Received: 4 July 2020 | Revised: 26 May 2021 | Accepted: 12 July 2021 | Published on: 27 August 2021

DOI: 10.1002/smj.3327

STRATEGIC MANAGEMENT JOURNAL WILEY

RESEARCH ARTICLE

Entrepreneurial learning and strategic foresight

Aticus Peterson | **Andy Wu**

Strategy Unit, Harvard Business School, Harvard University, Boston, Massachusetts, USA

Correspondence
Andy Wu, Strategy Unit, Harvard Business School, Harvard University, 15 Harvard Way, Morgan Hall 243, Boston, MA 02163-1011, USA.
Email: awu@hbs.edu

Abstract

Research Summary: We study how learning by experience across projects affects an entrepreneur's strategic foresight. In a quantitative study of 314 entrepreneurs across 722 crowdfunded projects supplemented with a program of qualitative interviews, we counterintuitively find that entrepreneurs make less accurate predictions as they gain experience executing projects: they miss their predicted timeline to bring a product to market by nearly six additional weeks on each successive project. Although learning should improve prediction accuracy in principle, we argue that entrepreneurs also learn of opportunities to augment each successive product, which drastically expands the interdependencies beyond what an entrepreneur can anticipate. We find that entrepreneurs encounter more unforeseen interdependencies in their subsequent projects, and they sacrifice on-time delivery to address these interdependencies.

Managerial Summary: Entrepreneurs consistently struggle to set timelines that they can meet. And, counterintuitively, accumulating experience can actually make this problem even worse: experienced entrepreneurs can miss timelines by even wider margins on subsequent projects. In our study of crowdfunding entrepreneurs launching hardware technology products, we find that entrepreneurs fail to anticipate how many more things can go wrong when they do something even just a little bit more challenging on their next project. In other words, the number of unknown unknowns in a project increases very rapidly even when making only simple improvements on a product. We argue that entrepreneurs can more accurately predict their timelines by intentionally accounting for the rapid increase in things that can go wrong.

KEYWORDS
complexity, crowdfunding, experience, prediction, timeline

1 | INTRODUCTION

Strategic foresight is the ability to accurately predict the consequences of a strategy and in turn pursue a superior course of action to build competitive advantage (Ahuja, Coff, & Lee, 2005; Gavetti & Menon, 2016). Heterogeneity in strategic foresight implicitly underlies many theories of competitive advantage (Csaszar & Laureiro-Martínez, 2018): by predicting the value that resources generate after being developed (Barney, 1986) and the attractiveness of potential opportunities (Porter, 1980), entrepreneurs with superior foresight can build competitive advantage. As such, understanding the antecedents of strategic foresight should shed critical light on the origins of competitive advantage (Csaszar, 2018), yet research on this topic has been sparse until recently. Recent studies find that individual cognition (Gary & Wood, 2011; Kapoor & Wilde, 2020) and organizational structure (Csaszar, 2012) are determinants of strategic foresight. In particular, recent work emphasizes the specific importance of strategic foresight for entrepreneurs as they formulate strategy (Eisenhardt & Bingham, 2017; Ott, Eisenhardt, & Bingham, 2017).

Although an entrepreneur may need strategic foresight to build competitive advantage, the conditions that enable an entrepreneur to build strategic foresight are unclear, particularly as she learns from past experience (Nelson & Winter, 2002) and applies it to the next entrepreneurial opportunity (Gavetti, 2012). An extensive body of work on serial entrepreneurship documents how entrepreneurs can improve performance from venture to venture (e.g., Gompers, Kovner, Lerner, & Scharfstein, 2010; Stuart & Abetti, 1990), but that improvement can arise from a variety of factors besides improved foresight. Through experience, a serial entrepreneur accumulates a multitude of advantages: resource access and relationships (Clough, Fang, Vissa, & Wu, 2018; Hsu, 2007), opportunities (Gruber, MacMillan, & Thompson, 2008), and knowledge about the consequences of past decisions (Minniti & Bygrave, 2001; Paik, 2014). Although most of this work does not specifically speak to whether experience improves the strategic foresight of the entrepreneur, it generally makes this implicit assumption. However, recent work calls this untested assumption into question altogether. Cognitive limitations constrain what an entrepreneur can learn from experience and use for effective judgment (Cassar, 2014; Cohen, Bingham, & Hallen, 2019). In an important study, Eggers and Song (2015) demonstrate that boundedly rational entrepreneurs may misattribute the sources of past performance. Thus, it remains an open question whether entrepreneurs learn from experience to improve strategic foresight.

This study explores this open question for entrepreneurial strategy. Specifically, how does experience from executing past projects affect the accuracy of an entrepreneur's strategic foresight on the subsequent project? Given that tackling complexity is a defining characteristic of the phenomenon of entrepreneurship and of strategy more generally (Leiblein, Reuer, & Zenger, 2018; Van den Steen, 2016), we take the view that accurate strategic foresight depends on whether the entrepreneur can anticipate the complexity in her strategy. There are two competing mechanisms through which experience can impact the accuracy of strategic foresight, depending on whether the experience addresses or exacerbates complexity. On the one hand, experience increases the accuracy of strategic foresight if an entrepreneur learns about complexity that can apply to a future project. On the other hand, experience decreases the accuracy of strategic foresight if an entrepreneur learns about opportunities to augment her project, which introduces additional complexity. We argue that, when complexity increases rapidly across projects, the latter effect dominates the former. As a result, we theorize that as entrepreneurs gain experience across projects, they can introduce additional complexity that causes their strategic foresight to become less accurate.

In a study of 314 entrepreneurs across 722 crowdfunded hardware technology projects along with a program of qualitative interviews with serial crowdfunding entrepreneurs, we find that entrepreneurs make less accurate predictions as they gain experience across projects: they miss their predicted timeline to bring a product to market by a wider margin on each successive project, even as they actually give themselves more time on later projects. On average, an entrepreneur misses the timeline by a gap that grows by nearly six additional weeks on each subsequent project, and this effect persists: the gap between the predicted timeline and the actual delivery date continues to widen for later and later projects. We specifically study timeline predictions given that these predictions rely on strategic foresight and have meaningful strategic implications for customer value and firm survival. For example, many entrepreneurs run out of money because they take more time than expected or, in other words, time is money.

To explain this intriguing pattern, we show that, as entrepreneurs gain experience across projects, their future projects include additions that lead to more and more unforeseen interdependencies that they do not account for when making ex ante predictions. In addition to documenting these patterns in a quantitative analysis, our interviews provide a detailed view of how these mechanisms result in less accurate predictions. For example, one entrepreneur initially launched a Bluetooth LEGO brick for his customers to control motors and lights in their LEGO creations, for example, a remote-controlled car. From this initial experience, the entrepreneur learned that it would be valuable for his next project to also add compatibility with LEGO sensors, for example, the car could sense darkness to turn on a light. As the entrepreneur set the timeline for the subsequent product with more features, he did give himself more time than the previous product by setting the delivery date further out. However, he did not give himself enough time: we show that even with a simple addition, entrepreneurs encounter an increasing number of unforeseen interdependencies during implementation, suggesting an increase in complexity beyond the ability of an entrepreneur to foresee. Despite having a working prototype when making his prediction, this LEGO entrepreneur failed to foresee how adding this feature would have major consequences for many steps in the manufacturing process, like requiring different, more sophisticated tooling. His original manufacturer was no longer able to produce the product, and he went through seven different manufacturers before finding one who could produce the updated brick. Of course, he then missed his predicted delivery date.

This study makes three contributions. First, we outline the role of complexity in strategic foresight, proposing that complexity can serve as an alternate or at least more nuanced explanation for documented patterns of entrepreneurial failure and excess entry—characterized by prior literature as overconfidence—and that learning from experience may not be a cure-all solution to inaccurate strategic foresight. Second, we put forth the notion that strategic foresight comprises multiple interdependent predictions. Third, we argue that timeline predictions are strategically important with direct implications for firm survival, and we provide suggestions for how managers can better predict timelines.

2 | THEORETICAL BACKGROUND

2.1 | Complexity and strategic foresight

To unpack the potential effect of project experience on an entrepreneur's strategic foresight, we need to first understand the role that complexity plays in this relationship.

Any given strategy that an entrepreneur might pursue, and need to make predictions about, entails complexity. By complexity, we mean the full set of interdependencies that exist between the components (or tasks) in the execution of a particular strategy (Simon, 1962). Thus, the complexity of a given strategy is a function of the number of components and the dependencies between those components, which together determine the total number of interdependencies that make up the full complexity of a strategy.[1]

Complexity is not just an idiosyncratic characteristic of some strategies, but a core part of all strategies: across the board, recent efforts to formally define strategy specifically invoke complexity and interdependencies as first-order and necessary characteristics of what makes a course of action strategic at all (Csaszar, 2018; Nickerson & Argyres, 2018). Prior work emphasizes that the complexity of a strategy can itself be a source of competitive advantage that limits imitation (Rivkin, 2000), such that an entrepreneur could justify a strategy with high complexity despite its associated difficulty.

We take the view that entrepreneurship can be characterized as strategic foresight under complexity. Strategic foresight—and the ability to make accurate predictions related to a potential strategy—depends critically on the entrepreneur's ability to anticipate the complexity and specific interdependencies she will face when later implementing or executing on the strategy (Gavetti & Menon, 2016). Entrepreneurs pursue more cognitively distant opportunities and then iterate on those opportunities as they learn (Gavetti, 2012). Due to the high velocity of entrepreneurial markets, entrepreneurship requires operating in novel settings of interdependencies (Eisenhardt & Bingham, 2017), where the entrepreneur, or anyone else for that matter, lacks prior experience with the interdependencies to be faced.

Thus, entrepreneurs have a particularly difficult challenge in anticipating the complexity they might face, limiting their effectiveness in making accurate strategic predictions.

2.2 | Experience and strategic foresight: Two channels

Our theory focuses on whether an entrepreneur can learn by experience across projects in such a way to improve strategic foresight for executing a project. By experience, we mean an

[1]To better align with our empirical context, our terminology for interdependencies differs subtly from how it is described in the NK modeling tradition (Kauffman, 1995; Levinthal, 1997). Although what we describe as the number of components or features roughly maps to N, what we refer to as the number of interdependencies is distinct from K. The general notion of K, as the *level* of interdependence, is traditionally defined as the dependencies that a single component $n \in N$ has on other components in the system. However, when we refer to the overall project complexity or the (total) number of interdependencies in a project, we mean the sum of all interdependencies across all components, which is closer to $N \times K$ rather than just K.

entrepreneurial firm's past exposure to the execution of tasks relevant to a given prediction. We identify two competing channels of learning through which past project experience might impact the accuracy of strategic foresight for a subsequent project.

2.2.1 | Learning about past complexity

On the one hand, an entrepreneur can learn about interdependencies by experiencing them when executing past projects: this experience would thus increase the accuracy of strategic foresight. Prior studies show that both organizations and individuals can learn from repeating interdependent tasks (Edmondson, Dillon, & Roloff, 2007; Ethiraj, Kale, Krishnan, & Singh, 2005). Denrell, Fang, and Levinthal (2004) show that learning in complex systems is best facilitated when there is continuity of personnel, like with serial entrepreneurs. In theory, if an entrepreneur and her organization execute the exact same project over and over again, she will have repeated instances of exposure to the interdependencies inherent to that project because the full set of interdependencies that the entrepreneur must address for that project remains the same. With repetition, the entrepreneur should approach a full understanding of the system of interdependencies in the project. Improved knowledge of the interdependencies that she will face in execution leaves fewer interdependencies that she overlooks in her mental model when she makes predictions, enabling more accurate strategic foresight for future projects.[2]

While our theorizing here intentionally remains agnostic to heterogeneity in the performance of past experience, Section 5.1 leverages empirical findings to post hoc theorize that experience with underperformance in predictions for past projects may be beneficial for making a more accurate future prediction.

2.2.2 | Learning about opportunities to increase complexity

On the other hand, project experience exposes an entrepreneur to opportunities to add new features to her next project, increasing its complexity: this experience risks decreasing the accuracy of strategic foresight. The entrepreneurship literature highlights how entrepreneurs identify opportunities to innovate in ways that emerge endogenously from their experience (Alvarez & Barney, 2007). These new opportunities are largely proximate to prior experience, involving incremental improvements to the prior pursuits.[3] Acting on these new opportunities by making

[2]Our theorizing here only focuses on the learning about interdependencies that comes about from actual experience with execution, independent of heterogeneity in the quality of that execution. The entrepreneur still needs to go through the motions of executing the project, which still exposes her to the interdependencies and gives her the knowledge she can take to future projects. We also consider an alternative and important behavioral mechanism of performance feedback, whereby past success or failure relative to aspiration levels may affect future behavior (e.g., Cho & Clough, 2015; Greve, 1998; Greve, 2003; Joseph & Gaba, 2015; Levinthal & March, 1993). Online Appendix Section A.9 further details this theoretical perspective and presents associated empirical tests evaluating the effect of experiencing success or failure on a past fundraising *campaign*—as opposed to our main focus of *project* execution—by raising more than or less than the desired amount of money from customers, respectively.

[3]Prior experience with project execution brings opportunities to an entrepreneur in two key ways. First, an entrepreneur discovers new opportunities when her experience exposes her to new information about customer needs and ways to serve the market. Second, an entrepreneur creates new opportunities through an enactment process where, in the course of prior experience, she may devise new ways of combining preexisting knowledge.

even just incremental additions to the product increases the complexity by adding new, previously unencountered interdependencies (Anderson, 1999). Thus, to make accurate predictions about the opportunity, the entrepreneur would have to be able to account for those interdependencies. In this way, gaining new knowledge through experience could even exacerbate the challenge of complexity and, as a result, increase the number of ways strategic foresight could be inaccurate (Townsend, Hunt, McMullen, & Sarasvathy, 2018).

To conceptually pinpoint the net effect of project experience on strategic foresight, we now need to identify which of these two channels dominates.

2.3 | Dominance of increasing complexity

We contend that—under certain conditions common to entrepreneurial settings—new complexity can outweigh the benefits of experience. The argument follows from assumptions we can make about the shape of the *Project Complexity* curve and the *Learning* curve, described here and visually illustrated in Figure 1. On the one hand, as traced by the increasing *Learning* curve, as an entrepreneur gains experience and learns she can anticipate an increasing number of *Foreseen Interdependencies*. On the other hand, as an entrepreneur gains experience across projects, she also learns about opportunities to add features to expand her next product. Adding these new features increases the *Project Complexity* by adding new, previously unencountered interdependencies. We argue that the latter effect can dominate the former: when the *Project Complexity* curve increases faster than the *Learning* curve, the entrepreneur ultimately faces an increasing number of *Unforeseen Interdependencies* that will be overlooked in the prediction process and impair strategic foresight.

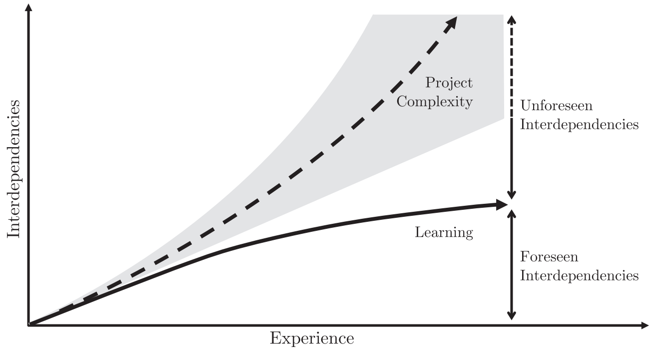


FIGURE 1 Conceptual model of experience and interdependencies. The vertical axis *Interdependencies* represents the number of interdependencies. The horizontal axis *Experience* represents an entrepreneur's level of project execution experience. The *Project Complexity* curve illustrates the total number of interdependencies in projects pursued by an entrepreneur at different levels of *Experience*. The shaded gray area reflects the range of possible *Project Complexity* curves: linear as a lower bound and geometric as an upper bound, where the black dotted line illustrates one possible scenario. The *Learning* curve illustrates the total number of interdependencies foreseen (*Foreseen Interdependencies*) by an entrepreneur at different levels of *Experience*. As *Experience* increases, the gap between the *Learning* curve and the *Project Complexity* curve increases and, as a result, the ratio of *Unforeseen Interdependencies* to *Foreseen Interdependencies* also increases.

Under the assumptions detailed below—at least a linearly increasing project complexity curve and a concave learning curve—we theorize that past project experience has a negative relationship with the accuracy of strategic foresight for a subsequent project.

2.3.1 | Increasing project complexity

Even when an entrepreneur makes merely incremental additions to a previous project, complexity increases. Adding a new feature requires adding one or more tasks interdependent with some or many tasks in their system of activities (Ethiraj, Ramasubbu, & Krishnan, 2012).[4] As a result, each new feature added must increase the total number of interdependencies in the project. The overall theoretical argument follows from the minimum baseline premise that the total number of interdependencies increases at least linearly, which assumes that the entrepreneur would have to add at least one component or task in a subsequent project and that the addition should be at least as interdependent as other components that already exist in the prior project.

That said, we posit that in most entrepreneurial ventures complexity can increase faster than linearly, well above the minimum assumption needed for the theory to hold. First, it can be the case that an entrepreneur adds multiple features or tasks in a subsequent project, particularly for a nascent entrepreneur improving on a sparse project far from a dominant design. Second, for projects with highly interdependent components, the addition of a single component can lead to a faster-than-linear increase in the total number of interdependencies; at the extreme, the number of interdependencies can increase geometrically.[5] While both these conditions vary based on context, entrepreneurs engaged in launching a new product—particularly a new hardware technology as in our empirical context—likely meet both of these conditions. The next section describes how these assumptions hold in context.

Product development entails highly interdependent components and tasks (Ulrich, Eppinger, & Yang, 2020), meaning that the entrepreneur faces a complex system that is inherently nonlinear (Anderson, 1999; Townsend et al., 2018). As a result, adding new components leads to a cascade of new interdependencies which grows rapidly and may outpace the comparatively incremental discovery of interdependencies encountered in past experience. Thus, as an entrepreneur gains experience across projects and implements new features for a subsequent project, demonstrating strategic foresight requires that the entrepreneur navigate more complexity, and perhaps substantially more, than previously faced.

2.3.2 | Bounding learning

As the entrepreneur takes on more complexity, the potential benefits of learning about interdependencies from prior experience are increasingly limited. Entrepreneurs operating in complex systems rely on simplified mental models that only account for a subset of the total interdependencies. Describing this simplification process, Eisenhardt and Bingham (2017) detail

[4]Our study focuses on hardware technology projects that force the entrepreneur to integrate components at some level: if there were no interdependencies, there would be no opportunity for value creation by the entrepreneur as the raw inputs could just be purchased separately by customers with no loss of value.

[5]For instance, a project with X components that are all interdependent with one another would have $X(X-1)$ total interdependencies, a function geometrically increasing in X.

entrepreneurs' use of simple models, Csaszar (2018) compares different simplified representations of complexity, and Gavetti (2012) outlines the necessity of associative thinking. Although the frameworks proposed in these studies make some distinctions, the broad consensus is that entrepreneurs simplify the system of interdependencies in making judgments. By definition, these simplified models are incomplete. Furthermore, due to the cognitive constraints on the number of interdependencies an entrepreneur is able to consider (Simon, 1969; Simon, 1990), these models will be less complete in more complex systems. As entrepreneurs implement increasingly complex successive projects, the portion of the total interdependencies the entrepreneur is able to foresee decreases. Consequently, expanding the total number of interdependencies increasingly penalizes the accuracy of an entrepreneur's strategic foresight.

3 | HYPOTHESIS DEVELOPMENT

From this conceptual viewpoint, we now develop a series of hypotheses situated in our empirical context: hardware technology entrepreneurs engaging in product crowdfunding on Kickstarter. In particular, we consider entrepreneurs serially crowdfunding across multiple distinct projects of the same subtype. To validate our aggregate empirical patterns and understand potential micro-mechanisms, we conduct a program of qualitative interviews with 11 entrepreneurs from our sample.[6] We weave in qualitative findings from these interviews into our hypothesis development purely for context and clarity. These examples and anecdotes are not intended as empirical proof for the theory, but as transparent illustrations of the logic underlying the theoretical mechanisms.[7]

3.1 | Increasing unforeseen interdependencies

We predict that as entrepreneurs gain experience across projects, they suffer from an increasing number of unforeseen interdependencies.

Each time an entrepreneur executes a project, she gains experience designing, prototyping, manufacturing, and delivering a product. Consider an entrepreneur repeatedly executing the exact same project with the same set of tasks and interdependencies again and again. We would expect her to learn and update her prior beliefs about the set of interdependencies for the next related pursuit (Raveendran, Silvestri, & Gulati, 2020). Under this scenario, experience improves strategic foresight. Consider the case of MaskCo, which creates sound-reactive LED masks. In 2015, MaskCo launched its first mask project on Kickstarter: a jaguar design outlined by basic LED strips. On its initial project, MaskCo experienced unforeseen manufacturing challenges, leading to production delays. However, if MaskCo continues to produce this exact same mask again and again, we would not expect it to continue to suffer from the same unexpected manufacturing challenges. Rather, we would expect the number of unforeseen interdependencies to decrease.

[6]Online Appendix Section A.1 describes our qualitative interview process.

[7]We intend for the theory and hypotheses to arise from conventional deductive arguments, which we then ground in our specific context using examples and quotes from the qualitative interviews, rather than using the qualitative evidence as a basis for inductive theory development.

However, this ceases to be the case when an entrepreneur implements new features discovered while executing past projects. In this scenario, the total number of interdependencies increases relative to the previous project. MaskCo's initial Kickstarter experience exposed it to additional opportunities to innovate based on consumer feedback suggesting demand for additional design options, leading MaskCo to add a host of new design options—including an owl, wolf, fox, skull, robot, wildcat, and even a version with President Obama's face—on its subsequent project. The MaskCo entrepreneur also discovered new ways of combining pre-existing knowledge: the initial mask would only light up in response to sound, but the entrepreneur deduced that it would be valuable to have pre-programmed light patterns so the mask could also light up without sound.

Each newly added feature interacts with some or many of the tasks and components required to complete the prior project, thus introducing new interdependencies. But when an entrepreneur makes predictions about this more complex product specification and the timeline on which she will deliver it, our theory suggests that the entrepreneur may do so with an incomplete view of the interdependencies that might arise. If new features added to a subsequent project increase the total number of project interdependencies in excess of the foreseen interdependencies gained through learning on prior projects, the number of unforeseen interdependencies will increase on each subsequent project.

> **Hypothesis 1.** *As entrepreneurs gain experience from past projects, they encounter an increasing number of unforeseen interdependencies on their next project.*

To illustrate this hypothesis in context, we continue with the example of MaskCo and highlight the seemingly small choice to introduce packaging to the company's subsequent project. Adding packaging to a product that is even otherwise the same introduces significant complexity given all the ways the new packaging is interdependent with the existing production tasks. This addition required MaskCo to arrange for the packaging to occur at a separate plant, which necessitated coordinating shipping between the plants and hiring a contractor to facilitate communication in a different language between the manufacturer and the packaging plant. Then, when the quality of the first finished batch was poor, correcting the problem took even more time given the additional interdependency of the finished product with packaging. Going back through the whole process to correct the problem and then repackage the products cost MaskCo an additional month. Then, the new packaging meant that the finished products could no longer be shipped by the shipping company used previously, so MaskCo ultimately had to move all the stock to a different warehouse for shipment.

Our interviewees repeatedly emphasized unexpected organizational issues that came up during execution. Given Kickstarter's requirement to have a working prototype before fundraising, many if not most of the interdependencies intrinsic to the product itself were already known prior to launching the project. However, "the prototypes are all handmade—they're more of a unique product that has more time put into it—but when you're doing production, you're not spending that much time on every single unit. You're doing large volume. That's where we end up having problems" (GPSCo CEO). Another entrepreneur shared, "our [second product] was more complicated because organizing all the different sourcing was a lot more difficult. For [the first product], it was basically, 'go to one supplier and then just put in an order.' But with [the second product], there was a lot of back and forth with a bunch of different suppliers" (CircuitsCo CEO). Indeed, the MaskCo entrepreneur noted that the ultimate set of steps required to add packaging involved "things [he] never thought about" in working with other organizations.

3.2 | Strategic foresight as multiple predictions

We now turn to how entrepreneurs respond when they encounter unforeseen interdependencies that conflict with the strategic foresight of their initial predictions. As a starting premise, we characterize strategic foresight as a set of multiple predictions. When our theory suggests that entrepreneurs make increasingly inaccurate or infeasible predictions on each subsequent project, we mean that with respect to the aggregate of all the entrepreneur's predictions that comprise their strategic foresight as a whole. The individual predictions are fundamentally connected: entrepreneurs have the choice to absorb the inaccuracy in one prediction while satisfying another prediction.

It is important to discuss predictions in context because strategic foresight in different contexts comprises different dimensions on which entrepreneurs make predictions. Crowdfunding entrepreneurs make two important, and readily observable, predictions: product specification and delivery timeline, meaning the date they will deliver the product to customers. Entrepreneurs make these predictions publicly to prospective customers who finance a project on the possibility that they will receive the specified product by the specified date. Based on our qualitative interviews, we find that entrepreneurs make these predictions first by detailing an anticipated product specification, and then setting a delivery date by breaking the production process down into concrete interdependent tasks, predicting the timeline for each task, and aggregating those timelines. In most cases, entrepreneurs also try to be conservative by adding some buffer time to their overall timeline.[8]

Product specification and delivery timeline are connected in such a way that the prediction relative to one can be met at the expense of the other. For example, if an entrepreneur makes an inaccurate timeline prediction, she could still choose to meet the timeline prediction by delivering a product that fails to meet the product specification (and vice versa).[9] In principle, an entrepreneur could choose to prioritize a predicted timeline by allocating a fixed amount of time to a project, even if the predicted product specification is not fully achieved, so she can move on to other activities.

3.3 | Prioritizing product specification over timeline

However, we argue that entrepreneurs in the crowdfunding context—and perhaps many in other settings—prioritize achieving the predicted project specification rather than adhering to the initially predicted delivery date. In other words, given inaccurate strategic foresight, most

[8]Online Appendix Section A.3 elaborates on this prediction process for hardware technology projects and provides qualitative context from entrepreneur interviews.

[9]Never delivering a product would be an asymptotic combination of these two ways of missing a prediction, that is, delivering a product of zero value with an infinite delay. We exclude this situation from our empirical analysis because this situation is rare and some potentially substantial number of those situations involve fraud by the entrepreneur (Mollick, 2015).

entrepreneurs tend to continue working towards achieving a predicted product specification, even if it requires going beyond the originally predicted delivery date. This tendency to prioritize achieving product specification over meeting a timeline follows if an entrepreneur holds certain beliefs about customer preferences and the resulting consequences of achieving (or not) either predicted dimension. While there are meaningful consequences for delay,[10] these consequences are overshadowed by both the negative consequences of failing to deliver the specified product as well as the positive benefits of succeeding in doing so. If a customer receives a product below the promised specification, this can cause severe reputational damage to the entrepreneur. However, delivering a product as specified (even a delayed product) can still lead to brand-building testimonials and organic growth. Additionally, succeeding in delivering the specified product allows an entrepreneur to get feedback on her actual intended product specification which she can then use to develop future projects.

When inaccurate strategic foresight leads to unforeseen interdependencies that make it impractical to achieve both initial predictions, entrepreneurs can choose which prediction they will ultimately prioritize and achieve and which to relegate and fail to address. We argue that most entrepreneurs prioritize achieving the predicted product specification over the predicted delivery date. As a result, as entrepreneurs gain experience implementing projects and encounter an increasing number of unforeseen interdependencies on subsequent projects, requiring additional effort beyond what was predicted (Ethiraj, 2007), we expect achieving their predicted product specification requires failing to achieve their predicted timeline by increasing margins. This will manifest in increasing delays.

> **Hypothesis 2.** *As entrepreneurs gain experience from past projects, they fail to achieve their predicted delivery date on their next project by a wider margin.*

Without exception, our interviews with crowdfunding entrepreneurs confirm this tendency to achieve their predicted product specification at the expense of their predicted delivery date. One explained, "At the end of the day, you have to make the decision: Do I want to ship a product that we don't feel meets the needs of the customer just to be able to ship it and be done with it? Or do we want to delay and end up shipping a quality product? I always want to ship a quality product" (GPSCo CEO). Another entrepreneur believed that "consumers can delay gratification for something better" (TabletCo CEO). To put it another way, "We wanted to first be able to deliver the highest-quality parts we could, and then second to do as best we can to deliver them on time" (3DPrintCo CEO).

We observe this tendency in both the LEGO brick and MaskCo entrepreneurs mentioned previously. The LEGO brick entrepreneur referenced in the introduction could have decided to deliver a product on the predicted delivery date that did not perform the predicted function of interfacing with LEGO sensors. Similarly, the MaskCo entrepreneur could have delivered a mask in whatever state it was in (perhaps without packaging) by the predicted delivery date. However, both entrepreneurs chose to delay in order to continue striving to meet the predicted product specification. The discussion highlights other prominent examples where entrepreneurs—like Elon Musk of Tesla—exhibit this tendency to spend more time working towards their predicted product specification rather than adjusting their product specification to meet the predicted allocation of time resources.

[10]Online Appendix Section A.11 expounds and quantifies these consequences of delay.

4 | EMPIRICAL METHODS

4.1 | Context

In order to test these hypotheses, we need a sample of entrepreneurs who complete multiple projects over time with clearly defined markers for experience, complexity, predictions, and outcomes. The crowdfunding platform Kickstarter provides an ideal setting that meets these criteria. Kickstarter, founded in 2009, is a popular crowdfunding platform that connects entrepreneurs to customers. Customers de facto pre-purchase specific products that the entrepreneurs promise to deliver by a future date. This fundraising process requires Kickstarter entrepreneurs to provide several predictions, including the features and qualities of the product they will produce and the timeline on which they will deliver the product. This setting allows us to identify metrics to capture each of the characteristics and outcomes of interest outlined in our hypotheses. Figure 2 provides specific examples of these metrics using the series of projects implemented by one of the entrepreneurs in our sample.

Using Kickstarter projects favorably standardizes several characteristics. All hardware technology projects are required to have a working prototype before they can raise capital, helping to reduce some of the variation in the starting point of new projects (Kickstarter PBC, 2020). The crowdfunded capital then funds the manufacturing and distribution of the product at scale. In addition, the platform is all-or-nothing, meaning that if the project does not reach the target financing level, the pledges are refunded to the customers and the entrepreneur does not

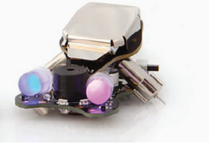
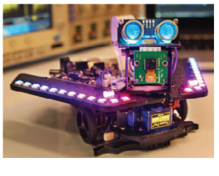
Name & Date	Image	Features Rank	Delay Duration	Delay Duration/ Predicted Time	Unforeseen Interdependencies
Ringo Feb 25, 2015		1 (Fewest)	66 Days	92%	"Our machine refused to pick up the programming ports... this programming port was just a bit [too] heavy."
Wink Oct 28, 2015		2 (Middling)	73 Days	115%	"The testing procedure is taking longer than expected... finding a few units with bad motors." "We ran out of motors and our replenishment shipment was held up."
Spirit Rover Sept 28, 2016		3 (Most)	340 Days	254%	"Found two mistakes on the boards... fixed with an extra step on our end, but I should have known better on both of these." "We finally found sources for all the screws, fasteners, washers, nuts, and spaces. I was surprised and unprepared at how difficult this part was going to be." "I made a mistake with two of the cables... as they are too short."

FIGURE 2 Example Products by an Entrepreneur Over Time. All projects by Plum Geek Robotics, founded by Kevin King, in the robotics subtype of the technology category. The *Unforeseen Interdependencies* column provides selected quotations from updates by the entrepreneur. All other variables mirror those defined in the paper.

receive any capital. As a result, we can assume that the entrepreneurs have sufficient financial resources to deliver the product relative to their expectations.

Although some associate Kickstarter with fun trinkets and games, our study focuses on manufactured hardware technology, the most complex products on Kickstarter and among the most complex that an entrepreneur could generally pursue.[11] First, the value of these products hinges on precisely and accurately addressing a large number of interdependencies. If a wire is cut a nanometer too short, it may not connect the necessary circuits for the product to function. In contrast, if the pair of dice in a board game is produced a nanometer smaller than planned, it has virtually no impact on the other game pieces. Second, modern manufacturing requires an international supply chain with multiple suppliers from different organizations, e.g., distinct suppliers for all the parts, assembly, packaging, and international shipping.[12]

4.2 | Data and sample

We construct a sample of Kickstarter entrepreneurs who complete multiple projects of the same project subtype. This should, in principle, keep experience gained on a past project relevant to the next project, which is ideal for reaping the benefits of learning. We collect basic project data and characteristics for all Kickstarter projects from Web Robots, which runs a monthly scrape of all past and present Kickstarter projects. We identify the 394 entrepreneurs with two or more projects that met the fundraising goal in one of the main project subtypes in the hardware technology space (i.e., gadgets, 3D printing, hardware, camera equipment, sound, DIY electronics, wearables, robots, and fabrication tools) with predicted delivery dates prior to the date of our analysis. We look specifically at entrepreneurs with multiple projects that meet the fundraising target because they gain execution experience from actually having to produce and deliver these projects. In order to maximize the potential impact of learning, we further segment our sample to the entrepreneurs who specialize in one of the selected project subtypes, refining our sample to 326 entrepreneurs.[13] After reviewing each entrepreneur's profile, we also exclude 12 entrepreneurs whose circumstances are disqualifying (e.g., a large, established company launches the campaign) or where it is apparent we have incomplete data (e.g., the entrepreneur is clearly doing many other projects outside of Kickstarter, in which case our data set does not capture much of their relevant experience).

These criteria result in a final sample of 314 entrepreneurs who recieved capital to execute on 722 projects from September 2010 through June 2019. For each of these projects, we scrape comprehensive information from its Kickstarter page, including the most recent 100 comments and all project updates posted by the entrepreneur. We manually collect data on actual delivery time and number of features. We link Kickstarter entrepreneurs with their Crunchbase profiles to track their external funding over time.[14]

[11]Online Appendix Section A.2 details the high and increasing degree of complexity in crowdfunded hardware technology products.

[12]Online Appendix Section A.3 further expounds the complexity inherent in this context as well as the implications of that complexity for the prediction process.

[13]While an entrepreneur could intentionally shift to a product subtype "distant" from her prior experience (e.g., Eggers & Song, 2015), this possibility falls outside the scope of this study.

[14]Online Appendix Section A.4 provides additional detail about the data collection and aggregation process.

4.3 | Variables

4.3.1 | Dependent variables: Features and unforeseen interdependencies

As a starting point, we define a set of measures to test the basic assumption leading into Hypothesis 1: entrepreneurs pursue increasingly complex projects, that is, projects with greater total interdependencies. An ideal measure would exactly measure the total interdependencies in a predicted project, but this is impossible to identify based on the public information available since we cannot see inside the product or organization. Instead, we identify a product's level of features relative to the other product(s) by the same entrepreneur. We hired five independent reviewers to rank each entrepreneur's set of products by number of features and then aggregated the rankings for each product across reviewers.[15] Specifically, we hired individuals with relevant educational and professional experience in computer programming, mechanical engineering, and robotics. The following measures are intended to at least roughly correlate positively with the total interdependencies in a planned project.

Features most

Features Most is a binary indicator equal to 1 if the product has the most features compared to the other products by the same entrepreneur (and 0 otherwise).

Features rank

Features Rank is the relative rank of the product compared to other products by the same entrepreneur, for example, if an entrepreneur completed two products, the product with the fewest features would have a *Features Rank* of 1 and the product with the most features would have a *Features Rank* of 2.

Features percentile

Features Percentile specifies the relative percentile of a project for an entrepreneur, for example, if an entrepreneur had three projects with *Features Rank* equal to 1, 2, and 3, the corresponding *Features Percentile* would be 0%, 50%, and 100%, respectively.

Unforeseen interdependencies

We then construct a measure of unforeseen interdependencies in a direct test of Hypothesis 1. *Unforeseen Interdependencies* is the total number of updates posted by the entrepreneur during project execution—after the fundraising campaign has ended and before the product is delivered—that cite unforeseen interdependencies. A member of our research team reviewed the most common words contained in updates relevant to unforeseen interdependencies. They identified two categories of relevant words. The first set relate to issues being unforeseen, which include the words (or any variants): unforeseen, unexpected, and unanticipated. The second set relate to typical interdependence-related issues that come up in our context, which include the words (or any variants): manufacturing, production, assembly, and factory. When defining *Unforeseen Interdependencies*, we include all updates that contain words from either set.[16]

[15]Online Appendix Section A.4 provides additional details on the background of each reviewer as well as the ranking and aggregation process.

[16]Online Appendix Section A.6 shows that all results hold if we define *Unforeseen Interdependencies* to contain updates with words from both sets.

4.3.2 | Dependent variables: Delivery time metrics

Delay indicator

If the actual delivery date is after the predicted delivery date or if the project has not yet shipped and the predicted delivery date is prior to the date when we collected our sample, *Delay Indicator* is set equal to 1 (and 0 otherwise). We identify *Delay Indicator* for 95% of projects in our sample.

Delay duration

Delay Duration is the time (in days) between the actual delivery date and the predicted delivery date. We identify the delay for 89% of our sample; for comparison, Mollick (2014) identifies outcomes for 81% of its sample.

Predicted time

To test whether *Delay Duration* is driven by more aggressive predictions versus missing static predictions by wider margins, we define *Predicted Time* as the time (in days) between the end of the fundraising campaign and the predicted delivery date.

Actual time

Actual Time is the time (in days) between the end of the fundraising campaign and the actual delivery date, that is, the sum of *Predicted Time* and *Delay Duration*.

4.3.3 | Main independent variable: Project experience

The main independent variable *Project Experience* measures an entrepreneur's total execution experience as her number of projects prior to her current project and of the same subtype. We only count projects that meet the funding threshold because they provide the entrepreneur with execution experience that exposes her to project interdependencies.

4.3.4 | Control variables

Entrepreneur fixed effects control for any time-invariant variation among entrepreneurs in our sample, so we add additional controls for other types of entrepreneur experience characteristics that may change over time, as well as project-specific characteristics.

We control for other types of entrepreneurial experience with executed *projects* (that meet the funding threshold) and attempts at funding *campaigns* (most of which become projects). Given the potential impact of fundraising failure on behavior,[17] *Failed Campaign Experience* is the cumulative count of Kickstarter campaigns of the same product subtype conducted by the

[17]Compared to the average 70.9% failure rate of technology Kickstarter projects, only 10.5% of the campaigns attempted by the entrepreneurs in our sample failed to reach their funding threshold. This is likely driven by key differences between the serial-project entrepreneurs in our sample who generally treat their projects as full-time jobs and the average person who casually launches a project more as a hobby.

entrepreneur where those campaigns did not reach their funding threshold.[18] In a similar vein, to account for the degree and direction of deviation from the funding threshold, *Prior Campaign Funding Deviation* is the percentage by which the entrepreneur's prior campaign exceeded (or missed) its funding threshold. Another way past performance could impact an entrepreneur's behavior on subsequent projects is the number of days by which the entrepreneur missed (or beat) their predicted timeline on the past project: *Prior Project Delay* is the entrepreneur's prior project's *Delay Duration* divided by *Predicted Time*.

We also include controls for changes in the entrepreneur's circumstances over time. Simultaneous execution of multiple projects could impact performance as compared to projects that are the sole focus of an entrepreneur. *Execution Overlap* is a binary indicator equal to 1 if the execution start date of the current project comes before the execution completion date of the prior project (and 0 otherwise).[19] To control for changes in entrepreneur quality over time, we use Crunchbase data and define *External Funding* as a binary indicator of whether the entrepreneur had raised venture capital funding prior to launching the current project. To account for the impact of switching industries documented by Eggers and Song (2015), we define *New Category* as a time-variant binary indicator of whether the project immediately prior to the focal project was of a different subtype. We also control for general experience and learning that may accrue to the entrepreneur naturally over time and separate from project execution, with *Elapsed Time* defined as the number of days since the entrepreneur launched her first successful project of the same subtype as the current project. *Baseline Updates* is the total number of updates posted prior to the end of the fundraising campaign, which allows us to control for the entrepreneur's time-variant propensity to post updates across projects.

We also control for project characteristics determined ex ante to initiating the fundraising campaign. These variables control for whether heterogeneity in project characteristics account for heterogeneity in measured outcomes. *Funding Period* is the time (in days) that the project accepted contributions; this window is set before the fundraising campaign launches and cannot be changed after the fact. *Funding Reward Tiers* is the total number of rewards available for funding backers to purchase. *Funding Reward Size* is the median price of the rewards available for funding backers to purchase. *Funding Threshold* is the amount of money (in thousands of USD) the entrepreneur set out to raise; since this amount is set at the start of the *campaign* and cannot be adjusted, all *projects* meet or exceed this threshold.

In addition, we control for project characteristics determined ex post after the fundraising period. We include these ex post controls in regressions where the dependent variable is realized after the fundraising period. *Funding Exceeded* is the amount of money (in thousands of USD) the project raised in excess of the *Funding Threshold*; Mollick (2014) finds that the degree to which projects exceed the funding threshold associates with delay. *Funding Backers* is the total number of people (in thousands) who contributed to the project.

[18]*Project Experience* plus *Failed Campaign Experience* is the total number of Kickstarter campaigns of the specific product subtype that the entrepreneur had launched; including both of these variables together also controls for the total number of campaigns in aggregate, which would be collinear.

[19]We look at overlap in execution rather than fundraising given that executing a project takes substantial time and other resources. This overlap only occurs in 4.7% of our sample (34 out of the 722 projects). This makes sense given that the entrepreneurs interviewed noted that executing even a single project generally requires a full-time commitment and the ideas for subsequent projects come through executing past projects.

4.4 | Descriptive statistics

Table 1 provides summary statistics.[20] To validate our measures, we compare our sample of 722 technology projects to the 843 technology projects in Mollick (2014): our sample has an average *Funding Threshold* of $23,272 (vs. $21,177) and *Funding Period* of 33.34 days (vs. 40.28 days). In addition, Mollick (2014) uses a similar manual process to collect actual

TABLE 1 Summary statistics

	Mean	*SD*	Min	Max
Dependent variables				
Features Most	0.45	0.50	0	1
Features rank	1.68	0.74	1	6
Features percentile	0.50	0.48	0	1
Unforeseen interdependencies	3.39	4.11	0	31
Delay Indicator	0.76	0.43	0	1
Delay duration	70.72	114.84	−77	946.60
Predicted time	90.48	52.97	5	414
Actual time	159.25	142.81	10	1,231.60
Independent variables				
Project experience	0.70	0.74	0	5
Failed campaign experience	0.10	0.36	0	4
Prior campaign funding deviation	3.24	8.86	−1	86
Prior project delay	0.42	1.02	−1	11
Execution overlap	0.05	0.21	0	1
External financing	0.09	0.29	0	1
New category	0.03	0.17	0	1
Elapsed time	322.72	426.76	0	2,458
Baseline updates	6.73	5.12	0	40
Funding period	33.34	10.02	2	60
Funding reward tiers	9.72	5.07	1	34
Funding reward size	234.83	493.38	4	5,995
Funding threshold	23.27	31.40	0.02	261.96
Funding exceeded	102.54	273.62	0	3,351.36
Funding backers	0.95	2.19	0.001	28.14

Note: 722 project-level observations. *Actual Time* and *Delay Duration* are based on 644 observations, and *Delay Indicator* is based on 686 observations. *Funding Threshold* (USD), *Funding Exceeded* (USD), and *Funding Backers* (count) are all in thousands.

[20]Online Appendix Section A.5 provides additional statistics and visualizations of variable distributions.

delivery dates and finds that "only 24.9% of projects delivered on time" (or 75.1% of projects are delayed). Our sample identifies a similar pattern, where 76.3% of projects are delayed.

Looking at the pairwise correlations between each of our independent variables in Table 2, we note the expected correlation (0.748) between *Funding Exceeded* and *Funding Backers*, since each new backer contributes additional funds to the project. We re-run all regressions taking turns excluding each of these variables and do not observe any meaningful changes to the results. In addition, there is an expected correlation (0.697) between *Project Experience* and *Elapsed Time*, given that each subsequent project occurs at a later time. All the results hold if we remove *Elapsed Time* from the regressions.

Given their importance, Figure 3 visualizes the distributions of *Predicted Time* and *Actual Time*. The distribution of *Actual Time* is shifted and skewed to the right of the distribution of *Predicted Time*, of course because the vast majority of projects are delayed.

4.5 | Statistical model

We estimate ordinary least squares (OLS) models across all analyses. These models include fixed effects to control for several dimensions of otherwise unobserved heterogeneity that could correlate with the observed independent variables. Entrepreneur fixed effects control for time-invariant entrepreneur characteristics, such as natural talent, intelligence, work ethic, and so forth. Product subtype fixed effects absorb any heterogeneity between the various categories of projects, for example, DIY electronics versus 3D printing. Month fixed effects control for seasonal cycles, for example, if projects that predict delivery dates in December are more likely to delay due to the holidays, month fixed effects would account for that seasonal heterogeneity. Year fixed effects control for any factors that change year to year but are common to all entrepreneurs who launch new projects in a given year. To account for potential correlation in the error term across projects by the same entrepreneur, we cluster robust standard errors at the entrepreneur level.

The models using the dependent variables *Features Most*, *Features Rank*, *Features Percentile*, and *Predicted Time*—determined ex ante to launching the fundraising campaign—include only the controls for project characteristics that exist ex ante and exclude the control variables realized ex post, *Funding Exceeded* and *Funding Backers*.

5 | RESULTS

Hypothesis 1 predicts that, as entrepreneurs gain experience, they encounter an increasing number of unforeseen interdependencies. Before we look at this directly, we first validate a key assumption leading to this hypothesis: entrepreneurs make their product specification more complex as they gain experience. We examine this by looking at the relationship between *Project Experience* and three measures of how complicated the proposed product specification is in terms of its observable features. In the first three columns of Table 3, we find that *Features Most* ($p = .047$), *Features Rank* ($p \sim .000$), and *Features Percentile* ($p = .016$) are all positively related to *Project Experience*.[21] Each subsequent project is 11.7% more likely to be the highest-ranked project in terms of number of features. The ranking of each subsequent project increases by an

[21]For the binary indicator variable *Features Most*, the results hold when using a conditional fixed-effects logit model.

TABLE 2 Pairwise correlation matrix of independent variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	Project experience	1														
(2)	Failed campaign experience	0.173	1													
(3)	Prior campaign funding deviation	0.251	−0.059	1												
(4)	Prior project delay	0.306	0.009	0.162	1											
(5)	Execution overlap	0.161	0.027	0.008	0.129	1										
(6)	External financing	−0.004	−0.091	0.124	0.036	−0.026	1									
(7)	New category	−0.036	−0.006	0.063	0.001	−0.001	−0.001	1								
(8)	Elapsed time	0.697	0.064	0.241	0.334	−0.049	0.124	0.001	1							
(9)	Baseline updates	−0.172	−0.156	−0.081	−0.038	−0.113	0.081	−0.027	−0.086	1						
(10)	Funding period	−0.010	−0.121	0.093	0.012	−0.121	0.061	−0.039	0.033	0.193	1					
(11)	Funding reward tiers	−0.056	−0.163	0.026	−0.004	−0.122	0.062	−0.046	0.024	0.277	0.218	1				
(12)	Funding reward size	0.005	−0.068	0.008	0.035	−0.019	−0.007	−0.054	0.057	0.148	0.010	0.017	1			
(13)	Funding threshold	−0.084	−0.160	0.002	0.050	−0.081	0.190	−0.052	0.065	0.215	0.156	0.187	0.254	1		
(14)	Funding exceeded	−0.076	−0.092	0.175	−0.003	−0.070	0.247	−0.054	−0.005	0.181	0.138	0.140	0.091	0.307	1	
(15)	Funding backers	−0.093	−0.091	0.110	0.004	−0.070	0.276	−0.053	−0.051	0.149	0.152	0.161	−0.085	0.227	0.748	1

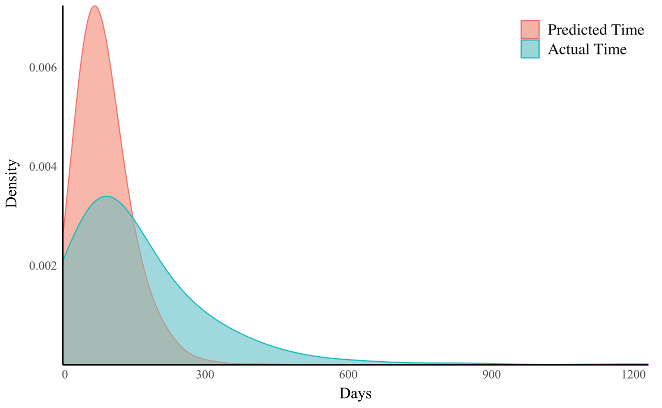


FIGURE 3 Density plot of *Actual Time* and *Predicted Time*. The distribution of *Actual Time* is shifted and skewed to the right compared to the distribution of *Predicted Time*. We adjust the bandwidth to smooth the distributions.

average of 0.37 in absolute terms or 13.8% on a percentile basis. If additional features increase the number of interdependencies, we posit that more experienced entrepreneurs take on projects with more total interdependencies.

To explicitly test Hypothesis 1, we examine the effect of experience on the number of unforeseen interdependencies. In column 3 of Table 3, we find that *Unforeseen Interdependencies* ($p \sim .000$) is positively related to *Project Experience*. On each subsequent project, entrepreneurs disclose encountering 1.3 additional unforeseen interdependencies. This increase in unforeseen interdependencies is consistent with our theory that limits to learning in increasingly complex systems might attenuate unforeseen interdependencies. *Ln Unforeseen Interdependencies* ($p = .002$) also positively associates with *Project Experience*. Each subsequent project increases unforeseen interdependencies by 21.0%.[22]

Hypothesis 2 predicts what entrepreneurs will do when they make inaccurate predictions. Specifically, we hypothesize that as entrepreneurs gain experience and encounter increasing unforeseen interdependencies, they miss their predicted delivery date by wider margins. As outlined in Table 4, we find that *Project Experience* is positively related to *Delay Indicator* ($p = .010$) and *Delay Duration* ($p = .001$). As a baseline, with each additional project of experience, the entrepreneur is 11.9% more likely to be delayed. Regarding the magnitude of delay, with each additional project of experience, the average entrepreneur is delayed by an additional 39.6 days. Although *Delay Duration* measures the absolute difference between the entrepreneur's actual and predicted timeline, it is also important to consider the difference on a percentage point basis to account for different predicted project lengths. We also find that *Project Experience* is positively related to *Delay Duration/Predicted Time* ($p = .001$). With each additional project of experience the average entrepreneur is delayed by an additional 53.0% relative to her predicted time. Taken together, these findings suggest that, given increasing prediction inaccuracies, entrepreneurs choose to absorb these inaccuracies in the project timeline, leading to increasing delay.

As important context for the above finding, column 4 of Table 4 shows that *Project Experience* positively associates with *Predicted Time* ($p = .014$). On average, entrepreneurs increase

[22]Online Appendix Section A.7 shows there is a significant and positive relationship between increasing unforeseen interdependencies and increasing number of features as well as between delay and increasing number of features.

TABLE 3 Features and unforeseen interdependencies

	Features most	Features rank	Features percentile	Unforeseen interdependencies	Ln Unforeseen interdependencies
Project experience	0.117 (.047)	0.370 (.000)	0.138 (.016)	1.298 (.000)	0.205 (.002)
Failed campaign experience	0.075 (.506)	0.169 (.245)	0.081 (.401)	0.672 (.066)	0.185 (.057)
Prior campaign funding deviation	0.001 (.779)	0.000 (.932)	0.001 (.858)	0.005 (.772)	−0.000 (.908)
Prior project delay	0.011 (.758)	−0.034 (.535)	0.003 (.941)	−0.698 (.000)	−0.128 (.000)
Execution overlap	−0.365 (.025)	−0.447 (.031)	−0.338 (.028)	−0.216 (.736)	0.096 (.410)
External financing	0.371 (.006)	0.286 (.055)	0.367 (.006)	1.122 (.317)	0.148 (.515)
New category	−0.063 (.685)	0.156 (.464)	0.020 (.895)	1.596 (.078)	0.246 (.231)
Elapsed time	−0.000 (.665)	0.000 (.879)	0.000 (.961)	0.004 (.009)	0.001 (.000)
Funding period	0.007 (.101)	0.008 (.119)	0.007 (.053)	0.028 (.172)	0.006 (.144)
Funding reward tiers	0.006 (.395)	0.007 (.539)	0.008 (.296)	−0.023 (.521)	−0.003 (.646)
Funding reward size	0.000 (.003)	0.000 (.000)	0.000 (.002)	−0.000 (.779)	0.000 (.848)
Ln Funding threshold	0.027 (.527)	0.048 (.356)	0.016 (.693)	0.754 (.004)	0.157 (.000)
Ln Funding exceeded				0.671 (.008)	0.076 (.109)
Ln Funding backers				−0.018 (.960)	0.074 (.268)
Baseline updates				0.172 (.001)	
Ln Baseline updates					0.271 (.000)
Entrepreneur FE	Yes	Yes	Yes	Yes	Yes
Product subtype FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.284	0.437	0.279	0.744	0.774
Entrepreneurs	314	314	314	314	314
Observations	722	722	722	722	722

Note: Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. *p*-values are shown in parentheses.

their *Predicted Time* by 8.4 days on each subsequent project. This means that entrepreneurs are not becoming more delayed because they are setting shorter, more aggressive timelines. To the contrary, entrepreneurs give themselves more time on each subsequent project, seemingly anticipating some increase in complexity or adjusting for time they learned that they needed, yet they still miss the prediction by a wider margin. Finally, column 5 of Table 4 shows that *Project Experience* is positively related to *Actual Time* ($p = .001$). On average, entrepreneurs increase their *Actual Time* by 46.4 days on each subsequent project.

To provide an intuitive illustration for interpreting the empirical findings, Figure 4 plots the relative trends of *Actual Time* and *Predicted Time* as the entrepreneur gains experience. Figure 4 plots coefficient estimates for an alternate nonparametric model of the relationship between experience and the dependent variables by including indicators for project number

TABLE 4 Delivery and delay

	Delay indicator	Delay duration	Delay duration/ Predicted time	Predicted time	Actual time
Project experience	0.119 (.010)	39.616 (.001)	0.530 (.001)	8.364 (.014)	46.386 (.001)
Failed campaign experience	0.139 (.123)	−2.720 (.870)	−0.071 (.749)	15.751 (.031)	11.345 (.620)
Prior campaign funding deviation	−0.003 (.062)	0.094 (.828)	−0.001 (.864)	0.095 (.578)	0.390 (.411)
Prior project delay	−0.042 (.042)	−21.689 (.020)	−0.111 (.690)	4.288 (.024)	−19.655 (.034)
Execution overlap	−0.052 (.457)	11.587 (.774)	1.183 (.233)	−3.993 (.636)	9.501 (.831)
External financing	0.138 (.196)	95.312 (.234)	0.371 (.481)	21.388 (.376)	124.811 (.205)
New category	0.082 (.611)	39.284 (.135)	0.425 (.156)	6.012 (.546)	46.345 (.168)
Elapsed time	−0.000 (.422)	−0.092 (.130)	−0.001 (.353)	−0.023 (.265)	−0.111 (.094)
Funding period	0.009 (.000)	1.302 (.059)	0.004 (.848)	0.147 (.555)	1.730 (.022)
Funding reward tiers	0.003 (.454)	0.785 (.474)	0.001 (.977)	−0.150 (.721)	0.996 (.441)
Funding reward size	0.000 (.807)	−0.011 (.721)	0.000 (.707)	0.005 (.533)	−0.008 (.830)
Ln Funding threshold	0.008 (.786)	22.716 (.103)	−0.090 (.533)	19.806 (.000)	40.817 (.011)
Ln Funding exceeded	0.034 (.195)	28.728 (.004)	0.201 (.085)		27.973 (.014)
Ln Funding backers	0.008 (.837)	−34.159 (.009)	−0.176 (.281)		−31.278 (.040)
Entrepreneur FE	Yes	Yes	Yes	Yes	Yes
Product subtype FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.662	0.717	0.656	0.752	0.744
Entrepreneurs	306	303	303	314	303
Observations	686	644	644	722	644

Note: Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. *p*-values are shown in parentheses.

instead of *Project Experience*.[23] This figure shows that the actual delivery time increases much more sharply relative to the predicted delivery time, with the gap between actual delivery time and predicted delivery time increasing as entrepreneurs gain experience. These empirical patterns are consistent with the theorized project complexity curve and learning curve, respectively, in Figure 1.

5.1 | Learning from prior project delay

While *Prior Project Delay* primarily serves as a control variable in the main analyses, we find several statistically significant relationships of note. Recall that *Prior Project Delay* is the

[23]Online Appendix Section A.8 details how this figure was created through the additional underlying regressions.

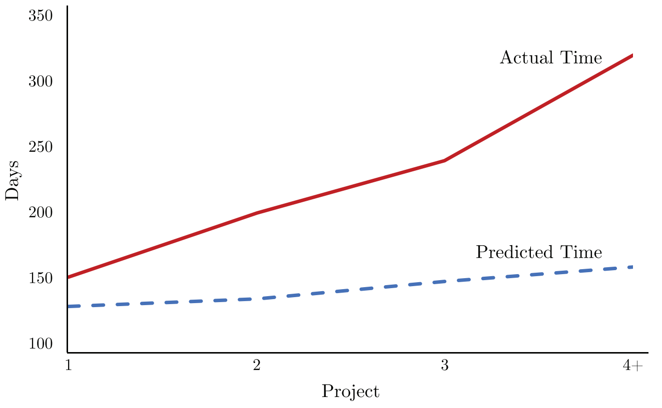


FIGURE 4 *Actual Time* and *Predicted Time* with experience. Visual representation of the relative coefficients of the average actual time entrepreneurs take to deliver a product versus the average time the entrepreneurs predict it will take to deliver, with this relative relationship shown over time as entrepreneurs gain experience. Figure based on coefficient estimates from a nonparametric model detailed in Online Appendix Section A.8 that includes indicators for project number instead of *Project Experience*.

duration of the delay divided by predicted time on the prior project, so a value of 1 or 100% means a project was delayed by the same amount of time the entrepreneur predicted the project would take. *Prior Project Delay* is significant and negatively related to *Unforeseen Interdependencies* ($p \sim .000$) and its logged value ($p \sim .000$). Each increase in days delayed on the prior project equal to the predicted time on the prior project leads to 0.7 fewer unforeseen interdependencies on the current project.[24] *Prior Project Delay* is significant and positively related to *Predicted Time* ($p = .024$). Each increase in days delayed on the prior project equal to the predicted time on the prior project leads to a 4.3 day increase in the predicted time on the current project, showing that entrepreneurs who experience delay give themselves more time on their current project. *Prior Project Delay* is significant and negatively related to *Delay Indicator* ($p = .042$), *Delay Duration* ($p = .020$), and *Actual Time* ($p = .034$). Each increase in days delayed on the prior project equal to the predicted time on the prior project leads to a 4.2% decrease in the chance the entrepreneur is delayed on the current project, a 21.7 day decrease in delay on the current project, and a 19.7 day decrease in the actual delivery time of the current project.

Although we do not formally a priori theorize on the implications of *Prior Project Delay*, the observed patterns have important theoretical implications for this line of research. Based on these empirical findings, we propose two post hoc theoretical explanations. First, it may be the case that learning from a delay, which could be characterized as a failure in a past execution-related prediction, may be more salient to the entrepreneur. From our specific theoretical view, it could be the case that past delays—that come from not accounting for the full set of interdependencies in a prediction—make past unforeseen interdependencies more salient and memorable for the entrepreneur. The mental model of interdependencies she uses to make predictions on the next project would then better account for more of the total interdependencies she would face. Prior work identifies several patterns of entrepreneurs learning from failure of this form (Politis, 2005). Early work by Sitkin (1992) proposes that failure can be

[24]For example, if the predicted time on the prior project is 45 days, then for every additional 45 days of delay on the prior project, the current project would have 0.7 fewer unforeseen interdependencies.

especially valuable for learning when the failure is: large enough to draw the attention of the entrepreneur, hard to predict, or able to stimulate the entrepreneur to try new ways of doing things. Indeed, a past delay is a notable experience that was hard to predict. On the entrepreneur's next project, this experience can prompt the entrepreneur to account for a previously unforeseen interdependency or at least to give herself more time.

Second, an entrepreneur suffering from a past delay may gain a sense of the shape of the complexity curve that she faces. Based on the premise of our main theory, an entrepreneur in general cannot fully anticipate the full set of interdependencies she will face when she executes her next, more complex project. An underlying assumption here is that the entrepreneur cannot fully anticipate that she cannot fully anticipate the full set of interdependencies. However, through a past delay, perhaps she can learn to anticipate that she cannot fully anticipate the interdependencies. If she does not experience a delay on the prior project, she could still be left assuming that she can anticipate the interdependencies on subsequent projects. To operationalize this awareness that might come from past delay, the entrepreneur could faster-than-linearly build in more extra time into her timeline on subsequent projects. Based on our interviews, most entrepreneurs already try to build in this extra time, but clearly they do so insufficiently. Theoretically, the ideal padding process can be interpreted as an entrepreneur developing an intuitive sense for the shape of the project complexity curve that she faces: she could make predictions of interdependencies based on an extrapolation of the curve, rather than on direct knowledge of the actual interdependencies she will face. This argument mirrors early work by Toffler (1985) and others that theorizes best practices for strategic planning and specifically warns against the pitfalls of straight-line thinking when extrapolating.

5.2 | Supplemental analyses

We empirically test for and rule out a number of potential alternative explanations that could lead to patterns similar to the main empirical findings or otherwise confound the estimates. First, performance feedback from success or failure on prior funding campaigns could generate an outcome–aspiration gap for the entrepreneur and affect prediction behavior on subsequent projects. Second, an entrepreneur may base predictions on the relative predictions made by her peers, for example, predict delivery times that match the average as opposed to predicting how long she actually thinks it will take to deliver. Third, as an entrepreneur gains experience, she may learn that there are limited to no consequences to delaying and, as a result, not care as much about whether she misses the delivery date on subsequent projects. In other words, she may learn that it is "acceptable" to miss delivery dates, especially for more complex projects, which would affect the accuracy of her prediction if it was somehow valuable to promise an aggressive delivery date known ex ante to be unrealistic. Fourth, if customers are more likely to fund projects that predict earlier delivery dates, an entrepreneur may be incentivized to over-promise and predict a delivery date that is sooner than her true predicted value. Fifth, higher-quality entrepreneurs may exit the sample when they gain sufficient experience, leaving increasingly lower-quality entrepreneurs in the sample at high levels of project experience. For example, higher-quality entrepreneurs may be able to raise external venture capital financing in lieu of crowdfunding and go to customers through another channel (e.g., direct-to-consumer or retail). Sixth, entrepreneurs who experience a project with significant delay may leave the sample after they "learn their lesson," resulting in a sample of entrepreneurs who disproportionately do not learn. In this scenario, the failure of missing a delivery time by a large margin could lead better-learning entrepreneurs to pursue an opportunity outside of crowdfunding or to quit altogether. We empirically test each of these alternative explanations and do not find evidence that these mechanisms drive the main results.[25]

6 | DISCUSSION AND CONCLUSION

This study addresses how an entrepreneur's experience affects the accuracy of her strategic foresight, reflected in the timeline prediction for a subsequent project. We theorize that as entrepreneurs gain experience, they learn about previously unforeseen interdependencies (which increases the accuracy of subsequent predictions), but they also learn about new opportunities to innovate by implementing new features on a subsequent project, which introduces new, previously unencountered interdependencies (which decreases the accuracy of subsequent predictions). When project complexity increases rapidly, we argue that the latter effect dominates the former, leading increasingly experienced entrepreneurs to make increasingly infeasible predictions. In our crowdfunding context, we show that entrepreneurs take on projects with an increasing number of features and encounter an increasing number of unforeseen interdependencies. In line with our conceptual model, we show that, on average, entrepreneurs miss their predicted timeline by a gap that grows by nearly six additional weeks (an additional 53.0% relative to their predicted timeline) on each subsequent project.[26]

6.1 | Strategic foresight under complexity

By taking the view that accurate strategic foresight depends on anticipating complexity in a strategy, we put forth an alternative explanation for the widespread challenge of making accurate predictions in entrepreneurial settings. In a review, Townsend et al. (2018) note that there has been sparse work on understanding entrepreneurship in a complex environment where the construct of "uncertainty has been stretched to try to address aspects of unknowingness that are better conceptualized as complexity" (p. 674). We seek to address this gap by taking a view that complexity presents a barrier to what can and cannot be learned, acting as an important constraint on the returns to experience. We assert that it is the challenge of accounting for complexity, rather than just uncertainty from a lack of available knowledge, that limits how much an entrepreneur can improve her ability to make predictions. Two important implications emerge when accounting for the role of complexity in strategic foresight.

First, the nuanced complexity-based mechanism we propose stands in contrast to the view of the extant literature that entrepreneurs' prediction inaccuracies stem from a general characterization of entrepreneurs as being "overconfident." Prior literature documents compelling

[25]The Online Appendix provides detailed descriptions of these supplemental analyses with full regression tables. In the order outlined here, the documentation for these analyses appears in Online Appendix Sections A.9–A.14, respectively.
[26]Our findings are reminiscent of the conventional managerial wisdom embodied by the Peter Principle (Peter & Hull, 1969), often phrased as "Employees rise to their 'level of incompetence' in a hierarchy," that is, managers who are promoted due to success in a prior job are then confronted with managing a new set of responsibilities unrelated to what made them successful previously. One could summarize the findings of this study as, "Entrepreneurs rise to their 'level of incompetence' in strategic foresight," that is, entrepreneurs who succeed in making a product and then continue to add features and increase the complexity of that product, are required to manage systems of interdependencies which they have never encountered previously and which they are ill-equipped to manage.

evidence that entrepreneurial entrants make infeasible predictions about their own future performance, leading them to enter markets they should not (e.g., Artinger & Powell, 2016; Cassar, 2010; Chen, Croson, Elfenbein, & Posen, 2019; Forbes, 2005; Hayward, Shepherd, & Griffin, 2006; Wu & Knott, 2006). This literature generally frames this observed pattern as a consequence of entrepreneurial overconfidence (Camerer & Lovallo, 1999). However, we assert that the inherent complexity involved in entrepreneurial strategy and new product development may be a key antecedent to what otherwise appears as overconfidence. Our view aligns with Hogarth and Karelaia (2012), whose simulation model shows how over-entry can occur among both overconfident and underconfident entrepreneurs. While an entrepreneur's lack of a full understanding of the complexity she faces may appear as overconfidence to an observer, the natural emergence of complexity likely accounts for at least some of the error in her predictions.

Our study documents empirical evidence for this nuanced characterization of entrepreneurs facing complexity rather than being generically overconfident. The entrepreneurs in our setting accumulate information through experience that should help address an overconfidence bias that stems from a lack of information. However, inconsistent with a basic overconfidence explanation, we find that entrepreneurs actually become less accurate as they accumulate knowledge from experience. That said, our arguments do not rule out the possibility that overconfidence still exists.

Second, accounting for the role of complexity implies that learning-from-experience may not be a cure-all solution for inaccurate strategic foresight. In a seminal study of the automobile industry, Levitt, List, and Syverson (2013) show that model changeovers disrupt the learning curve; when firms add new model variants, prior learning is less helpful. So, the outstanding question is why that is the case? We propose that it is the emergence of new complexity unrelated to prior experience that impairs strategic foresight.

As entrepreneurs learn from prior projects, an important manifestation of this learning is to add new features to their products, which in turn drives complexity that impairs strategic foresight. Ethiraj et al. (2012) find that firms face pressure to address customer requests with incremental product innovations, but even incremental changes can precipitate a cascade of impacts across interdependent parts of the product and organization. The entrepreneurs we study face this exact challenge, with severe consequences for the accuracy of their strategic foresight. Under the assumptions that entrepreneurs inevitably face this incentive to improve over time and that complexity is difficult to address and anticipate, the unfortunate implication is that strategic foresight will face a perpetual headwind.

6.2 | Strategic foresight as multiple predictions

To empirically study strategic foresight, we make a key advance with our explicit interpretation of strategic foresight as not just one prediction but the combination of a set of predictions. In contrast, the broader set of work on strategic decisions—and specific studies on foresight—focus on whether a manager or another actor can make a sole prediction or decision, for example, enter into a market (Camerer & Lovallo, 1999) or invest in a specific firm (Csaszar & Laureiro-Martínez, 2018). We argue that strategic planning must inherently invoke several predictions simultaneously, whether articulated or not, because the predictions depend on one another. Predicting a value proposition also entails predicting a cost structure for delivering that value proposition such that the aggregate strategy is viable.

At a general level, our findings suggest that as entrepreneurs gain experience across projects, their strategic predictions on a successive project will be less accurate; but that characterization would be far from a complete story. We show a trade-off among the aggregate predictions that comprise strategic foresight broadly (Ethiraj & Levinthal, 2009; Talbot, 1982). We gain several advantages by studying product specification, delivery timeline, and complexity simultaneously. In our study, entrepreneurs pursue success in achieving the predicted product specification but at the cost of delivering their product on time. But that is a choice they made. In principle, the entrepreneur could deliver the product on time but at a lower value proposition than they originally predicted.

There are many high-profile examples of entrepreneurs prioritizing the delivery of an initially specified product over staying within the initially predicted timeline. In July 2017, Elon Musk promised Tesla would deliver 20,000 Model 3 cars in December of that same year. However, Tesla only produced 2,425 cars the entire fourth quarter of 2017, falling short of Musk's prediction by 93%. Tesla eventually reached their predicted product specification, and even exceeded it, reaching over 10,000 vehicles per week in 2018, but far behind the initially predicted timeline. Speaking of Tesla's tradeoff between delivering on predicted product specification versus timeline, Musk himself said, "It pretty much always happens, but not exactly on the time frame."

By considering several predictions simultaneously in a holistic view of strategic foresight, future research can provide more nuance in the ways in which entrepreneurs who have previously been categorized one-dimensionally as failures (or successes) might actually have succeeded (or failed) along other overlooked dimensions. In doing so, we might show that some failures are driven by an intentional choice to succeed on other dimensions. By recognizing the multiple predictions inherent in strategic foresight and their relative prioritization, entrepreneurs and investors may be able to improve performance. For example, given that additional costs may be required to achieve a fixed product specification, especially as entrepreneurs gain experience from past projects and take on increasingly complex projects, future research could explore how entrepreneurs and investors can identify situations where adjusting the product specification may be preferable to accruing high costs or missing delivery timelines.

6.3 | Predicting timelines: Strategic implications

This research brings attention to the strategic problem of predicting and managing timelines. In the context of product crowdfunding, we show that entrepreneurs—even and especially those with experience—consistently struggle to predict accurate timelines. This struggle extends well beyond our context to entrepreneurs generally. For instance, consider Chinese electric vehicle company Faraday Future, which initially predicted it would begin production on its flagship SUV in 2018. When this timeline turned out to be wrong, the company raised an extra $225 million in emergency bridge financing in order to keep the company alive and get the company and its product to where they needed to be for a future public offering. While Faraday Future recovered from its poor timeline prediction, many other electric vehicle startups were not so fortunate: early pioneer Fisker Automotive was forced to shut down due to a poor timeline prediction that led to them running out of cash before being able to raise more money.

Large, established firms face this same timeline challenge. Apple missed its predicted timeline to ship the HomePod in 2017, AirPods in 2016, and the Apple Watch in 2015. Similarly, Microsoft missed its predicted timeline to release many of its new operating systems, to ship

Surface Earbuds in 2019, and to push a security update in 2017. Missing predicted timelines is also common in other settings such as big box office movie releases. In two high-profile examples, unanticipated post-production complexity led to the delayed release of *Titanic* (from July to December of 1997) and *Gravity* (from November 2012 to November 2013).

Based on our theoretical framework and our empirical observations, we propose three ways a manager can make more accurate timeline predictions for firm strategy. First, we see an opportunity for firms to make an intentional effort to better anticipate the nonlinear nature of complexity by accounting for the faster-than-linear increase in unforeseen interdependencies when building out projects. In our setting, both unforeseen interdependencies and delays are ubiquitous and increasing over time. Just as becoming aware of personal biases or tendencies toward overconfidence can allow managers to make better decisions (Lee & Huang, 2018; Pope, Price, & Wolfers, 2018), becoming self-aware of the true realities of complexity could theoretically empower managers to make more accurate timeline predictions.

To put this argument in more colloquial terms: we all face known knowns, known unknowns, and unknown unknowns. The interdependencies that an entrepreneur could face fall into these buckets. Through experience, it is theoretically possible that an entrepreneur could become more aware of the rate at which unknown unknowns will arise—in essence, allowing an entrepreneur to treat them as known unknowns—and to account for those unknowns when making predictions through extrapolation based on a higher level of intuition for the shape of the project complexity curve. How does one take this to practice? As one suggestion, we document that entrepreneurs already engage in a process of padding their timelines with extra time, albeit to an insufficient degree. We recommend that entrepreneurs act on the insight of this research by padding timelines with the complexity curve in mind, way more than their prior (incorrect) intuition would suggest.

Second, firms can learn to make more accurate timeline predictions by internalizing salient experiences with interdependencies. We find that the delay on a subsequent project is partially offset by experiencing a delay on the prior project. Thus, previously delayed firms have a unique opportunity to carefully identify the specific unforeseen challenges that contributed to the delay and then to account for those factors when making subsequent predictions. Of course, we would not suggest that firms intentionally cause a delay in pursuit of this benefit. But certain circumstances allow firms to engineer controlled experimental experiences that make unforeseen interdependencies salient; these intentional experiences could potentially offer many of the same benefits as a prior project delay appears to offer in our study, but with much less of the downside. For example, we spoke with an Apple manufacturing manager about how they now stress-test prototypes and test-run manufacturing small batches to try to identify interdependencies before a high-stakes product launch.

Third, future research should explore whether firms can improve timeline predictions in complex situations by increasing their knowledge diversity (Keller, 2001; Olson, Walker, & Ruekert, 1995). A more diverse knowledge base increases the breadth of interdependencies a firm will be aware of when making predictions. An increased breadth of awareness should lead to improved foresight (Csaszar & Laureiro-Martínez, 2018). As the fundamental challenge of complexity, a firm cannot ex ante anticipate all the relevant interdependencies—which means the firm cannot ex ante plan for which knowledge it will need. Thus, there may be value in intentionally maintaining a diverse set of experience at the table beyond what the firm ex ante expects to be directly relevant to a given project: increasing diversity could increase the chances that someone will anticipate a relevant interdependency. If firms only hire or seek input from a narrow set of people assumed to be relevant, the value of the marginal voice for identifying unknown interdependencies is limited. Diversity could also be sought outside the boundaries of the firm (Aggarwal, Hsu, & Wu, 2020). For example, crowdsourcing (e.g., open innovation tournaments) provides access to more diverse knowledge and improves performance when searching for the global optimum (Afuah & Tucci, 2012). While the current study does not empirically measure this channel, future work could directly measure the impact of knowledge diversity on timeline predictions.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge feedback from Daniel Albert, Juan Alcacer, Goran Calic, David Clough, Felipe Csaszar, Gary Dushnitsky, J. P. Eggers, Martin Ganco, Giovanni Gavetti, Sourobh Ghosh, Laura Huang, David Hsu, Laura Katsnelson, Chengguang Li, Rory McDonald, Cynthia Montgomery, Jan Rivkin, Daniel Sands, Kourosh Shafi, Mary Tripsas, Eric Van den Steen, Bala Vissa, Maciej Workiewicz, and participants at the Strategy Science Conference, Wharton Technology and Innovation Conference, Academy of Management Conference, Strategic Management Society Conference, City University of London Bayes Business School Brown Bag Seminar, HBS Strategy Unit Brown Bag Seminar, and HBS Doctoral Student Seminar. The authors thank Sendil Ethiraj and two anonymous reviewers for valuable editorial guidance. This research was made possible by financial support from the HBS Division of Research and Faculty Development. Jaeho Kim and Miaomiao Zhang provided excellent research assistance. Jeff Strabone provided copyediting support. All opinions expressed herein are those of the authors only, and all errors are the responsibility of the authors.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are not publicly available due to privacy restrictions.

ORCID

Aticus Peterson https://orcid.org/0000-0002-5964-8173
Andy Wu https://orcid.org/0000-0002-9107-5731

REFERENCES

Afuah, A., & Tucci, C. L. (2012). Crowdsourcing as a solution to distant search. *Academy of Management Review*, *37*(3), 355–375.

Aggarwal, V. A., Hsu, D. H., & Wu, A. (2020). Organizing knowledge production teams within firms for innovation. *Strategy Science*, *5*(1), 1–16.

Ahuja, G., Coff, R. W., & Lee, P. M. (2005). Managerial foresight and attempted rent appropriation: Insider trading on knowledge of imminent breakthroughs. *Strategic Management Journal*, *26*(9), 791–808.

Alvarez, S. A., & Barney, J. B. (2007). Discovery and creation: Alternative theories of entrepreneurial action. *Strategic Entrepreneurship Journal*, *1*(1), 11–26.

Anderson, P. (1999). Perspective: Complexity theory and organization science. *Organization Science*, *10*(3), 216–232.

Artinger, S., & Powell, T. C. (2016). Entrepreneurial failure: Statistical and psychological explanations. *Strategic Management Journal*, *37*(6), 1047–1064.

Barney, J. B. (1986). Strategic factor markets: Expectations, luck, and business strategy. *Management Science*, *32*(10), 1231–1241.

Camerer, C., & Lovallo, D. (1999). Overconfidence and excess entry: An experimental approach. *American Economic Review*, *89*(1), 306–318.

Cassar, G. (2010). Are individuals entering self-employment overly optimistic? An empirical test of plans and projections on nascent entrepreneur expectations. *Strategic Management Journal*, *31*(8), 822–840.
Cassar, G. (2014). Industry and startup experience on entrepreneur forecast performance in new firms. *Journal of Business Venturing*, *29*(1), 137–151.
Chen, J. S., Croson, D. C., Elfenbein, D. W., & Posen, H. E. (2019). The impact of learning and overconfidence on entrepreneurial entry and exit. *Organization Science*, *29*(6), 989–1009.
Cho, H. S. & Clough, D. R. (2015). 'If at first you don't succeed': Learning and aspiration level adjustment in venture fundraising on Kickstarter. In Academy of Management Annual Meeting.
Clough, D. R., Fang, T. P., Vissa, B., & Wu, A. (2018). Turning lead into gold: How do entrepreneurs mobilize resources to exploit opportunities? *Academy of Management Annals*, *13*(1), 240–271.
Cohen, S. L., Bingham, C. B., & Hallen, B. L. (2019). The role of accelerator designs in mitigating bounded rationality in new ventures. *Administrative Science Quarterly*, *64*(4), 810–854.
Csaszar, F. A. (2012). Organizational structure as a determinant of performance: Evidence from mutual funds. *Strategic Management Journal*, *33*(6), 611–632.
Csaszar, F. A. (2018). What makes a decision strategic? Strategic representations. *Strategy Science*, *3*(4), 606–619.
Csaszar, F. A., & Laureiro-Martínez, D. (2018). Individual and organizational antecedents of strategic foresight: A representational approach. *Strategy Science*, *3*(3), 513–532.
Denrell, J., Fang, C., & Levinthal, D. A. (2004). From T-mazes to labyrinths: Learning from model-based feedback. *Management Science*, *50*(10), 1366–1378.
Edmondson, A. C., Dillon, J. R., & Roloff, K. S. (2007). Three perspectives on team learning. *Academy of Management Annals*, *1*(1), 269–314.
Eggers, J. P., & Song, L. (2015). Dealing with failure: Serial entrepreneurs and the costs of changing industries between ventures. *Academy of Management Journal*, *58*(6), 1785–1803.
Eisenhardt, K. M., & Bingham, C. B. (2017). Superior strategy in entrepreneurial settings: Thinking, doing, and the logic of opportunity. *Strategy Science*, *2*(4), 246–257.
Ethiraj, S. K. (2007). Allocation of inventive effort in complex product systems. *Strategic Management Journal*, *28*(6), 563–584.
Ethiraj, S. K., Kale, P., Krishnan, M. S., & Singh, J. V. (2005). Where do capabilities come from and how do they matter? A study in the software services industry. *Strategic Management Journal*, *26*(1), 25–45.
Ethiraj, S. K., & Levinthal, D. (2009). Hoping for A to Z while rewarding only A: Complex organizations and multiple goals. *Organization Science*, *20*(1), 4–21.
Ethiraj, S. K., Ramasubbu, N., & Krishnan, M. S. (2012). Does complexity deter customer-focus? *Strategic Management Journal*, *33*(2), 137–161.
Forbes, D. P. (2005). Are some entrepreneurs more overconfident than others? *Journal of Business Venturing*, *20*(5), 623–640.
Gary, M. S., & Wood, R. E. (2011). Mental models, decision rules, and performance heterogeneity. *Strategic Management Journal*, *32*(6), 569–594.
Gavetti, G. (2012). Toward a behavioral theory of strategy. *Organization Science*, *23*(1), 267–285.
Gavetti, G., & Menon, A. (2016). Evolution cum agency: Toward a model of strategic foresight. *Strategy Science*, *1*(3), 207–233.
Gompers, P., Kovner, A., Lerner, J., & Scharfstein, D. (2010). Performance persistence in entrepreneurship. *Journal of Financial Economics*, *96*(1), 18–32.
Greve, H. R. (1998). Performance, aspirations, and risky organizational change. *Administrative Science Quarterly*, *43*(1), 58–86.
Greve, H. R. (2003). A behavioral theory of R&D expenditures and innovations: Evidence from shipbuilding. *Academy of Management Journal*, *46*(6), 685–702.
Gruber, M., MacMillan, I. C., & Thompson, J. D. (2008). Look before you leap: Market opportunity identification in emerging technology firms. *Management Science*, *54*(9), 1652–1665.
Hayward, M. L., Shepherd, D. A., & Griffin, D. (2006). A hubris theory of entrepreneurship. *Management Science*, *52*(2), 160–172.
Hogarth, R. M., & Karelaia, N. (2012). Entrepreneurial success and failure: Confidence and fallible judgment. *Organization Science*, *23*(6), 1733–1747.

Hsu, D. H. (2007). Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research Policy*, *36*(5), 722–741.

Joseph, J., & Gaba, V. (2015). The fog of feedback: Ambiguity and firm responses to multiple aspiration levels. *Strategic Management Journal*, *36*(13), 1960–1978.

Kapoor, R. & Wilde, D. (2020). Peering into a crystal ball: Foresight during periods of industry change. Wharton School Working Paper.

Kauffman, S. A. (1995). *At home in the universe*. New York: Oxford University Press.

Keller, R. T. (2001). Cross-functional project groups in research and new product development: Diversity, communications, job stress, and outcomes. *Academy of Management Journal*, *44*(3), 547–555.

Kickstarter PBC (2020). *Our rules*. Retrieved from https://www.kickstarter.com/rules.

Lee, M., & Huang, L. (2018). Gender bias, social impact framing, and evaluation of entrepreneurial ventures. *Organization Science*, *29*(1), 1–16.

Leiblein, M. J., Reuer, J. J., & Zenger, T. (2018). What makes a decision strategic? *Strategy Science*, *3*(4), 558–573.

Levinthal, D. A. (1997). Adaptation on rugged landscapes. *Management Science*, *43*(7), 934–950.

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. *Strategic Management Journal*, *14*(S2), 95–112.

Levitt, S. D., List, J. A., & Syverson, C. (2013). Toward an understanding of learning by doing: Evidence from an automobile assembly plant. *Journal of Political Economy*, *121*(4), 643–681.

Minniti, M., & Bygrave, W. (2001). A dynamic model of entrepreneurial learning. *Entrepreneurship Theory and Practice*, *25*(3), 5–16.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing*, *29*(1), 1–16.

Mollick, E. (2015). Delivery rates on Kickstarter. SSRN Working Paper.

Nelson, R. R., & Winter, S. G. (2002). Evolutionary theorizing in economics. *Journal of Economic Perspectives*, *16*(2), 23–46.

Nickerson, J., & Argyres, N. (2018). Strategizing before strategic decision making. *Strategy Science*, *3*(4), 592–605.

Olson, E. M., Walker, O. C., & Ruekert, R. W. (1995). Organizing for effective new product development: The moderating role of product innovativeness. *Journal of Marketing*, *59*(1), 48–62.

Ott, T. E., Eisenhardt, K. M., & Bingham, C. B. (2017). Strategy formation in entrepreneurial settings: Past insights and future directions. *Strategic Entrepreneurship Journal*, *11*(3), 306–325.

Paik, Y. (2014). Serial entrepreneurs and venture survival: Evidence from U.S. venture-capital-financed semiconductor firms. *Strategic Entrepreneurship Journal*, *8*(3), 254–268.

Peter, L. J., & Hull, R. (1969). *The Peter principle*. London: Souvenir Press.

Politis, D. (2005). The process of entrepreneurial learning: A conceptual framework. *Entrepreneurship: Theory and Practice*, *29*(4), 399–424.

Pope, D. G., Price, J., & Wolfers, J. (2018). Awareness reduces racial bias. *Management Science*, *64*(11), 4988–4995.

Porter, M. E. (1980). *Competitive strategy: Techniques for analyzing industries and competitors*. New York, NY: Free Press.

Raveendran, M., Silvestri, L., & Gulati, R. (2020). The role of interdependence in the microfoundations of organization design: Task, goal, and knowledge interdependence. *Academy of Management Annals*, *14*(2), 828–868.

Rivkin, J. W. (2000). Imitation of complex strategies. *Management Science*, *46*(6), 824–844.

Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society*, *106*(6), 467–482.

Simon, H. A. (1969). *The sciences of the artificial*. Cambridge, MA: MIT Press.

Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology*, *41*(1), 1–20.

Sitkin, S. B. (1992). Learning through failure: The strategy of small losses. In L. Cumming & B. Staw (Eds.), *Research in organizational behavior* (pp. 231–266). Greenwich, CT: JAI Press.

Stuart, R. W., & Abetti, P. A. (1990). Impact of entrepreneurial and management experience on early performance. *Journal of Business Venturing*, *5*(3), 151–162.

Talbot, F. B. (1982). Resource-constrained project scheduling with time-resource tradeoffs: The nonpreemptive case. *Management Science*, *28*(10), 1197–1210.

Toffler, A. (1985). *The adaptive corporation*. New York, NY: McGraw-Hill.

Townsend, D. M., Hunt, R. A., McMullen, J. S., & Sarasvathy, S. D. (2018). Uncertainty, knowledge problems, and entrepreneurial action. *Academy of Management Annals*, *12*(2), 659–687.
Ulrich, K., Eppinger, S., & Yang, M. (2020). *Product design and development* (7th ed.). New York: McGraw-Hill Education.
Van den Steen, E. (2016). A formal theory of strategy. *Management Science*, *63*(8), 2616–2636.
Wu, B., & Knott, A. M. (2006). Entrepreneurial risk and market entry. *Management Science*, *52*(9), 1315–1330.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Peterson, A., & Wu, A. (2021). Entrepreneurial learning and strategic foresight. *Strategic Management Journal*, *42*(13), 2357–2388. https://doi.org/10.1002/smj.3327