencing performance. Although prior research has shown growing up in a family–firm environment affects the propensity to engage in entrepreneurship (Gimeno et al., 1997), less is known about its relationship with performance (Sørensen, 2007). To account for this possibility, we included a dummy variable for individuals who, growing up, had parents who were entrepreneurs. This information also came from the LISA database.

5.5.6. Investment of financial capital

Better performance could be a result of new financial investments. Thus, we controlled for this with a variable based on the natural log percentage change in equity from one year to another. The sources of additional capital could be retained earnings or additional investments by the entrepreneur. This is an annually time-varying variable.

5.5.7. Past performance in serial entrepreneurship

To offset the potential endogeneity in performance across individual entrepreneurs, we use a lagged performance measure (Delmar and Shane, 2006; Hamilton and Nickerson, 2003). We constructed this measure based on individuals' average yearly performance and applied it over the entire period they were active entrepreneurs, using the same entrepreneurial earnings definition as our dependent variable.

5.5.8. Firm survival

Using a longitudinal sample to study performance can elevate survival bias resulting from terminated firms leaving the sample (e.g., Denrell, 2003; Wooldridge, 2002). In our dataset, 15,628 firms (23.9%) were terminated during the period of observation. If only surviving firms are included, there is a risk that those variable coefficients having a statistically significant effect on both survival and performance will be biased downward in regressions predicting performance. To correct for this problem, we used Lee's (1983) generalization of the Heckman selection model to create a selection-correction variable (Lambda). This involved the use of a Cox regression model with the same variables as in main models to predict termination. By introducing the selection variable Lambda in all models, we lowered the risk of observing spurious results based on sample selection bias.

5.5.9. Industry affiliation

Since we are interested in switches across industries among serial entrepreneurs, our analysis depends on a cross-industry sample. To account for industry-specific characteristics affecting performance, we included industry-fixed effects in our models. (Please refer to Appendix 1 for a list of industries).

5.5.10. Time and industry controls

We controlled for other time-varying and cross-industry economic effects that may affect the average level of performance across ventures by including year and industry dummies (SIC-2 equivalent).

5.6. Empirical strategy

We used hierarchical Generalized Least Squares (GLS) regression models to test our predictions for the following reasons. GLS models accommodate the panel structure of our data, especially the time-varying entrepreneurial performance dependent variable. These models address the heterogeneity across time and between individuals more effectively than Ordinary Least Squares (OLS) models. This feature is especially important because of the possibility that entrepreneurial earnings might accrue in an entrepreneur's own savings and be retained in their own firms (Hamilton, 2000). We also specified our models with random effects because including individual fixed effects eliminated variance in several of our individual-level predictor variables (such as the number of prior ventures). We also ran pooled-GLS models (without panel effects) and found similar results.

To gauge the level of multicollinearity between all constitutive variables, we computed variance inflation factors (VIF), and we report them in Table 1. Among the main-effect linear variables, VIF values are less than 5.32, below the generally accepted threshold of 10 (Kutner et al., 2004). Multicollinearity between non-linear and interaction variables are common but not necessarily a problem for inferential purposes (Allison, 1998; Brambor et al., 2006). We took additional steps to verify this; we tested all interaction effects separately and estimated a series of robustness models with mean-centered interactions. Both approaches yielded similar findings in terms of directions and levels of significance, reassuring us that multicollinearity among the non-linear and interaction variables are not a source of error in our hypotheses testing.

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6. Results

In Table 3, we report results from our multivariate analyses. In Hypothesis 1, we predicted entrepreneurial experience has a non-monotonically increasing relationship with venture performance such that learning benefits decrease in the range of low to moderate experience and increase in the range of moderate to high experience. In Model 1, we began by testing only the linear term for entrepreneurial experience (# of ventures founded). This term is positive and statistically significant, which confirms the null argument derived from experience curve theory: that performance (i.e., ln entrepreneurial earnings) improves linearly as entrepreneurial experience increases.

To test the non-linear prediction in Hypothesis 1, we included the squared term (# of ventures founded^2) in Model 2, which shows a negative relationship in the linear term (representing the consequences of superstitious learning occurring with limited experience; $b = -1.074$, $p < 0.01$) and a positive relationship in the squared term (representing the benefits of learning only realized after gaining moderate experience; $b = 1.377$, $p < 0.001$). This supports Hypothesis 1 in full. Further, our findings suggest that while the gains from prior experience of venturing clearly have a non-monotonic effect on financial performance of entrepreneurs, the effect is not quite U-shaped as indicated by the stronger coefficient in the squared term. The delayed learning benefits from experience begin after the second venture.

Table 3
Panel GLS models on (log) performance effects of serial entrepreneurship.

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	1.535 ***	2.582 ***	2.584 ***	2.582 ***	2.822 ***
	(0.117)	(0.118)	(0.119)	(0.119)	(0.119)
Age	0.019 ***	0.008 ***	0.008 ***	0.007 ***	0.007 ***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Female	−0.017	−0.080 *	−0.087 *	−0.094 *	−0.102 *
	(0.037)	(0.037)	(0.039)	(0.039)	(0.039)
Education	0.031 ***	0.023 ***	0.018 ***	0.018 ***	0.018 ***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Management experience	0.538 ***	0.444 ***	0.444 ***	0.475 ***	0.430 ***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Parents as entrepreneurs	0.009	−0.003	−0.002	−0.002	−0.002
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ln (capital)	0.042 ***	0.033 ***	0.033 ***	0.034 ***	0.034 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Firm survival (lambda)	0.449 ***	0.416 ***	0.413 ***	0.410 ***	0.402 ***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
ln (past performance as serial ent.)	0.098 ***	0.248 ***	0.236 ***	0.271 ***	0.242 ***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Industry similarity	0.342 ***	0.377 ***	0.212 **	0.378 ***	0.363 ***
	(0.012)	(0.010)	(0.042)	(0.011)	(0.010)
Geographic similarity	0.002 ***	0.001 ***	0.001 ***	0.001	0.003 **
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Temporal similarity	0.018 ***	0.016 ***	0.016 ***	0.015 **	0.012
	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)
# of ventures founded	1.532 **	−1.074 **	−1.062 *	−1.052 *	−1.075 *
	(0.120)	(0.290)	(0.431)	(0.495)	(0.453)
# of ventures founded^2		1.377 ***	0.943 *	1.764 ***	1.112 ***
H1: affirmed		(0.023)	(0.043)	(0.070)	(0.030)
# Ventures × industry similarity			−0.120 **		
			(0.011)		
# Ventures^2 × industry similarity			0.183 ***		
H2: affirmed			(0.013)		
# Ventures × geographic similarity				−0.002 *	
				(0.001)	
# Ventures^2 × geographic similarity				0.007 ***	
H3: affirmed				(0.001)	
# Ventures × temporal similarity					−0.001
					(0.001)
# Ventures^2 × temporal similarity					0.002 **
H4: affirmed					(0.001)
Fixed industry effects	Yes	Yes	Yes	Yes	Yes
R-sq: within	0.134	0.144	0.145	0.148	0.144
Between	0.125	0.141	0.152	0.135	0.147
Overall	0.127	0.147	0.155	0.151	0.149
Wald chi^2	40555.38***	44900.43***	45502.43***	44914.43***	34147.43***
LR test (null model in parentheses)		vs (1) 68.15***	vs (2) 41.23***	vs (2) 13.41***	vs (2) 34.52***

Notes: Estimates based on 356,835 individual-year observations and 65,390 individuals: All models include time dummies. Standard errors clustered on individuals in parentheses.

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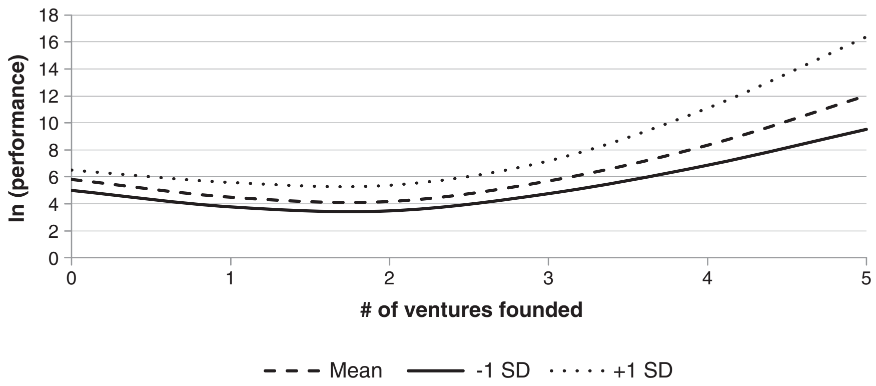

Fig. 1. Marginal effects of industry similarity on performance in serial entrepreneurship.

In Hypotheses 2–4, we predicted the moderating effects of context-domain similarity on the direct, non-monotonic relationship between entrepreneurial experience and venture performance. We focused on industry (H2), geographic (H3), and temporal (H4) domain similarities. For each of these three context-domain characteristics, we predicted that, at low to moderate levels of experience, high context similarity weakens the negative direct relationship between experience and venture performance. At moderate to high levels of experience, high context similarity *strengthens* the positive direct relationship between experience and venture performance. In Models 3–5, we report results for each interaction variable separately following standard practices for testing interactions (Aiken et al., 1991).

In Model 3, we report results for the industry-similarity moderation. We observe a statistically significant positive moderating relationship ($b = 0.183$, $p < 0.001$), confirming our prediction in H2. To properly interpret the nature of this relationship, we found it useful to display the relationships graphically. We plotted the predicted marginal effects of venture performance [y-axis = ln(entrepreneurial earnings)] for the range of # of ventures founded (x-axis) at high (+1SD), average, and low (−1SD) values of industry similarity. We produced three different curves—see Figs. 1–3. All other variables were held constant at their mean values.

We describe the graphs from left (low to moderate experience) to right (moderate to high experience). In the low to moderate experience range of Fig. 1 (from zero to two prior ventures), we observe a weaker negative relationship between experience and performance at high industry similarity (+1SD). Comparing the point estimates of the effects of zero versus two prior ventures on ln(entrepreneurial earnings) at a high level (+1SD) of industry similarity, we calculate a decrease in expected entrepreneurial earnings by 19.2% (compared to a 42.8% decrease at the low level (−1SD) of industry similarity). For the same level of industry similarity in the moderate to high experience range (the point estimates of three versus five prior ventures), we notice a stronger positive relationship with performance by 127% (compared to a 97.9% increase at the low level of industry similarity). This fully supports H2. The knowledge depreciation in the low to moderate experience range of prior venturing is markedly lower for those starting ventures in a similar industry. Also, the gains from prior venturing in the moderate to high experience range are noticeably higher for those starting ventures in a similar industry.

We observed similar results for the other two context-domain similarity moderators. In Figs. 2 and 3, we plotted the interaction results from Model 4 for geographic similarity ($b = 0.007$, $p < 0.001$) and Model 5 for temporal similarity ($b = 0.002$, $p < 0.01$), respectively. Both figures show similar patterns to Fig. 1 regarding the moderating effects of geographic and temporal similarity. Comparing the point estimates of the effects of zero versus two prior ventures on ln(entrepreneurial earnings) at a

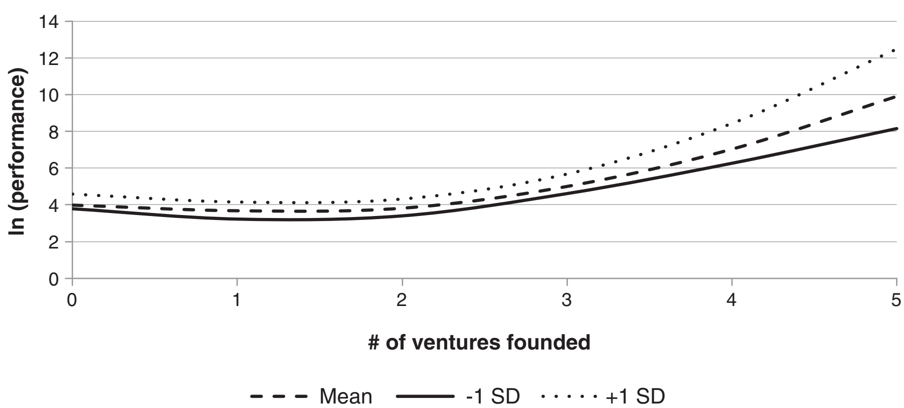

Fig. 2. Marginal effects of geographic similarity on performance in serial entrepreneurship.

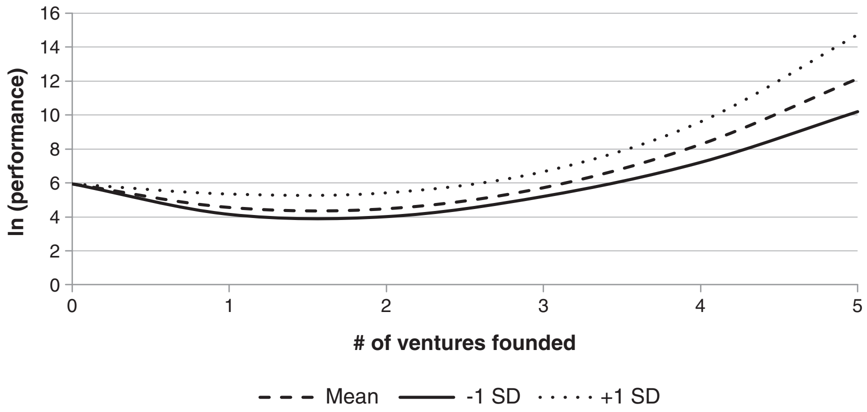

Fig. 3. Marginal effects of temporal similarity on performance in serial entrepreneurship.

high level (+1SD) of geographic similarity, we observe a decrease in expected entrepreneurial earnings by 4.6% (compared to a 8.6% decrease at the low level (−1SD) of geographic similarity). For the same level of geographic similarity in the moderate to high experience range (the point estimates of three versus five prior ventures), we notice a stronger positive relationship with performance by 117.5% (compared to a 64% increase at the low level of geographic similarity). This also confirms Hypothesis 3.

In Fig. 3, comparing the point estimates of the effects of zero versus two prior ventures on ln(entrepreneurial earnings) at a high level (+1SD) of temporal similarity, we observe a decrease in expected entrepreneurial earnings by 11.1% (compared to a 50% decrease at the low level (−1SD) of temporal similarity). For the same level of temporal similarity in the moderate to high experience range (the point estimates of three versus five prior ventures), we see a stronger positive relationship with performance by 120.9% (compared to a 96% increase at the low level of temporal similarity). This confirms Hypothesis 4.

When comparing the moderating influences among the three contextual similarities, we observe slight differences in the strength of their influences between novice and expert entrepreneurs. For novices, geographic similarities have the strongest alleviating influence on the negative direct experience–performance relationship. The top plot (high geographic similarity) in the left half of Fig. 2 shows that the slope is nearly flat, almost overcoming the learning barrier encountered by novices. For experts, industry similarities have the strongest enhancing influence on the positive direct experience–performance relationship. The top plot (high industry similarity) in the right half of Fig. 1 shows the slope is more positive, further strengthening the positive returns from learning by experts.

6.1. Supplementary analyses

As a further test of our theory, we conducted additional analyses investigating whether or not the time decay of learning from prior venturing is higher in rapidly changing industries (or industry volatility). We report these results in Appendix 2. Since we estimated all models in Table 3 with fixed-industry effects—to prevent them from being tainted by between-industry effects in barriers to entry and exit or other sources of industry heterogeneity—we could not investigate the time-decay question simply as a three-way interaction (# of ventures founded^2 × temporal similarity × industry volatility). We therefore re-estimated the models in Table 3 without fixed-industry effects and with abbreviated control variables. The table in Appendix 2 includes two models, the first identical to Model 2 of Table 3 but without industry effects. The second and third models include three-way interactions with industry volatility above and below the mean. This allowed us to conduct chi^2 tests of the difference of the effects of temporal similarity on new venture performance depending on whether *industry volatility* is above or below the sample mean. Model 2 in Appendix 2 reveals the coefficient for # of ventures founded^2 × temporal similarity to be positive if industry volatility is above the sample mean (0.003, $p < 0.05$), but this effect does not appear in Model 3 when industry volatility is below the sample mean. A test of the coefficient across the two models reveals that they are significantly different from each other ($chi^2 = 11.03$, $p < 0.01$, d.f. = 2). This means that the performance effects of re-engaging in entrepreneurship more rapidly (higher temporal similarity) is increasingly beneficial in highly volatile industries, providing further support for our overall argument about the non-linear effects of learning from prior experiences.

6.2. Robustness tests

Learning theory suggests that experience curves exist if we can observe increased levels of performance between spells (Argote and Epple, 1990; Yelle, 1979). Yet, a potential confounder exists if some entrepreneurs possess unobservable traits that lead to higher performance. Then, those entrepreneurs could be more likely to continue starting new ventures than others. If this is the case, inferring learning from increasing levels of performance could be attributed to a sub-sample of highly skilled entrepreneurs having consistently higher performance than others, meaning they are also more likely to become serial entrepreneurs (Chen, 2013; Eesley and Roberts, forthcoming). Without access to a suitable instrument or the potential to specify models with fixed individual effects, we implemented an alternate method. We investigated the potential for self-selection by looking at performance among novice entrepreneurs by each decile (i.e., groups of 10%) in the year prior to exit. We then looked at the rates of serial entrepreneurship for all ten groups to see whether the better-performing entrepreneurs would be more likely to re-engage in entrepreneurship. From this analysis, we found no clear patterns in the data. Entrepreneurs in the third-performance decile were most likely to re-engage (12.4%), followed by the seventh (11.1%), fourth, (10.3%), first (10.1%) and sixth (9.4%) deciles. These results imply that there are no obvious patterns of self-selection into serial entrepreneurship due to individual-specific high performance levels.

To investigate if our results were affected by a small number of influential observations, we fitted alternative models after omitting the largest/smallest outliers from the data using a Winsoring algorithm (STATA command WINSOR). The results were identical in directions and levels of significance of all coefficients; effect sizes differed only marginally depending upon the threshold of outliers being removed (available upon request). This test further reassured us of the robustness of our main findings.

7. Discussion

Our study investigated the relationship between entrepreneurial experience and venture performance. Specifically, we found evidence to support our framework predicting why limited experience lowers performance while enhanced financial performance only occurs at substantial levels of experience. We also observed that contextual similarities among prior and current ventures, such as industry, geographic, and temporal characteristics, positively moderated the direct experience–performance relationship. Our work advances our understanding of how entrepreneurial expertise is developed through entrepreneurial experience, the conditions under which this expertise translates into improved venture performance, and also why entrepreneurship can be learned through sufficient opportunities to practice it (Kim et al., 2009; Parker, 2012; Ucbasaran et al., 2008). In the following sections, we describe our study's specific contributions to the serial entrepreneurship and experience curves literature.

7.1. Contributions to the Serial Entrepreneurship Literature

Our primary finding—that performance returns to entrepreneurial experience initially decline and then increase—and its underlying rationale clarify how expertise formed through experience affects serial entrepreneurial venture performance. We build on Delmar and Shane's (2006) study by highlighting the importance of studying serial entrepreneurs over time to unearth the nature and extent of learning from past experience. Specifically, our work shows that both positive and negative performance implications exist, depending on the level of experience and similarity in content domains of starting ventures (Hypothesis 1). These results reveal the limitations of having only limited experience (Kim et al., 2009); because of superstitious learning and competence traps, novice entrepreneurs are unable to generalize accurately from their prior ventures into their current efforts (Bingham et al., 2007; Dencker et al., 2009; Levitt and March, 1988). Drawing on experience with only one cognitive anchor as a reference (e.g., the first venture) makes it difficult to extrapolate applicable knowledge to the current venture because of inherent differences in the content and context of starting ventures (Wilson et al., 1996). Only when entrepreneurs have completed several ventures do they have multiple reference points from which they can determine appropriate ways to handle different business start-up situations effectively (Tversky and Kahneman, 1992). This finding is important because of the mixed evidence reported in the literature regarding the experience–performance relationship (e.g., Delmar and Shane, 2006; Dencker et al., 2009; Eesley and Roberts, forthcoming; Oe and Mitsuhashi, in press; Reuber and Fischer, 1994; Stuart and Abetti, 1990; Ucbasaran et al., 2006).

In addition to our direct experience–performance relationship, our moderating relationship results also convey new insights for the serial entrepreneurship literature. For novice entrepreneurs, the barriers to learning erected from content-domain differences between prior and focal ventures can be alleviated if the contexts between them are similar. Contextual similarities help novice entrepreneurs to generalize better from previous experience (Gick and Holyoak, 1987) and to minimize negative knowledge transfers (Cohen and Bacdayan, 1994; Haleblian and Finkelstein, 1999; Novick, 1988). Thus, we find complementary support for Parker's (2012) “mean reversion” hypothesis in regards to the performance returns to serial entrepreneurship. Distinctively from the all-positive relationship suggested in classic learning curve theory and several prior studies in entrepreneurship, our findings of superstitious learning at low levels of experience provide further support of non-linear relationships between entrepreneurial experience and subsequent performance (Parker, 2012).

For expert entrepreneurs, contextual similarities can further strengthen the positive experience–performance relationship. Bringing both sets of findings together, our results indicate that an “entrepreneurial-experience curve” exists, one that follows a U-shaped trajectory. Entrepreneurs can benefit even more from knowledge drawn from similar industry contexts, local resources, and shorter time gaps between their prior and current ventures (Parker, 2012).

Our findings are based on a longitudinal study designed to analyze the experience–performance relationship and its boundary conditions. This design provides greater precision in assessing how and why prior venturing experience influences current venturing efforts. Many prior studies have relied on cross-sectional samples, or they measured entrepreneurial experience using a simple binary indicator of having any prior entrepreneurial experience. (Ucbasaran et al., 2013). We employed an experience curve approach—a spell-based assessment of the relationship between experience and performance across a series of events (Argote and Todorova, 2007). This analytical method matches the sequential nature of serial entrepreneurship (Parker, 2012).

Our non-linear findings of the experience–performance link reveal the benefits of employing a longitudinal design with a continuous measure of entrepreneurial experience (Delmar and Shane, 2006; Ucbasaran et al., 2008). Entrepreneurial experience is distinct from many other types of experiences (including management experiences in established firms) in that it is both self-initiated and self-terminated (Sarasvathy, 2004), provides exposure to uncertain and ambiguous operating situations (Morris et al., 2011), involves development of diverse sets of skills (Lazear, 2004), and is frequently associated with high volatility in outcomes (Shane and Khurana, 2003; Shepherd, 2003). The longitudinal study design is also more consistent with the learning theories upon which serial entrepreneurship investigations are based. Learning is an iterative and dynamic process, and a longitudinal study design is better suited to measure how expertise (as a function of experience) evolves over time (March, 2010).

Our study implies that successful entrepreneurship requires the ability for entrepreneurs to leverage prior experiences appropriately (Eesley and Roberts, forthcoming). Because of content and contextual barriers to learning, this expertise takes time to develop through multiple venturing experiences. As reflected in our analyses, our study design addresses these characteristics of serial entrepreneurship and provides greater clarity into the conditions for which greater experience promotes higher venture performance.

7.2. Contributions to the experience curve literature

Our work provides new insights for the experience curve literature by challenging the assumption that repeated task experience generates automatic and consistent returns to performance (Yelle, 1979). Rather than confirming a positive linear effect of experience on performance, our non-linear results mean that not all levels of experience or contexts in which these experiences occur produce positive returns for performance. In fact, our results show the reality of negative performance implications from poor knowledge transfer among novice entrepreneurs who are unable to overcome fully their barriers to learning. These results are also useful for advancing the micro-foundations of experience curve theory in management. While prior work has shown the limitations of averaging individual-level tasks to an aggregate output (Brown and Heathcote, 2003; Newell and Rosenbloom, 1981), we avoid this complication by focusing on individual founder-managers and employing a study design that adequately measures these experiences.

7.3. Limitations and future research

We completed our study with rigor and care, but future research may address some issues more extensively. Although we examined several content- and context-domain differences among prior and current ventures centrally emphasized by prior studies, future studies on serial entrepreneurial performance may consider other differences beyond ours. Our results show that learning in entrepreneurship is possible but conditional upon a number of important barriers. This work also opens up avenues for exploring additional conditions for when and how barriers to learning interfere with entrepreneurial learning (Delmar and Shane, 2006; Parker, 2012). For example, more fine-grained measures of similarity beyond industry-based measures (such as similarity in business model or organizational design) could be employed to assess similarities across ventures. Alternatively, deeper investigation could be pursued about learning from failed experiences (Shepherd, 2003; Shepherd et al., 2009). Given the founder-manager focus of our study, future work can also apply experience curve theory to predict how team-level experiences are associated with performance. Finally, future research endeavors may also examine how our study findings generalize to other industrial sectors and national contexts.

8. Conclusion

Our study investigated the puzzle of why some experienced entrepreneurs do not perform better than others. As a corrective to present research on the topic, we developed theory based on the experience curve literature to show a number of barriers to learning based on content- and context-domain differences. From our analysis of a unique longitudinal sample of individual founder-managers, we showed how experience can negatively affect performance among novice entrepreneurs and how positive performance returns occur among expert entrepreneurs. Context similarities between prior and current ventures strengthen this direct effect. Furthermore, our study has implications for researchers in fields of entrepreneurship and learning theory, as well as practitioners considering how entrepreneurial experience contributes to new venture success. For scholars, we demonstrate the contours of entrepreneurial-experience curves. For aspiring entrepreneurs, our work indicates that extensive practice enables them to learn entrepreneurship and makes for the possibility of better performing ventures.

Appendix 1. Industries in sample.

Type of industry	Frequency	Percent	Volatility above mean = 1
Chemicals and fiber manufacturing	358	0.55%	1
Machinery	490	0.75%	0
Electrical and optical equipment	2,864	4.38%	0

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Appendix 1 (*continued*)

Type of industry	Frequency	Percent	Volatility above mean = 1
Transport equipment	1,300	1.99%	0
Networks, radio and TV	234	0.36%	1
Finance	2,689	4.11%	1
Real estate business	4,312	6.59%	0
Computers/software	3,477	5.32%	0
Research and development	1,447	2.21%	0
Accounting/auditing	2,358	3.61%	0
Construction/engineering	4,848	7.41%	1
Advertising	2,402	3.67%	1
Management consulting	5,140	7.86%	1
Law firms	655	1.00%	0
Other consulting services	3,710	5.67%	1
Education	2,293	3.51%	0
Entertainment services	10,846	16.59%	0
Health and medicine	12,120	18.53%	0
News and entertainment	2,212	3.38%	1
Military & security	1,635	2.50%	0

Appendix 2. Panel GLS models on performance effects of serial entrepreneurship.

	Model 1 (=Model 2 in Table 3 without industry FE)	Model 2 (high industry volatility)	Model 3 (low industry volatility)
Intercept	2.531**	2.377*	2.356*
	(0.251)	(0.248)	(0.260)
Industry similarity	0.321***	0.320***	0.321***
	(0.009)	(0.010)	(0.009)
Geographic similarity	0.003**	0.002**	0.003**
	(0.001)	(0.001)	(0.001)
Temporal similarity	0.016**	0.015*	0.016**
	(0.007)	(0.007)	(0.007)
# Ventures × Temporal similarity		−0.001	−0.001
		(0.001)	(0.001)
# Ventures^2 × Temporal similarity		0.003**	0.003**
		(0.001)	(0.001)
# Ventures^2 × Temporal similarity × Industry volatility dummy		0.004**	−0.003
		(0.001)	(0.003)
R-sq: within	0.123	0.123	0.123
Between	0.120	0.129	0.127
Overall	0.121	0.125	0.124
Wald chi^2	32320.12**	32381.42***	32321.10***
LR test (null = model 1)		16.10**	1.16

Notes: Estimates based on 356,835 individual-year observations and 65,390 individuals. All independent variables in Table 3 maintained as controls (unreported). Standard errors clustered on individuals in parentheses.

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