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Entrepreneurial Learning and Strategic Foresight

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Entrepreneurial Learning and Strategic Foresight *

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Abstract. 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.

Keywords: Entrepreneurship, Learning, Experience, Complexity, Interdependency, Strategic Foresight, Prediction, Crowdfunding, Product Development, Timeline, Delay, Forecasting, Planning

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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 et al., 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 et al., 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 et al., 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 et al., 2018; Hsu, 2007), opportunities (Gruber et al., 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 judgement (Cassar, 2014; Cohen et al., 2019). In an important study, Eggers & 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 et al., 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 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, e.g., 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, e.g., 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, e.g., 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 (Nickerson & Argyres, 2018; Csaszar, 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

[1]To better align with our empirical context, our terminology for interdependencies differs subtly from how it is described in the NK modeling tradition (Levinthal, 1997; Kauffman, 1995). 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.

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 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.

Learning about Past Complexity On 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 et al., 2007; Ethiraj et al., 2005). Denrell et al. (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]

[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., Levinthal & March, 1993; Greve, 2003, 1998; Joseph & Gaba, 2015; Cho & Clough, 2015). 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.

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.

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 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 et al., 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 prod-

[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.

uct. 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.

— INSERT FIGURE 1 CONCEPTUAL MODEL OF EXPERIENCE AND INTERDEPENDENCIES. —

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.

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 et al., 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—

[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.

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 et al., 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.

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 & Bingham (2017) detail 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, 1990, 1969), 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. In order to validate our aggregate empirical patterns and understand potential micro-mechanisms, we conduct a program of qualitative interviews with 11 entrepreneurs from our sample. Appendix Section A.1 describes our qualitative interview process. 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.[6]

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 et al., 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.

However, this ceases to be the case when an entrepreneur implements new features discovered while implementing 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 com-

[6] 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.

bining 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 new 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 hand made—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.[7]

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).[8] 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 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,[9] 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

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

[8]Never delivering a product would be an asymptotic combination of these two ways of missing a prediction, i.e., 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).

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

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.

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 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.

— Insert Figure 2 Example Project Series. —

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 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.[10] 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

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

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.[11]

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.[12] 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 created 722 projects from September 2010 through June 2019. For each of these projects, we scrape comprehensive information from its Kickstarter pages, including the most recent 100 comments and all project updates posted by the entrepreneur. We manually collect data on actual delivery time and

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

[12] 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.

number of features. We link Kickstarter entrepreneurs with their Crunchbase profiles to track their external funding over time.[13]

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, i.e., 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.[14] 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, e.g., 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, e.g., 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

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

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

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.[15]

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 his 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, i.e., 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.

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

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,[16] *Failed Campaign Experience* is the cumulative count of Kickstarter campaigns of the same product subtype conducted by the entrepreneur where those campaigns did not reach their funding threshold.[17] 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).[18] 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 & Song (2015), we define

[16] 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.

[17] *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.

[18] 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 is generally a full-time job and the ideas for subsequent projects come through executing past projects.

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.

4.4 Descriptive Statistics

Table 1 provides summary statistics.[19] 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 (versus \$21,177) and *Funding Period* of 33.34 days (versus 40.28 days). In addition, Mollick (2014) uses a similar manual process to collect actual delivery dates and finds that "only 24.9% of projects delivered on time" (or 75.1% of projects are delayed).

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

Our sample identifies a similar pattern, where 76.3% of projects are delayed.

— Insert Table 1 Summary Statistics. —

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.

— Insert Table 2 Pairwise Correlation Matrix. —

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.

— Insert Figure 3 Distribution of Actual Time and Predicted Time. —

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, etc. Product subtype fixed effects absorb any heterogeneity between the various categories of projects, e.g., DIY electronics versus 3D printing. Month fixed effects control for seasonal cycles, e.g., 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* ($p = 0.047$), *Features Rank* ($p = 0.000$), and *Features Percentile* ($p = 0.016$) are all positively related to *Project Experience*.[20] 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 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.

— Insert Table 3 Complexity and Unforeseen 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* ($p \sim 0.000$) 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 of decreasing prediction accuracy in increasingly complex systems when bounded rationality limits the learning that might attenuate unforeseen interdependencies. *Ln Unforeseen Interdependencies* ($p = 0.002$) also positively associates with *Project Experience*. Each subsequent project increases unforeseen interdependencies by 21.0%.[21]

Hypothesis 2 predicts what entrepreneurs will do when they make inaccurate predictions. Specifically, we hypothesize that as entrepreneurs gain experience and encounter increas-

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

[21] 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.

ing 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* ($p = 0.010$) and *Delay Duration* ($p = 0.001$). 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* ($p = 0.001$). 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.

— Insert Table 4 Delivery and Delay. —

As important context for the above finding, column 4 of Table 4 shows that *Project Experience* positively associates with *Predicted Time* ($p = 0.014$). On average, entrepreneurs increase 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* ($p \sim 0.001$). 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 non-parametric model of the relationship between experience and the dependent variables by including indicators for project number instead of *Project Experience*.[22] This figure shows that the actual delivery time increases much

[22] Appendix Section A.8 details how this figure was created, including the additional underlying regressions.

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.

— INSERT FIGURE 4 ACTUAL TIME AND PREDICTED TIME WITH EXPERIENCE. —

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 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* ($p \sim 0.000$) and its logged value ($p \sim 0.000$). 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.[23] *Prior Project Delay* is significant and positively related to *Predicted Time* ($p \sim 0.024$). 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* ($p \sim 0.042$), *Delay Duration* ($p \sim 0.020$), and *Actual Time* ($p \sim 0.034$). 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

[23]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.

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 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, e.g., 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 overpromise 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.[24]

[24]The Appendix provides detailed descriptions of these supplemental analyses with full regression tables. In the order outlined here, the documentation for these analyses appears in Appendix Sections A.9, A.10, A.11, A.12, A.13, and A.14, respectively.

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.[25]

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

[25]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," i.e., 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," i.e., 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.

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 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 et al., 2019; Forbes, 2005; Hayward et al., 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 & 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 et al. (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 strategy 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, e.g., 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 dates.

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 $225M 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 non-linear 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 towards overconfidence can allow managers to make better decisions (Pope et al., 2018; Lee & Huang, 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 delays 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 like a prior project delay but without the same costs. 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 (Olson et al., 1995; Keller, 2001). 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 et al., 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.

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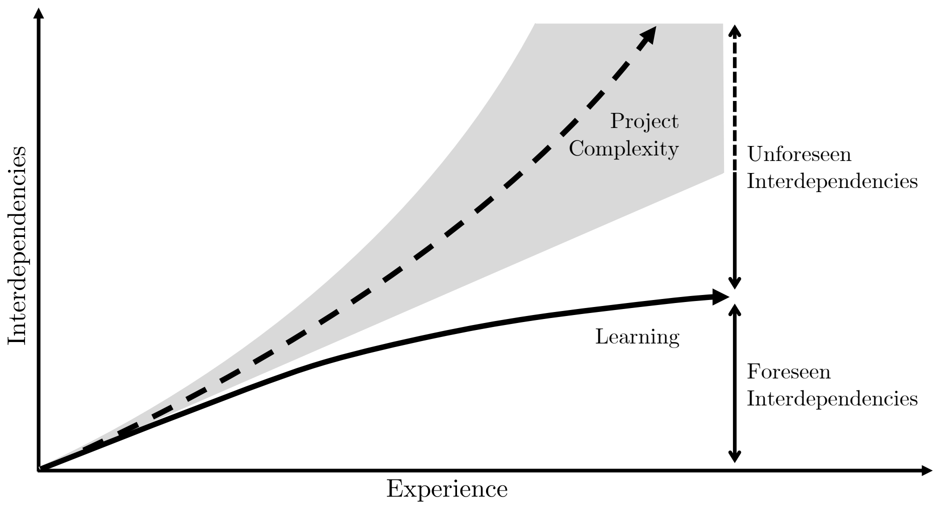


Figure 1: Conceptual Model of Experience and Interdependencies. The vertical axis *Interdependencies* represents the number of interdependencies. The horizontal axis *Experience* represents an entrepreneur's level of project execution experience. The *Project Complexity* curve illustrates the total number of interdependencies in projects pursued by an entrepreneur at different levels of *Experience*. The shaded grey area reflects the range of possible *Project Complexity* curves: linear as a lower bound and geometric as an upper bound; 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.

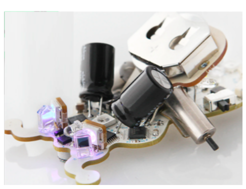
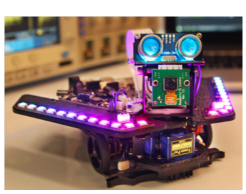
Name & Date	Image	Features Rank	Delay Duration	Delay Duration/ Predicted Time	Unforeseen Interdependencies
Ringo Feb 25, 2015		1 (Fewest)	66 Days	92%	"Our machine refused to pick up the programming ports. . . this programming port was just a bit [too] heavy."
Wink Oct 28, 2015		2 (Middling)	73 Days	115%	"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 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 quotations from updates by the entrepreneur. All other variables mirror those defined in the paper.

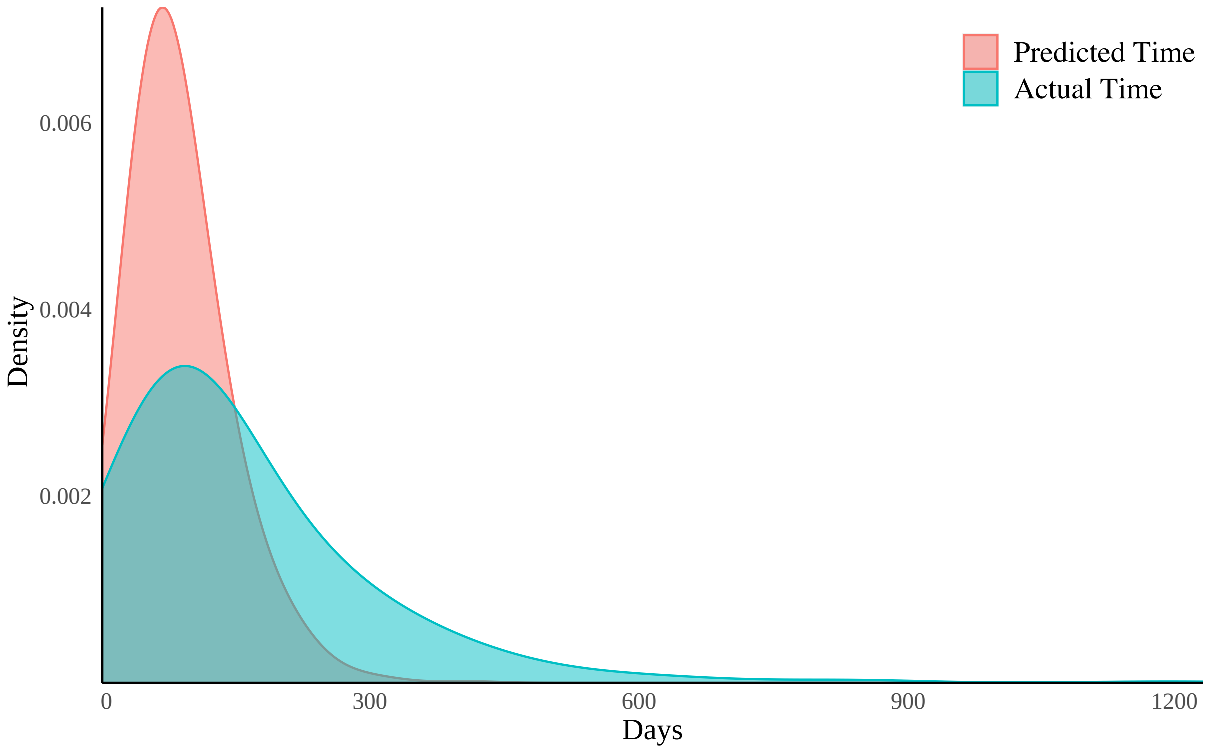


Figure 3: Density Plot of *Actual Time* and *Predicted Time*. The distribution of *Actual Time* is shifted and skewed to the right compared to the distribution of *Predicted Time*. We adjust the bandwidth to smooth the distributions.

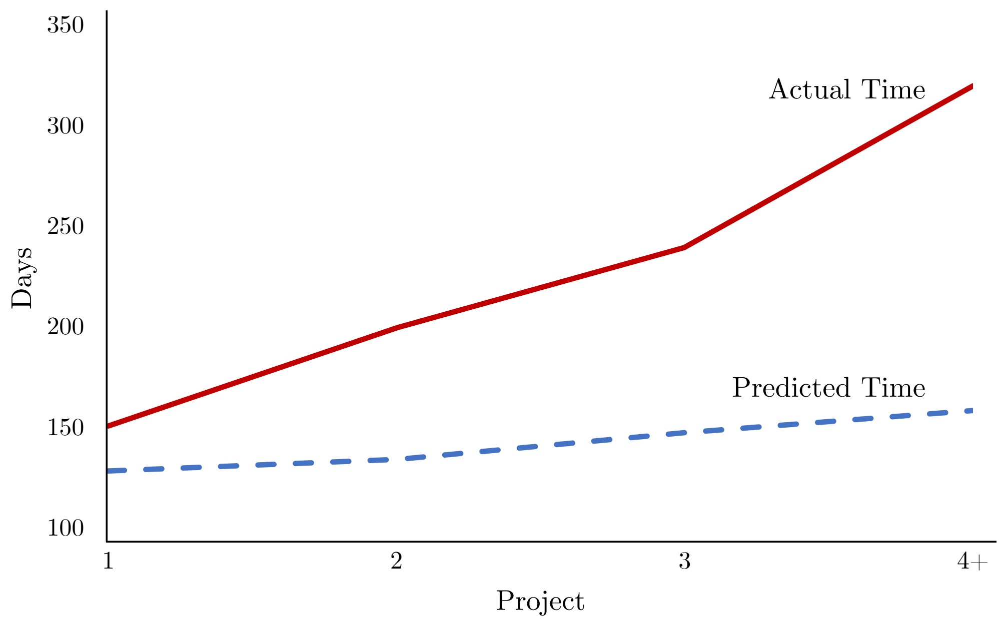


Figure 4: *Actual Time* and *Predicted Time* with Experience. Visual representation of the relative coefficients of the average actual time entrepreneurs take to deliver a product versus the average time the entrepreneurs predict it will take to deliver, with this relative relationship shown over time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

Table 1: Summary Statistics. 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.

Dependent Variables	Mean	Std. Dev.	Min	Max
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	Mean	Std. Dev.	Min	Max
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

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

Table 3: Features and Unforeseen Interdependencies. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Features Most	Features Rank	Features Percentile	Unforeseen Interdependencies	Ln Unforeseen Interdependencies
Project Experience	0.117	0.370	0.138	1.298	0.205
	(0.047)	(0.000)	(0.016)	(0.000)	(0.002)
Failed Campaign Experience	0.075	0.169	0.081	0.672	0.185
	(0.506)	(0.245)	(0.401)	(0.066)	(0.057)
Prior Campaign Funding Deviation	0.001	0.000	0.001	0.005	−0.000
	(0.779)	(0.932)	(0.858)	(0.772)	(0.908)
Prior Project Delay	0.011	−0.034	0.003	−0.698	−0.128
	(0.758)	(0.535)	(0.941)	(0.000)	(0.000)
Execution Overlap	−0.365	−0.447	−0.338	−0.216	0.096
	(0.025)	(0.031)	(0.028)	(0.736)	(0.410)
External Financing	0.371	0.286	0.367	1.122	0.148
	(0.006)	(0.055)	(0.006)	(0.317)	(0.515)
New Category	−0.063	0.156	0.020	1.596	0.246
	(0.685)	(0.464)	(0.895)	(0.078)	(0.231)
Elapsed Time	−0.000	0.000	0.000	0.004	0.001
	(0.665)	(0.879)	(0.961)	(0.009)	(0.000)
Funding Period	0.007	0.008	0.007	0.028	0.006
	(0.101)	(0.119)	(0.053)	(0.172)	(0.144)
Funding Reward Tiers	0.006	0.007	0.008	−0.023	−0.003
	(0.395)	(0.539)	(0.296)	(0.521)	(0.646)
Funding Reward Size	0.000	0.000	0.000	−0.000	0.000
	(0.003)	(0.000)	(0.002)	(0.779)	(0.848)
Ln Funding Threshold	0.027	0.048	0.016	0.754	0.157
	(0.527)	(0.356)	(0.693)	(0.004)	(0.000)
Ln Funding Exceeded				0.671	0.076
				(0.008)	(0.109)
Ln Funding Backers				−0.018	0.074
				(0.960)	(0.268)
Baseline Updates				0.172	
				(0.001)	
Ln Baseline Updates					0.271
					(0.000)
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

Table 4: Delivery and Delay. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Delay Indicator	Delay Duration	Delay Duration/ Predicted Time	Predicted Time	Actual Time
Project Experience	0.119	39.616	0.530	8.364	46.386
	(0.010)	(0.001)	(0.001)	(0.014)	(0.001)
Failed Campaign Experience	0.139	−2.720	−0.071	15.751	11.345
	(0.123)	(0.870)	(0.749)	(0.031)	(0.620)
Prior Campaign Funding Deviation	−0.003	0.094	−0.001	0.095	0.390
	(0.062)	(0.828)	(0.864)	(0.578)	(0.411)
Prior Project Delay	−0.042	−21.689	−0.111	4.288	−19.655
	(0.042)	(0.020)	(0.690)	(0.024)	(0.034)
Execution Overlap	−0.052	11.587	1.183	−3.993	9.501
	(0.457)	(0.774)	(0.233)	(0.636)	(0.831)
External Financing	0.138	95.312	0.371	21.388	124.811
	(0.196)	(0.234)	(0.481)	(0.376)	(0.205)
New Category	0.082	39.284	0.425	6.012	46.345
	(0.611)	(0.135)	(0.156)	(0.546)	(0.168)
Elapsed Time	−0.000	−0.092	−0.001	−0.023	−0.111
	(0.422)	(0.130)	(0.353)	(0.265)	(0.094)
Funding Period	0.009	1.302	0.004	0.147	1.730
	(0.000)	(0.059)	(0.848)	(0.555)	(0.022)
Funding Reward Tiers	0.003	0.785	0.001	−0.150	0.996
	(0.454)	(0.474)	(0.977)	(0.721)	(0.441)
Funding Reward Size	0.000	−0.011	0.000	0.005	−0.008
	(0.807)	(0.721)	(0.707)	(0.533)	(0.830)
Ln Funding Threshold	0.008	22.716	−0.090	19.806	40.817
	(0.786)	(0.103)	(0.533)	(0.000)	(0.011)
Ln Funding Exceeded	0.034	28.728	0.201		27.973
	(0.195)	(0.004)	(0.085)		(0.014)
Ln Funding Backers	0.008	−34.159	−0.176		−31.278
	(0.837)	(0.009)	(0.281)		(0.040)
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

A Appendix

A.1 Qualitative Interviews

We conducted a program of qualitative interviews after deductively theorizing hypotheses and testing those hypotheses empirically to determine the mean effect. These interviews were not used to draw inductive conclusions. Instead, the purpose of these interviews was to better understand and confirm the mean effect observed in the quantitative data. Given that intent, we identified and reached out to entrepreneurs in our sample who match the observed empirical trends to gain additional color on what drove those outcomes. These interviews confirmed the mechanisms outlined in our theory, which we established prior to conducting the interviews.

We reached out to entrepreneurs via LinkedIn messages, company contact forms, Kickstarter messages, or email, depending on what was available in each case. We received 18 responses to our outreach. Two of these entrepreneurs were not willing to participate and five dropped out in the scheduling process. In the end, we conducted interviews with 11 entrepreneurs from our sample. Table A.1 and Table A.2 provide summary information and statistics for each of these entrepreneurs. We conducted all interviews via Zoom videoconferencing except for one interview conducted via Google Hangouts per the entrepreneur's request. All interviews conducted via Zoom were recorded after obtaining the entrepreneur's verbal consent and transcribed for review. Interviews were conducted between January 29, 2020 and June 24, 2020. The interviews were scheduled for 30 minutes, with most interviews lasting between 30 and 45 minutes.

— Insert Table A.1 Qualitative Interview Sample. —

— Insert Table A.2 Qualitative Interview Sample Summary Statistics. —

Each interview followed a semi-structured format. Interview questions covered a broad range of topics roughly mirroring the topics outlined in our theory, hypothesis development, and supplemental analysis, as well as general background. We asked entrepreneurs: why they decided to launch crowdfunding projects on Kickstarter (and why they stopped); what they learned implementing an earlier project and how that impacted future projects; what their process was for determining the predicted product specification and predicted timeline; what unforeseen challenges they encountered; what they did when they encountered unforeseen challenges, etc.

A.2 Complexity in Crowdfunded Hardware Technology Projects

We provide contextual evidence that: (1) entrepreneurs tend to add multiple features to subsequent projects, and (2) even relatively "low" complexity projects in our sample were still highly complex and required addressing a large number of interdependencies.

A.2.1 Within Entrepreneur: Tendency to Add Multiple Features

Close examination of specific products in our sample make it clear that entrepreneurs generally add multiple features as they advance from project to project, leading to increased complexity across an entrepreneur's hardware technology crowdfunding projects. Continuing from Figure 2, we use the example of Plum Geek Robotics to illustrate this progression across various quantitative and qualitative measures. Figure A.1 presents a detailed breakdown of the product features in Plum Geek Robotics's first and third projects.

— Insert Figure A.1 Plum Geek Robotics Product Features. —

The first project, Ringo Robot, has six colored lights, multi-frequency sound abilities, a light sensor, 360-degree visibility edge sensors, an accelerometer, a gyroscope, etc. By the time the company reached their third project, the Spirit Rover, the product had significantly more features, with a total of 27 colored lights, new computer vision capabilities, retractable gripper arms, wireless network capabilities, etc.

If we consider this example in the language of the NK model (Kauffman, 1995), N increased rapidly from the first to the third project. Based on our oversimplification of the product, we might imagine that N went from 5 to 15 to 35 across three projects. This increase in N is one way that the total number of interdependencies can increase rapidly from project to project.

A.2.2 Across Entrepreneur: "High" Complexity on Different Project Types

The hardware technology projects in our sample generally have high complexity, with both a large number of features and high level of interdependencies. That said, there is certainly variation in both the number of features and the level of interdependencies among those features—particularly when the features are modularized and separate from one another.

Before we highlight our context, we want to start with an extreme example of a type of product that is outside of our sample: board games. Board games are a popular crowdfunded project type, and it would certainly be the case that the printing of a game board is quite modular and separate from the die casting of game tokens. In this example, the entrepreneur would face limited interdependence when executing on the game board and the game tokens, except perhaps when packaging them together in a box, e.g., if the game tokens might scratch the game board in shipping. This example illustrates a product where both components and the level of interdependencies are comparatively low in the scheme of possible projects. However, this board game example is vastly different from the hardware technology projects that we study, where the numbers of components and interdependencies remain high across the different project types.

Figure A.2 shows how complexity can vary across projects in our sample. We highlight two examples from our sample: one project selected to exemplify what a low-complexity project looks like, and another strongly contrasting example of what high complexity looks like.

— INSERT FIGURE A.2 EXAMPLE PRODUCTS BY ENTREPRENEUR OVER TIME. —

Process for Identifying Projects and Complexity To identify these two examples, we systematically reviewed product images and descriptions on the campaign webpages. We isolate that sample to smaller and smaller subsamples based on the following criteria. First, the projects needed to provide enough images of the product to allow for a visual examination of the product. Second, the projects needed to have most of their features observable from the images. Projects which sophisticated internal components were only considered if they provided images of the internal workings of the product. We also excluded projects where most of their capabilities were enabled by embedded software or firmware, which would not be observable to us. The ideal projects were the ones where most of their capabilities were exposed on the exterior of the product. Third, we focused on products where most of their value or innovation came from improvements in the fabrication of a custom circuit board to avoid examples that were not transparent to laypersons. For the projects that meet these criteria, we take discretionary liberties to focus on products that readers of the manuscript could appreciate the value and novelty of. We selected the two projects among that set that had among the least and most complexity based on the process described next. The low-complexity project is the Griffin Pocket Tool XL, a metal multi-purpose tool. The high-complexity project is the Obsidian 3D Printer.

We take a deep dive to document the complexity of these projects in as much detail as possible, describing the exact process that was used and subsequently independently verified by an expert hardware technology entrepreneur. First, as detailed as we can possibly observe from public records, we list out all the possible components or modules that make up the product. One can think of the set of components that generally reflect the feature set of the product. Each of these components is associated with several organizational tasks, which can happen within the focal entrepreneurial firm or by third-party suppliers to the entrepreneur.

We then list out the interdependencies that we know must exist relative to these product components and modules. These are just the ones that we can infer from a best-case scenario of how the product would be manufactured. To be clear, our effort in listing out these interdependencies is subject to the same bounded rationality limitations as the entrepreneur. To be even clearer, we are likely underestimating the total number of interdependencies by a substantial degree relative to the actual entrepreneur who obviously knows more about the product than we do. But the point we want to make is simple: the total number of interdependencies starts getting out of hand very rapidly. We are certain that our examination is incomplete and that we have left many "unforeseen interdependencies" off our list.

Implications of Illustrative Projects From Figure A.2, there are two takeaways. First, the number of components or tasks, even on one of the simplest projects, is legitimately quite high already. Second, and more importantly, this results in an enormous number of interdependencies that need to be addressed, even for the simplest project. This suggests that we should infer that the general level of interdependencies, and even the lowest levels of interdependencies, is indeed quite high, and high enough to allow for interdependencies to increase rapidly as features are added.

A.3 Entrepreneurial Prediction Process

We provide contextual background and supporting evidence for (1) the challenges inherent in making predictions and (2) the practical steps the entrepreneurs take to make these predictions.

A.3.1 What Predictions Entail

Through our qualitative interviews, we sought to understand the details of the prediction process undertaken by entrepreneurs, including the specific steps taken and items considered when predicting the project timeline.

Making predictions in any system with many interdependencies is very difficult. The entrepreneurs in our sample consistently recognize the complexity of the entrepreneurial endeavors they undertake. One noted, "The hardware game is hard. Even if you've been through... so many form factors and production issues, you think you would have perfected it. There is no perfecting manufacturing" (TabletCo CEO). Another highlighted the specific difficulties with launching hardware projects: "Software is very different if something goes wrong. You just push an update on the back end and it's there in the morning. When you're doing hardware and you miss a washer, that's a huge freakin' problem, and you're for sure going to miss a washer sometime" (WidgetsCo CEO).

Our interviews suggest that the main source of prediction difficulty revolves around uncertainty relative to the interdependencies rather than the distinct components. The WidgetsCo CEO knew that the washer was a component of the project, but it was interdependencies with other parts of the project that could lead to the washer's omission that was the source of uncertainty. Entrepreneurs generally know all or most of the components required to complete the project, whereas a large number of the interactions between all the different components are unknown. In the language of the NK model (Kauffman, 1995), we interpret entrepreneurs making predictions in our context as having some reasonable sense for the value of N, but they also recognize that the bulk of the work in execution revolves around K, for which they have a much less accurate sense prior to actually executing the projects.

This is evident in our review of the entrepreneurs' own assessments of uncertainty, as they publicly report as "Risks and Challenges" required for every Kickstarter funding campaign. We review this content for a large set of projects and observe that the top risks that concern entrepreneurs relate to the interdependencies they might face in execution. They know the various components of the project (N) but don't yet know how these components fit together

(K). One entrepreneur writes, "Every single component of this product is well known," but we "only have a 3D-printed prototype right now, and...don't have any experience with injection moulding at this point." Others note interdependencies inherent in "Coordination with multiple manufacturers, with various lead times"; "testing the pre-mass production sample device"; and obtaining "CE, FCC, IC compliance...certificates."

Part of this knowledge around components and uncertainty around interdependencies is true by construction in our setting. Kickstarter requires all entrepreneurs to have a working prototype. As a result, the entrepreneurs are already aware of the various components needed to produce the product. The complexity lies in the interdependencies that may not have surfaced when making the prototype: "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).

A.3.2 How Predictions Are Made

Based on our qualitative interviews, we find that entrepreneurs generally make predictions by breaking down the project into specific tasks, making predictions relative to each specific task, and then aggregating the task-level predictions to the project level. CircuitsCo CEO described how, "I just took basically all the things I knew would take time—like waiting for Kickstarter to wire the money, manufacturing, shipping-—and I added all of them together." 3DPrintCo CEO detailed a similar process for making the timeline prediction: "We've got a lot of experience in manufacturing. So it was a matter of understanding what our supply chain would look like and understanding how our product design could deviate from the design that we launched with so that whatever unforeseen challenges we may have faced we could have accomplished or overcome those challenges with deviations in our plan. So we tried to create basically a risk mitigation program for the possible design variations that we would have expected."

Our interviews also support the notion that entrepreneurs are making these predictions for execution that follows a local search (Sommer & Loch, 2004). AccessoryCo CEO emphasized how his execution involved sequentially changing "one component after another" and "one iteration" at a time. For example, he first changed "the quality of the plastic, then the color of the plastic, ... then the adhesive tape." This local search execution process is complementary to the process of aggregating the individual, step-by-step task-level predictions to the project level.

Once entrepreneurs determine their best project-level prediction, they seem to systematically "pad" their timelines with extra time as a precaution. CircuitsCo CEO said he usually "added like a month of buffer or something" and TabletCo CEO said he urges other entrepreneurs, "Don't be too aggressive...definitely build in like two or three months extra." This sentiment is echoed by WidgetsCo CEO who said, "Obviously, things go wrong. So another thing I do is I take my timeline and I add 30% to it. I don't care what it is because you're going to fuck it up so yeah. So that's my rule for financial modeling and project modeling. Always add 30% because something's gonna go wrong."

As detailed in Appendix Section A.10, we find no evidence that the prediction process for delivery timelines involves social comparison or competitive benchmarking with or against other entrepreneurs.

A.4 Data Collection

A.4.1 Features Rank

To collect the *Features Rank* variable, we hired five independent reviewers to rank each entrepreneur's projects by the number of features.[a] We made two separate efforts to make sure this data generation process would be fruitful. First, to ensure a potential reviewer could handle what was asked of them, we carefully selected among reviewers to make sure they met a general qualification level. We sought out individuals with educational and professional experience in fields relevant to understanding and evaluating hardware products. Second, given that the projects span a relatively diverse set of product subtypes—although limited to only hardware products—it was important that we bring in a diverse set of reviewers such that, for any given project, the majority of reviewers would be qualified to make an assessment. We sought out reviewers of different genders and generations to obtain a balanced perspective. Table A.3 summarizes the backgrounds of the reviewers.

[a]The reviewers also ranked the projects according to technical sophistication, which is closely correlated to number of features.

— Insert Table A.3 Project Reviewer Backgrounds. —

Each reviewer reviewed the photographs and product descriptions of each project by the same entrepreneur. We provided the reviewers with an Excel document containing sets of projects grouped by entrepreneur. The order of the projects within each entrepreneur group was randomized. The reviewers opened the links for the Kickstarter project page for each of the projects in the entrepreneur group. They then assigned a rank to each of the projects by the same entrepreneur. Even when projects seemed almost identical or very similar, we required the reviewers to force a ranking between all projects. Each reviewer repeated this process for all the groups of projects by the same entrepreneur.

We aggregate the rankings across the reviewers. In the case of disagreement between reviewers, we take the average rank between the two reviewers and then re-rank the projects based on the averaged scores. We allow for ties (which only occur in the case of conflicting rankings). Given that we force a ranking even when projects are nearly identical or very similar, this means that rank assignment is close to random in those circumstances. As a result, we expect some disagreement between reviewer rankings. This design gives more weight to the rankings that are more clear-cut and less weight to the rankings that are more ambiguous. If two projects tie for the most features, the binary indicator turns on for both projects, which washes out with the inclusion of entrepreneur fixed effects.[b]

A.4.2 Delay Duration and Actual Time

To collect the actual shipment date for all the projects in our sample, we hired two contractors on UpWork.[c] We provided them with an Excel file containing a link to each project and a row for each of the rewards associated with that project. The contractor followed the link to the

[b]For example, if an entrepreneur has two total projects and the two reviewers disagree on which of the two projects has more features, then both projects would have an average rank of 1.5 (being rated as 1 by one reviewer and 2 by the other). After re-ranking based on these average scores, both of the entrepreneur's projects would have a 1 for *Features Most*. Because we include entrepreneur fixed effects in the regression, this entrepreneur would show no change across projects. As a result, in our model the variation in number of features across an entrepreneur's subsequent projects is driven by the projects where the ranking between projects is clearer and more objective and is not driven by the projects where the ranking is ambiguous.

[c]We use the date shipped as opposed to the date the product arrived on the customer's doorstep. Shipment date is more standardized and consistent across all projects regardless of customer location. There are also generally only one or two shipment dates per project as opposed to many more unique dates when the backers receive the reward. And, as a practical matter, the data on when customers receive rewards is much sparser and more inconsistent than the data on when the rewards ship.

project page and read through the updates and comments to record (at the individual reward level) the date on which the reward first began to ship, the date on which all the rewards were shipped, whether it was apparent that the reward had still not shipped, or whether there was no mention of shipping. Across the 722 projects in our sample, there are 7,019 different rewards with an average of 9.7 rewards per project. We exclude the $1 cash donation reward option included on most projects as well as rewards that were not backed. We were able to identify the date the reward started shipping for 71% of rewards and the date the reward finished shipping for 49% of rewards.

At the reward level, we take the later of the date the reward first shipped and the date the reward finished shipping. We take the later date because the entrepreneur's prediction is for the date all rewards will be delivered, not when the entrepreneur would deliver the first reward. This allows us to measure the actual shipment date for 80% of all rewards in our sample (which includes all rewards that list either the date the reward first shipped or the date the reward finished shipping). The actual delivery date has a day, month, and year whereas the predicted delivery date is just a month and a year. To be conservative, the delay for each reward is computed as the difference between the actual shipment date and the first day of the month after the month of the predicted delivery date. We then aggregate this reward-level data to the project level to compute the *Delay Duration* by taking the mean delay of all the rewards in each project. This same method of aggregating from the reward level to the project level is used for *Predicted Time*. The results are almost identical if we use the median. Using this approach we are able to measure the *Delay Indicator* for 89% of projects in the sample. This includes all projects with shipment information for at least one reward in the project.

A.4.3 External Funding

To define our *External Funding* control variable, we collect data on venture financing from Crunchbase. We hired an RA to search both the entrepreneur name and the company name (if available) for each project to look for any matches on Crunchbase. For those entrepreneurs with a Crunchbase page, we collected data on each fundraising round (excluding those classified as crowdfunding, which would reflect the Kickstarter projects). This binary indicator turns on if the date the project launched comes after the date the entrepreneur of that project raised external capital from another source. The results do not change in any substantive way if we use the cumulative number of external funding rounds instead of this binary indicator.

A.5 Variable Distributions

A.5.1 Quantile Summary Statistics

For transparency and clarity, we supplement the summary statistics provided in Table 1. Table A.4 includes the 0%, 25%, 50%, 75%, and 100% quantiles for each independent variable used in analysis.

— Insert Table A.4 Variable Quantiles. —

A.5.2 Distribution Visualization

In addition, we include a visualization of the distribution of the variables. Figure A.3 contains plots of the distribution of each independent variables used in analysis. Density plots are used for continuous measures, and histograms are used for measures that fall into a small number of finite values or categories.

— Insert Figure A.3 Variable Distributions. —

A.6 Unforeseen Interdependencies Alternative

We find that all results hold if, instead of using *Unforeseen Interdependencies*, we define a new variable, *Alternative Unforeseen Interdependencies*, which is equal to the count of updates that contain words from *both* sets of relevant words. As shown in Table A.5, we find that this alternative definition of *Alternative Unforeseen Interdependencies* ($p \sim 0.002$) is still positively related to *Project Experience*. On each subsequent project, entrepreneurs disclose encountering 0.114 additional unforeseen interdependencies that contain references to both being unforeseen and dealing with interdependencies. Using this alternative definition, *Ln Alternative Unforeseen Interdependencies* ($p = 0.001$) also positively associates with *Project Experience*. Each subsequent project increases unforeseen interdependencies by 6.4%. The effect size is smaller using this alternative definition given that requiring updates to contain words from both sets is a stricter criterion than including updates with words from either set and, as a result, fewer total updates meet this criterion.

— Insert Table A.5 Unforeseen Interdependencies Alternative. —

A.7 Increasing Features, Unforeseen Interdependencies, and Delay

We first test the assumption that, as more features are added to a project, the unforeseen interdependencies will increase, showing a positive relationship between an increase in the number of features and an increase in unforeseen interdependencies.

We define *Features Increase* as a binary indicator of whether the entrepreneurs add more features for their next projects, which is equal to 1 if the current project has more features than the prior project and 0 otherwise. We use *Features Increase* as the main independent variable for this analysis and look at the relationship between it and three different measures of whether the unforeseen interdependencies will increase as dependent variables. *Unforeseen Interdependencies Increase Binary* is a binary indicator equal to 1 if the current project has more updates related to unforeseen interdependencies than the prior project. *Unforeseen Interdependencies Increase Count* is equal to the number of additional updates related to unforeseen interdependencies than the prior project. *Unforeseen Interdependencies Increase IHS* takes the inverse hyperbolic spline of *Unforeseen Interdependencies Increase Count* in order to account for any potential non-linearities in the relationship and to reduce the impact of any outliers. We find a significant and positive relationship between *Features Increase* and each of our three measures of increasing unforeseen interdependencies. If features are added to the project, the project is 27% more likely to have more unforeseen interdependencies than the prior project or on an absolute basis will encounter 1.721 more unforeseen interdependencies (an increase of 0.735 when taking the inverse hyperbolic spline).

We then test the assumption that, as more features are added to a project, the delay will increase, showing a positive relationship between an increase in the number of features and an increase in delay. We use the same independent variable, *Features Increase*, as defined above. We look at the relationship between this independent variable and two measures of delay, *Delay Indicator* and *Delay Duration* as defined in the main paper. We use all the same controls and fixed effects as specified in the main paper. We find that, if features are added to a project, that project is 9.4% more likely to be delayed and, on average, will be delayed by 18.298 additional days.

A.8 Non-Linear Effect of Experience

We find empirical evidence for a faster-than-linear increase in unforeseen interdependencies and delay duration. This empirical evidence suggests that we more than meet the minimum set of assumptions required by our theory, e.g., the project complexity curve increases faster than a concave learning curve. Figure 4 of the main manuscript is the visual representation of the estimates from the regression models we describe next.

We considered several econometric models—including those that specify a specific functional form of the relationship—but we decided that it would be best to remain agnostic to functional form. Instead, we construct a series of indicator variables representing different levels of *Project Experience* that allow us to flexibly and non-parametrically identify the relationship. This type of specification allows the functional form to "reveal" itself to us without us having to pre-specify its exact shape.

In place of *Project Experience*, we include a set of indicator variables. *Project Experience: Second* takes a value of 1 if the focal project is the entrepreneur's second project, and 0 otherwise. *Project Experience: Third* and *Project Experience: Fourth or More* follow similarly. We group together experience for entrepreneurs on their fourth or later project because the number of observations on these higher levels of experience is quite sparse and thus noisy; the observed pattern of statistically significant results is robust to the exclusion of projects that are the entrepreneur's fifth or later project. Since we omit the indicator for an entrepreneur's first project (zero experience), all coefficients on these three indicators should be interpreted as relative to the scenario of the entrepreneur's first project. Table 3 and Table 4 are replicated in Table A.6 and Table A.7, respectively, swapping out *Project Experience* for this set of indicator variables.

— Insert Table A.6 Non-Linear Analysis of Complexity and Unforeseen Interdependencies. —

— Insert Table A.7 Non-Linear Analysis of Delivery and Delay. —

We outline the effects for a subset of the key variables here, with the full results shown in the regression tables.

A.8.1 Features

All relative to the entrepreneur's first project, the average entrepreneur's second project has 0.417 higher feature rank, the third project has an average of 0.541 higher feature rank, and the fourth or later project has 1.468 higher feature rank. To give an idea of the comparison across projects, we can look at the difference between these coefficient values, with the second project having a feature rank 0.417 higher than the first project, the third project having a feature rank 0.124 higher than the second project, and the fourth or later project having a feature rank 0.927 higher than the third project. We also look at the same interpretation for unforeseen interdependencies.

A.8.2 Unforeseen Interdependencies

All relative to the entrepreneur's first project, the average entrepreneur's second project encounters 1.457 more unforeseen interdependencies, the third project encounters an average of 2.721 more unforeseen interdependencies, and the fourth or later project encounters 4.116 more unforeseen interdependencies. To give an idea of the comparison across projects, we can look at the difference between these coefficient values, with the second project encountering 1.457 more unforeseen interdependencies than the first project, the third project encountering 1.264 more unforeseen interdependencies than the second project, and the fourth or later project encountering 1.395 more unforeseen interdependencies than the third project.

A.8.3 Delay Duration

All relative to the entrepreneur's first project, the average entrepreneur's second project is delayed by an additional 44.858 days, the third project is delayed by an additional 75.369 days, and the fourth or later project is delayed by an additional 145.106 days. To give an idea of the comparison across projects, we can look at the difference between these coefficient values, with the second project delayed by 44.858 more days than the first project, the third project delayed by 30.511 more days than the second project, and the fourth or later project delayed by 69.737 more days than the third project.

Furthermore, to provide readers with more intuition on the holistic pattern implied by the above regression estimates, we generate a visualization of the estimates for the effect of various levels of project experience on *Actual Time* and *Predicted Time*. In some sense, these variables intuitively map to actual project complexity and predicted project complexity curves, respectively. Figure 4 of the main manuscript plots the coefficients, with the project number on the horizontal axis and the *Actual Time* and *Predicted Time* (both in days) on the vertical axes.[d] 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.

A.9 Prior Campaign Funding and Behavior

A.9.1 Theoretical Background

We explore in depth whether prior campaign funding outcomes impact an entrepreneur's behavior on subsequent projects. We do not intend to make any groundbreaking theoretical claims on this point: our primary goal is to make sure we properly account for and apply classic behavioral theory on performance feedback and outcome–aspiration gaps (Cyert & March, 1963; Greve, 1998). We apply this theory to product introductions (Joseph & Gaba, 2015). In short, we consider the theoretical argument that when an entrepreneur suffers from an outcome–aspiration gap in their prior experience—specifically, they suffer from a failed funding campaign on the previous project—the entrepreneur would have higher risk tolerance and engage in problemistic search on the next project (Greve, 2003). Assuming that this feedback is sufficiently unambiguous to trigger the entrepreneur to respond (Joseph & Gaba, 2015), the entrepreneur would take on a project that has a greater likelihood of unforeseen complexity that could delay the project. As shown in Figure A.4, this relationship can be visualized as a "V", where the outcome–aspiration gap is on the x-axis and the accuracy of strategic foresight is on the y-axis. This "V" shape would manifest if these were a linear relationship; however, if the relationship is non-linear, we would see more of a "U" shape, which is also included in the visualization.

—– Insert Figure A.4 Outcome–Aspiration Gap and Accuracy of

[d] To set the level of the omitted coefficient of the entrepreneur's first project—–and thus the level of all the estimates as they are relative to that baseline—–we calculate the mean value of each variable used in the regression and multiply that average value by the corresponding coefficient. We sum those values and then add the mean entrepreneur fixed effect.

Strategic Foresight. —

Recent research adds additional nuance to the theory that would strengthen the argument. Keum & Eggers (2018) argue that mangers would set more aggressive aspirations, like on project complexity and timeline, when facing increased pressure to acquire resources, like if they feared missing funding targets on the next project because they missed them on the prior project. Eggers & Kaul (2018) argue that firms over-invest in radical invention when performance is moderately below aspiration, whereas in our setting a radical invention would be a radical departure from their previous project (which would add a lot of new complexity).

A.9.2 Empirical Context

Turning to our specific empirical context, it is quite rare for these serial-project entrepreneurs to fail in their fundraising efforts. Of the 314 entrepreneurs who completed successful projects in our sample, only 33 entrepreneurs had previously run a failed funding campaign (10.5% of entrepreneurs), with 42 failed funding campaigns total out of 782 total funding campaigns (5.4% of funding campaigns). At a project level, our level of analysis, only 36 (5.0%) out of 722 projects in our sample (i.e., the successful projects) had a failed funding campaign of the same product subtype immediately prior to the focal project. In comparison, Kickstarter reports that 61.6% of all projects fail in their funding campaigns, and specifically 79.0% of technology projects (where our sample originates) fail in their funding campaigns.[e]

Clearly, there is a compositional difference between our sample of projects and entrepreneurs and the universe present on Kickstarter. First, we study serial-project entrepreneurs, a more professional set of entrepreneurs who tend to treat their projects as full-time jobs; in many cases, there are entrepreneurial firms behind the effort. Second, we focus on technical hardware product categories, of which there might be more consumer interest and that may have a higher barrier to entry, i.e., it takes a significant amount of effort to even create the prototype that gets presented on the fundraising page.

Thus, our sample of entrepreneurs may not be the best sample on which to study the implications of prior funding failure as a general phenomenon. Nevertheless, we proceed with an empirical exploration that accounts for this past project funding failure (and success).

[e]https ://www.kickstarter.com/help/stats, accessed December 2020.

A.9.3 Variables

As the main independent variable capturing the outcome–aspiration gap, we use *Prior Campaign Funding Deviation*, which is equal to the percentage by which the prior funding campaign exceeded (or missed) its funding goal. Values of *Prior Campaign Funding Deviation* less than 0 occur when the entrepreneur failed to meet her prior campaign's funding threshold, and greater than or equal to 0 occur when the entrepreneur succeeded. We interact *Prior Campaign Funding Deviation* with an indicator variable *Prior Campaign Funding Success* that takes a value of 1 if *Prior Campaign Funding Deviation* is greater than or equal to 0, and 0 otherwise. This interaction term allows us to estimate separate slopes for the two halves of the "V" shape outlined in the theoretical background.

A.9.4 Statistical Model

We need to also consider that the effect of performance feedback may be heterogeneous and non-linear, e.g., greater degrees of success or failure have a greater effect size per unit of deviation than success or failure that is close to the aspiration level. In other words, a U-shaped relationship rather than a V-shaped relationship. Thus, we also test a model that enters in a quadratic term for *Prior Campaign Funding Deviation*, and we interact both the base term and the quadratic term with *Prior Campaign Funding Success* to allow estimates of different "curves" above and below the aspiration level. In theory, this would allow us to estimate the two halves of a theoretical "U."

A.9.5 Descriptive Visualization

Before we turn to the regression analysis, we generate descriptive plots of the relationship between *Prior Campaign Funding Deviation* and our two main measures of performance: (i) *Delay Percent* (defined as *Delay Duration* divided by *Predicted Time*) and (ii) *Unforeseen Interdependencies*. When generating the plots, we exclude outliers for clarity in visualization, but all trends and interpretations hold when including outliers. Examining these plots in Figure A.5 and Figure A.6, we see similar trends in both plots, with a positive slope where *Prior Campaign Funding Deviation* is less than zero (though with a very wide confidence interval given the very limited number of observations) and a flat or very slightly increasing trend where *Prior Campaign Funding Deviation* is greater than zero (though again with an increasingly wide confidence interval moving away from the bulk of the data).

— Insert Figure A.5 Deviation and Delay. —

— Insert Figure A.6 Deviation and Unforeseen Interdependencies. —

A.9.6 Results

Table A.8 shows this relationship when including controls and fixed effects. Given the focus on the lagged funding deviation, we exclude first projects where there is no defined lagged funding deviation. As a result, we also exclude entrepreneur fixed effects which are not appropriate for entrepreneurs with only a single project after their first project, leaving no variation within the entrepreneur's set of projects. As suggested by the visual evidence, we do not observe any significant relationship between *Prior Campaign Funding Deviation* and *Delay Percent* or *Unforeseen Interdependencies*. The directionality of the point estimates matches the visual evidence, with a positive coefficient on *Prior Campaign Funding Deviation*, suggesting a positive slope when *Prior Campaign Funding Success* is equal to zero (the area to the left of zero on the plots) and then a flat slope when *Prior Campaign Funding Success* is equal to one and the coefficients are summed to give a slope around zero. We also find no significant relationships when including a quadratic term.

— Insert Table A.8 Deviation and Unforeseen Interdependencies. —

Given the small sample size of projects that missed their funding goal, we are limited in our ability to interpret the trend where *Prior Campaign Funding Success* is equal to zero. We do have ample data where *Prior Campaign Funding Success* is greater than zero, but again we find no significant relationship. One possible explanation is that the impact of deviation from the funding target on the prior project is overshadowed by the impact of deviation from the funding target on the current project (which is included as a control). Another possible explanation is that *Delay Percent* and *Unforeseen Interdependencies* are both measures of execution and are therefore one step removed from the impacts of fundraising outcomes.

A.10 Social Comparison

We seek to address potential ambiguity around what could be driving prediction failure in this setting. If the entrepreneur believes that setting a delivery timeline comparable to her peers is important to fundraising, the prediction failures could be interpreted as a matter of entrepreneurs socially informed about their competitive context. To test, and ultimately rule out, this alternative explanation, we define the entrepreneur's peer group and then empirically test the impact of the peer group on the entrepreneur's predicted time as well as the impact of deviation from the peer group on ability to fundraise.

A.10.1 Defining Entrepreneur Peer Group

We consider two dimensions when defining an entrepreneur's peer group that may impact their behavior through social comparison. First, we define a set of comparable projects the entrepreneur could reasonably view as competition. At a reductive level, all Kickstarter projects that are soliciting the same dollars are in competition. The most competitive set of projects seem to be those within same product subtype, e.g., 3D printing, camera equipment, wearables. The key assumption we make here is that the entrepreneur perceives that she is competing with those projects, based on our assumption of the entrepreneur's assumption that her customers navigate and search through Kickstarter by product subtype. That said, based on our interviews, entrepreneurs do not seem to view competition for crowdfunding as a zero-sum game, given that the vast majority of customer spending is not on Kickstarter projects and that many backers find their way directly to a project without navigating through the Kickstarter platform, e.g., by a direct link from an organic social media campaign or direct-response online advertising.

Second, we define a time window during which the entrepreneur could reasonably have taken into account comparable projects prior to specifying her prediction for her own product specification and delivery date. As first order, we should only include projects prior to the launch of the focal campaign. We decided to include only peer projects that successfully completed their funding prior to the focal campaign; it seems unlikely the entrepreneur would benchmark herself against failed funding campaigns. In addition, intuitively it seems unlikely the entrepreneur would search deeply into the distant past to benchmark herself: more recent projects likely matter more since they reflect the current state of the market the entrepreneur would face. We set a threshold of one year, meaning that we only include peer funding campaigns launched within one year of the focal campaign. In summary, we specify the entrepreneur's peer group as the projects within the last year by other entrepreneurs in the sample that successfully met their funding threshold.

A.10.2 Setting Delivery Time

We consider whether the peer group timeline has an effect on the predicted timeline set by the entrepreneur. The dependent variable *Predicted Time* is the time in days between the end of the fundraising campaign and the predicted delivery date. Using the definition of the peer group previously explained, the main independent variable *Peer Group Predicted Time* is the average *Predicted Time* across all projects in the focal project's peer group.[f]

Results As shown in Table A.9, we find no statistically significant relationship between *Peer Group Predicted Time* and *Predicted Time*. The coefficient and statistical significance of *Project Experience* remains consistent. These findings align with our understanding of how entrepreneurs in our study actually set their project timelines, based on our qualitative interviews. To summarize our understanding of this process, which is outlined in more detail in Appendix Section A.3, entrepreneurs seem to be giving their best estimate of how long they believe the project will actually take—summing the estimated time for each project component—and then adding some buffer time on top of their best guess at the predicted time. No entrepreneur in any of our interviews mentioned benchmarking their predicted time against the predicted time of other projects, or trying to game the predicted time in any other way.

— Insert Table A.9 Predicted Time and Peer Group Comparison. —

A.10.3 Incentive Alignment

We also explore whether the difference between an entrepreneur's predicted time from the average predicted timeline of other comparable projects impacts the amount of money the entrepreneur is able to raise. If estimating a shorter predicted time has pecuniary benefits in the fundraising process, entrepreneurs would be incentivized to benchmark against their peer projects. If this is not the case, that would imply that exceeding the funding threshold would not rely on benchmarking against a social comparison.

[f] For example, one entrepreneur in the sample launched a hardware project on October 11, 2018. His peer group contains all hardware projects launched prior to October 11, 2018 but after October 11, 2017 (one year prior). This defines a set of 11 projects with predicted times ranging from 10 days to 149 days. Taking the average predicted time across all 11 projects gives a *Peer Group Predicted Time* of 89 days.

In this analysis, and as alluded to above, the main independent variable *Peer Group Deviation* is the difference between the *Predicted Time* of the focal project and the *Peer Group Predicted Time* of the focal project. We examine the relationship between *Peer Group Deviation* and two measures of exceeding the funding threshold. *Funding Exceeded* is equal to dollars raised in the focal project in excess of the *Funding Threshold*. *Funding Positive Deviation* is the percentage by which the funding threshold was exceeded, equal to *Funding Exceeded* divided by *Funding Threshold*. Because *Funding Threshold* is used in the derivation of both *Funding Exceeded* and *Funding Positive Deviation*, we include regressions including and excluding it as a control.

Results As shown in Table A.10, we see a mixture of significant and insignificant relationships between *Peer Group Deviation* and our measures of exceeding the funding threshold. However, in the cases where the result is significant, the value is small and positive. This would suggest that entrepreneurs would be incentivized to give themselves slightly more time than the average among their peers, which is the exact opposite of the narrative that increasing delays are due to pressure to predict shorter delivery times relative to the peer group. Together, these regressions provide insignificant or contradictory evidence of the alternative explanation.

— INSERT TABLE A.10 FUNDING AND PEER GROUP COMPARISON. —

While entrepreneurs are incentivized to maximize funds raised, they also recognize and experience real pecuniary consequences for failing to meet their predicted time, as outlined in Appendix Section A.11. As a result, even if there were some benefits to predicting shorter delivery times, entrepreneurs that we interviewed seemed unwilling to make the tradeoff of estimating a shorter delivery time now with the expectation to need to delay later. For example, one notes that, "Whatever goodwill you built up beforehand, it's like so discounted by the time you have to announce delays" (TabletCo CEO).

A.11 Learning That Delay Is "Acceptable"

To test whether entrepreneurs could learn that a delay is acceptable, we need to test whether entrepreneurs face consequences for delay. Li & Martin (2019) study this exact question in the Kickstarter context. Specifically, they look at the impact of failing to meet predictions on the entrepreneur's reputation and subsequent ability to raise money. Importantly, they find that, all else equal, if an entrepreneur defaults on what they promised, the probability that they reach their funding goal on their subsequent project drops by 50%. The key mechanism for reputation formation is the project comments left by investors. As a result, they conclude that "entrepreneurs likely have incentives to deliver the product or service they promised as long as the backers have the ability to provide product/service feedback to the public."

Given that public comments are a demonstrated mechanism for reputation formation and, as a result, present real, pecuniary consequences to the entrepreneur, we empirically measure the relationship between delay and public comments in our sample. Specifically, we find a positive relationship between *Delay Duration* and both *Total Comments* ($p \sim 0.002$) and *Negative Comments* ($p = 0.000$). To calculate comment sentiment, we use a standard R package (Rinker, 2019) to calculate the sentiment of each of the most recent 100 project comments (excluding comments by the entrepreneur). We then sum the number of negative comments for each project. As summarized in Table A.11, for each additional day of delay, there are 1.7 additional comments and the number of negative comments increases by 0.016. This suggests that entrepreneurs do experience consequences when they delay and are, therefore, incentivized to deliver on time. In addition, to allow for the possible moderating effect of *Project Experience* on the effect of *Delay Duration* on the *Negative Comments* generated by customers, we also include a model with an interaction term for *Delay Duration* and *Project Experience*. We find that the interaction term has a significant and positive coefficient. Overall, we find no evidence, in terms of their public feedback, that customers are less concerned with a project delay because the entrepreneur is more experienced. In fact, the customers seem to penalize the entrepreneur with more negative comments on the entrepreneur's subsequent projects.

— Insert Table A.11 Consequences of Delay. —

However, it could be the case that customers are more lenient towards delay for projects with more features. If this is the case, and the entrepreneur becomes aware of this fact as they gain experience, they may learn that delay is acceptable particularly for projects with more features. To test whether this is the case, we analyze the relationship between number of negative comments (*Negative Comments*) and the complexity of the product in terms of features: *Features Most*, *Features Rank*, *Features Percentile*. We include models both with standalone terms for these measures of features as well as a model for each features measure interacted with *Delay Duration*, with the dependent variable of *Negative Comments*. Note that *Negative Comments* are roughly proportional to *Delay Duration*, given that there is more time for customers to enter negative feedback the longer the delay (in a hazard model sense) and that longer delays would of course agitate customers more. We interact the measures of features with *Delay Duration* to explore whether there is any heterogeneity in the possible customer leniency mechanism, e.g., the interaction term would be significant and negative if, at higher levels of product complexity, the customers made fewer *Negative Comments*, particularly under longer *Delay Duration* situations. As reported in Table A.12, we find that the interaction term between *Delay Duration* and all three measures of features is insignificant, as well as negligibly small.

— INSERT TABLE A.12 FEATURES AND NEGATIVE COMMENTS. —

Our interviews with entrepreneurs confirm these findings. One entrepreneur notes, "There is definitely some pressure to deliver things on time...There definitely is pressure making sure things are right, making sure you don't have to take additional steps" (CircuitsCo CEO). And entrepreneurs do believe that there are consequences to delay: "[When a project gets delayed,] people really bash the product on review channels and pages and the comments section" (TabletCo CEO). Or, in the words of another, "[When a project gets delayed,] you get angry people. For us, image and branding is the most important thing, and you want to strive to deliver a really good product....and it does hurt your image when people are saying you're delayed" (GPSCo CEO).

As an additional test for whether entrepreneurs continue to care about their image and the impact of negative comments (which are driven by delays), we look at whether entrepreneurs reduce the effort and care they put into customers over time. Specifically, we define a new variable, *Creator Engagement*, which is the total word count of the updates and comments posted by the entrepreneur on a given project. As shown in Table A.13, we find that there is a significant and positive relationship between *Creator Engagement* and *Project Experience*, indicating that entrepreneurs are posting and engaging with their backers more on each subsequent project. This suggests that there is no evidence in terms of their public engagement that entrepreneurs are less concerned with pleasing their customer base and defending their public reputation. In fact, the empirical evidence in our setting suggests the opposite. Again, the qualitative evidence aligns. TabletCo CEO described how even on his most recent project, he would "have people monitor the customer comments around the clock...to feed into consumer confidence."

— Insert Table A.13 Creator Engagement. —

A.12 Incentive to Overpromise

Despite facing consequences for delay, it could be the case that the ex post consequences are offset by ex ante benefits. While making unrealistic predictions likely leads to negative consequences down the road when entrepreneurs fail to meet those predictions, if making aggressive predictions is helpful in the fundraising process entrepreneurs may still be incentivized to overpromise. We construct dependent variables for the amount of money raised in total and the amount of money raised in excess of the fundraising goal. We regress these dependent variables on an independent variable of the predicted delivery time. If there was a benefit to overpromising, we would expect to see a negative relationship here, with an increase in promised delivery time decreasing the amount of funds raised. As shown in Table A.14, we do not find a statistically significant relationship, suggesting that there is no general incentive to make unrealistic predictions for the sake of upfront financing.[g] This is of course peculiar given the assumed desire of customers to get their products faster, but customers may mentally discount aggressive delivery times because they know they are unrealistic and thus not place any value on them. Overall, we contend that overpromising aggressive delivery times is not the major driver of the main findings.

— Insert Table A.14 Incentive to Overpromise. —

[g] We recognize that the product specification is likely correlated with both the predicted time and the funds raised (e.g., really fancy product specifications have longer predicted times, but also raise more money). We include *Features Most* in the regression to try to serve as a proxy for the product specification; however, given that this is an imprecise measure of product specification there is likely still some omitted variable bias. The results are similar if we include *Features Ranks* or *Features Percentile* as controls.

A.13 Exiting After VC Financing

We then turn to whether certain types of entrepreneurs are exiting our sample, looking first at whether entrepreneurs are more likely to exit the sample after raising external capital from another source (generally an indicator of higher quality or ability). We test whether high-quality entrepreneurs might exit the sample. In particular, we test the assumption that these higher-quality entrepreneurs may desire and be able to raise venture capital financing and leave crowdfunding. We define a binary indicator of whether the entrepreneur goes on to do a subsequent project as the dependent variable. For projects completed towards the end of our sample timeline, it is unclear whether the entrepreneur has truly exited the sample or is in the process of preparing another campaign. As such, we drop the projects from the last year of our sample when performing this analysis. We then regress the binary indicator of going on to do a subsequent project on a binary indicator of whether the entrepreneur has raised external capital at that time. As shown in Table A.15, we find that raising venture funding does not impact whether entrepreneurs exit the sample or continue on and do another Kickstarter project.

— INSERT TABLE A.15 EXITING AFTER VC FINANCING. —

A.14 Exiting After Delay

We now evaluate whether entrepreneurs disproportionately exit the sample after they delay, which might suggest that entrepreneurs who learn leave while those who do not learn stay. Using the same dependent variable of whether the entrepreneur goes on to do another project and the same sample as the prior section, we regress this indicator of going on to do another project on the delay duration of the current project and do not find a significant effect. This result is shown in Table A.16. As an additional check, we also looked at the distribution of the difference in delay between the second project of entrepreneurs who went on to do a third project matched with the most similar second project by an entrepreneur who did not go on to do a third project. If entrepreneurs left the sample after they delayed, we would expect to see a distribution skewed toward negative values (implying that the second project delay of those who went on to do a third project is smaller than the second project delay of those who exited the sample after two projects). However, we see a roughly normal distribution centered around zero.

— Insert Table A.16 Exiting After Delay. —

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Ringo Robot　　　　　　Spirit Rover

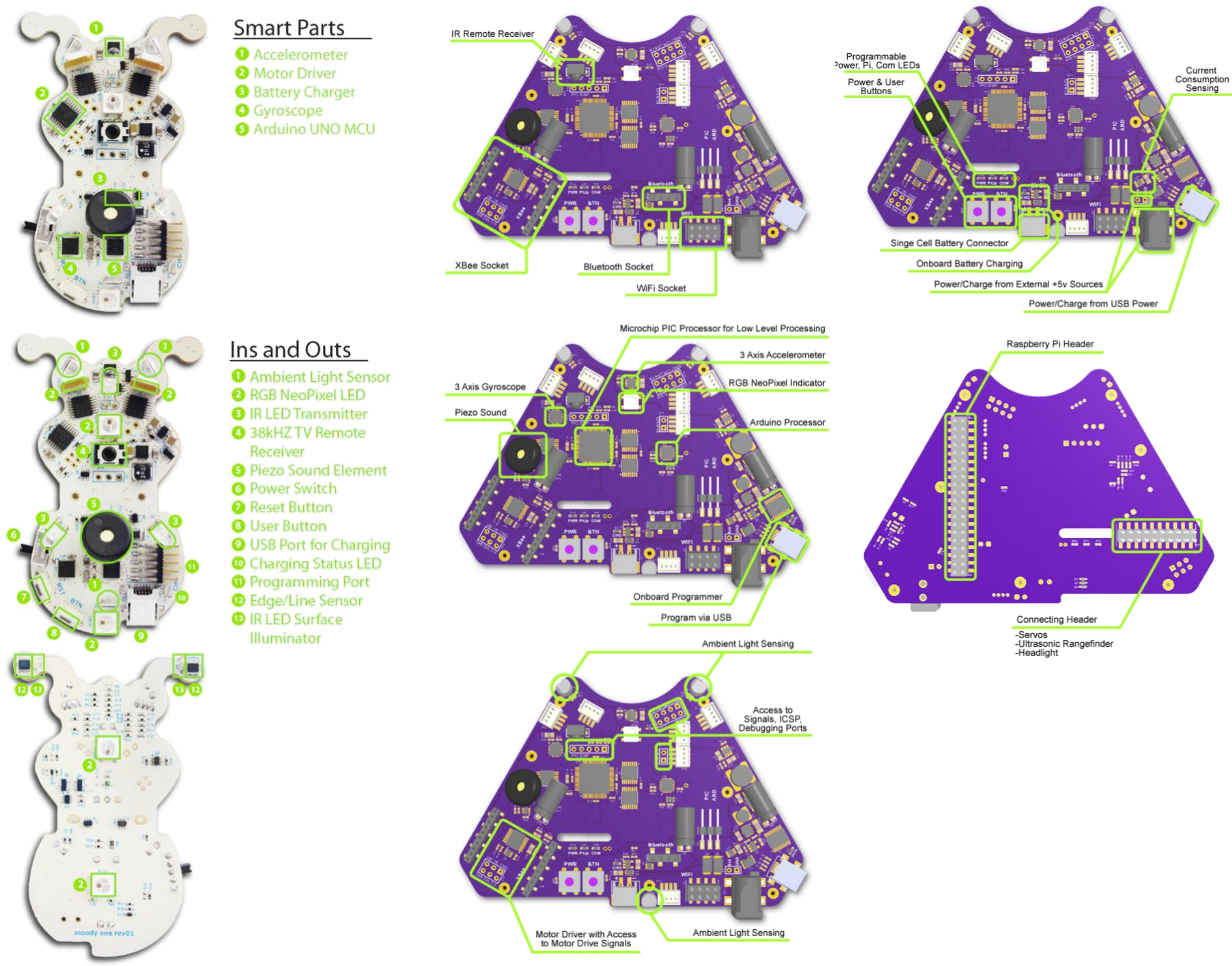
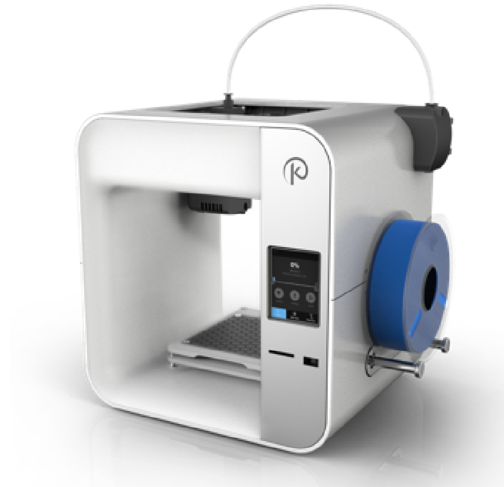


Figure A.1: Plum Geek Robotics Product Features. Reproduction of breakdowns of product features provided by Plum Geek Robotics on its company website. Ringo Robot was its first Kickstarter project, launched on February 25, 2015. The Spirit Rover was its third project, launched on September 28, 2016.

Low Complexity	**High Complexity**
	

Components	**Components**
Metal casing	Nozzle
Left bevel	Printing bed
Wrench cutout	Heating apparatus
Written measurements	Camera
	LED lights
	Color touchscreen
	Bearing spool holder
	Casing
	Power cords
	Circuit board
	Software operating system

Interdependencies to be Addressed	**Interdependencies to be Addressed**
Metal casing dimensions match specified measurements.	*Only subset included for heating apparatus, bearing spool holder, and casing.*
Metal casing will fit in the machine that adds the measurements.	Power supply is sufficient for heating apparatus, camera, LEDs, touch screen, etc.
Writing color will show up and adhere to the metal surface.	Bearing spool holder can hold weight of spool and remains balanced with added weight.
Separate machine can accommodate metal casing to add left bevel.	Heating mechanism does not impair function of screen or other electronics.
Separate machine can accommodate metal casing to add wrench hole.	Heating apparatus creates correct temperature for input material.
Intended functions of the metal casing are not impaired by cutout wrench hole.	Casing accommodates LED lights, printing bed, nozzle, touch screen, etc.
Upper ruler cutout does not fall off or weaken the tool's structural integrity.	Casing provides appropriate spacing between camera and printing bed for optimal focus.
	Casing allows nozzle sufficient range of motion when printing.
	Bearing spool holder fits the input material.
	Bearing spool holder attaches to casing.

Figure A.2: Project Complexity Examples. Selected projects from sample to illustrate a typical "low" complexity and "high" complexity project. *Components* (or modules) and *Interdependencies to be Addressed* represent only those confirmed by the researchers and likely constitute only a subset of those actually faced by the entrepreneurs. In the context of the NK model, the separate *components* represent N, and *Interdependencies to be Addressed* represent (an observable subset of) K.

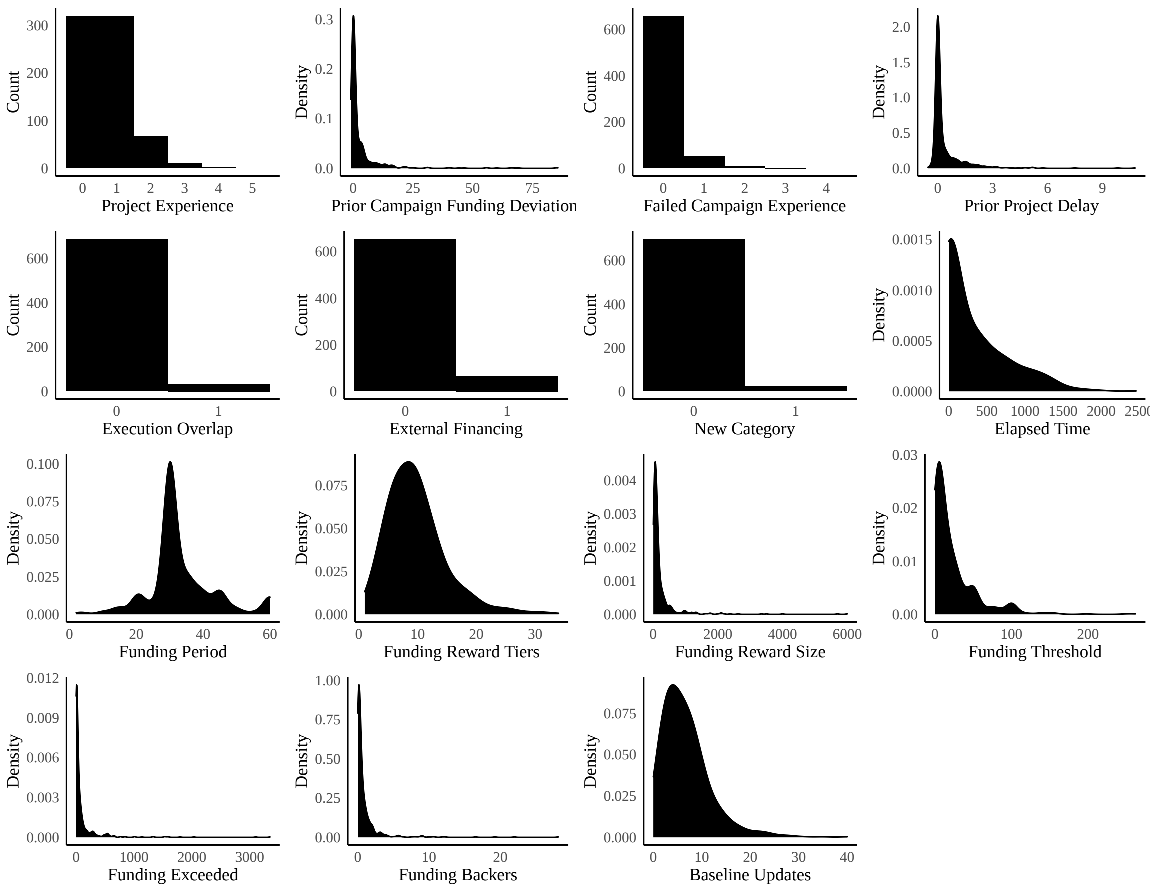


Figure A.3: Variable Distributions. Visualizations of the distributions of independent variables, with density plots for continuous measures and histograms for those with finite discrete values.

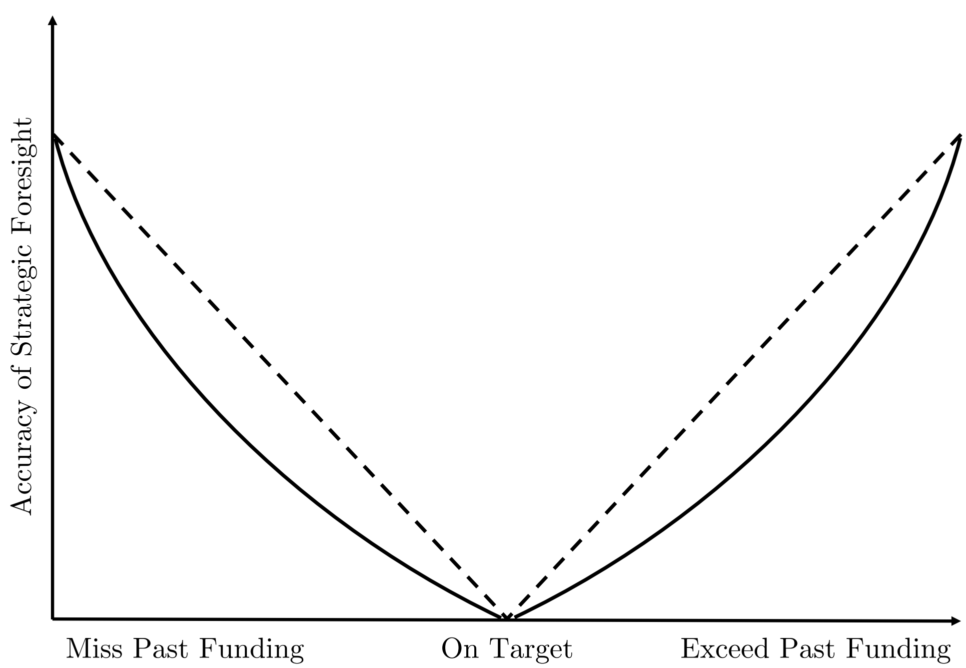


Figure A.4: Outcome–Aspiration Gap and Accuracy of Strategic Foresight. In our context, we operationalize the accuracy of strategic foresight as *Unforeseen Interdependencies* and *Delay Duration*.

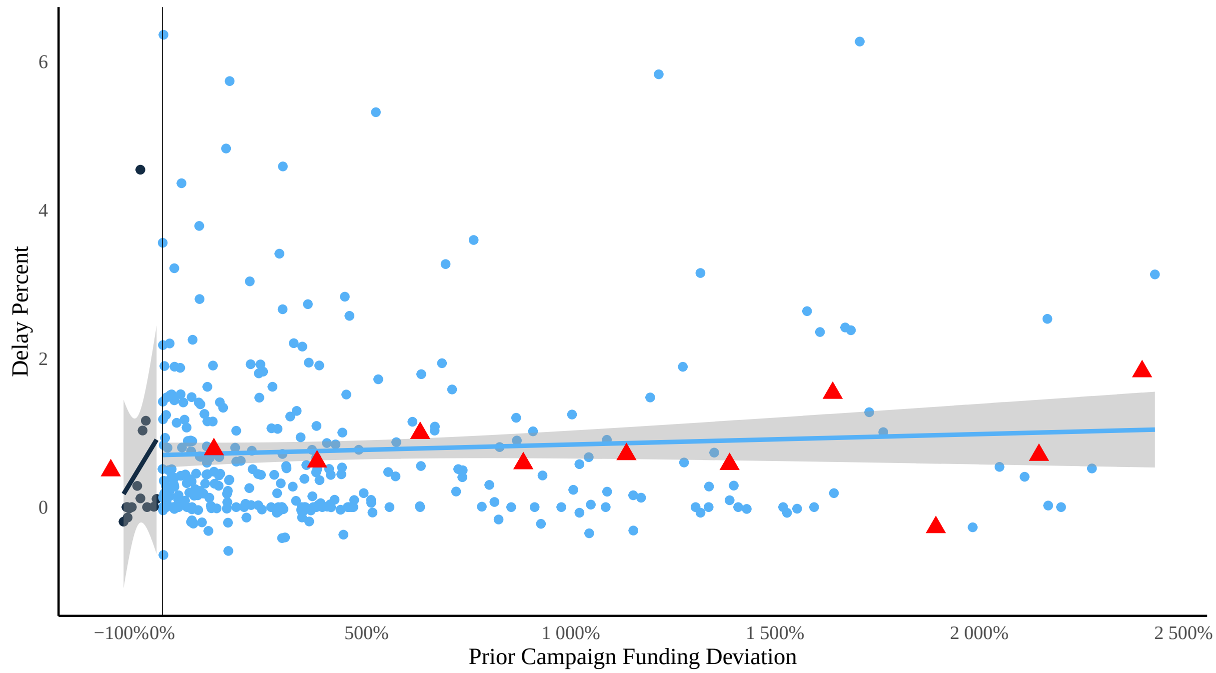


Figure A.5: Deviation and Delay. The binned scatter and linear fit to the left of 0% *Prior Campaign Funding Deviation* show the relationship with *Delay Percent* on the current project and the extent to which the entrepreneur failed to meet her funding threshold on the prior project. To the right, they show the same relationship but for the extent to which the entrepreneur met or exceeded her funding threshold on the prior project.

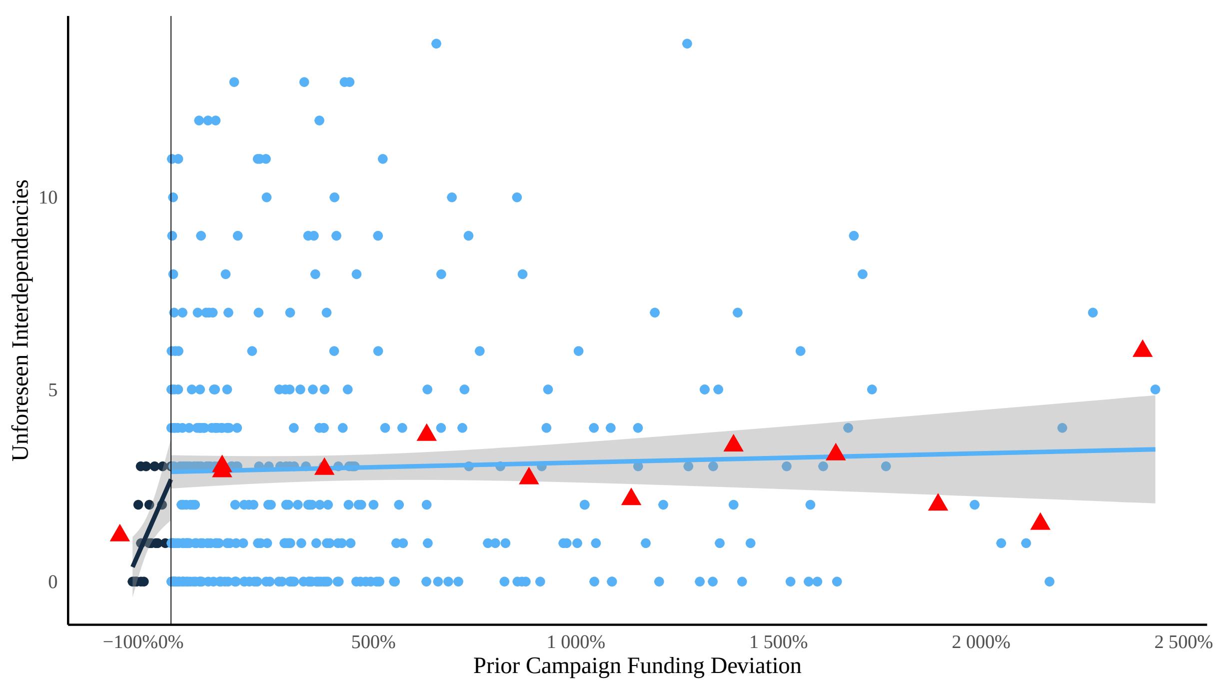


Figure A.6: Deviation and Unforeseen Interdependencies. The binned scatter and linear fit to the left of 0% *Prior Campaign Funding Deviation* show the relationship with *Unforeseen Interdependencies* on the current project and the extent to which the entrepreneur failed to meet her funding threshold on the prior project. To the right, they show the same relationship but for the extent to which the entrepreneur met or exceeded her funding threshold on the prior project.

Table A.1: Qualitative Interview Sample. Indexed set of interviewed entrepreneurs. All interviews lasted 30 to 45 minutes and were conducted between January 29, 2020 and June 24, 2020.

	Entrepreneur	Product Subtype	Location	Location Type
1	3DPrintCo CEO	3D Printing	Spicer, MN	Town
2	AccessoryCo CEO	Hardware	Izhevsk, Russia	Town
3	CircuitsCo CEO	DIY Electronics	North Sydney, AU	Suburb
4	ElectronicsCo CEO	DIY Electronics	Preston, UK	Suburb
5	GPSCo CEO	Gadgets	Seattle, WA	Town
6	LEGOCo CEO	Hardware	London, UK	Town
7	MaskCo CEO	Wearables	Montreal, Canada	Town
8	MusicCo CEO	Sound	Austin, TX	Town
9	SecureCo CEO	Hardware	Dublin, Ireland	Town
10	TabletCo CEO	Hardware	Beijing, China	Town
11	WidgetsCo CEO	DIY Electronics	Boulder, CO	Town

Table A.2: Qualitative Interview Sample Summary Statistics. Indexed set of interviewed entrepreneurs. All values are averaged across all the projects in the sample by the individual entrepreneur. *Funding Threshold*, *Funding Exceeded*, and *Funding Backers* are all in thousands.

	Funding Threshold	Funding Exceeded	Funding Backers	Unforeseen Interdependencies	Delay Duration	Predicted Time	Actual Time
1	12.5	22	0.1	5.0	33.6	96.8	130.4
2	230.0	504	3.9	14	381.9	148.3	530.2
3	1.1	12	0.5	3.5	27.8	89.5	117.3
4	3.1	14	0.5	1.0	3.7	51.8	55.5
5	10.0	145	2.3	3.0	37.0	59.0	96.0
6	76.4	128	1.1	4.5	154.5	79.6	234.1
7	8.6	165	3.3	1.0	53.5	91.7	145.2
8	42.5	108	0.9	3.5	128.7	107.4	236.1
9	86.7	121	0.5	4.0	359.5	165.6	525.1
10	75.0	929	11.6	2.0	14.0	51.9	65.9
11	8.2	25	0.3	0.5	4.9	112.3	117.2

Table A.3: Project Reviewer Backgrounds. Education and experience backgrounds of each of the five individuals hired to rank each entrepreneur's set of projects according to number of features.

Reviewer	Education	Experience
Reviewer 1	MBA graduate with additional technical masters	12 years experience in computer programming
Reviewer 2	College degree in engineering	Career working at robotics company
Reviewer 3	College degree in business or engineering	2+ years work experience in consulting, banking, or engineering
Reviewer 4	Mechanical engineering and computer science	Freelance web design
Reviewer 5	Senior in high school	Experience in VC diligence and health technology

Table A.4: Variable Quantiles. 722 project-level observations. *Funding Threshold*, *Funding Exceeded*, and *Funding Backers* are all in thousands.

	Quantiles				
Variables	0%	25%	50%	75%	100%
Project Experience	0	0	1	1	5
Failed Campaign Experience	0	0	0	0	4
Prior Project Funding Deviation	-1	0	0.05	2.94	85.65
Prior Project Delay	-0.53	0	0	0.42	10.78
Execution Overlap	0	0	0	0	1
External Financing	0	0	0	0	1
New Category	0	0	0	0	1
Elapsed Time	0	0	112.50	538.75	2,458
Prior Updates	0	3	6	9	40
Funding Period	2	30	30	37	60
Funding Reward Tiers	1	6	9	12	34
Funding Reward Size	4	50	99	201.63	5,995
Funding Threshold	0.02	3.85	10.15	30	261.96
Funding Exceeded	0	3.51	17.59	74.92	3,351.36
Funding Backers	0.001	0.12	0.30	0.92	28.14

Table A.5: Unforeseen Interdependencies Alternative. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Alternative Unforeseen Interdependencies	Ln Alternative Unforeseen Interdependencies
Project Experience	0.114	0.064
	(0.002)	(0.001)
Failed Campaign Experience	0.052	0.030
	(0.369)	(0.422)
Prior Campaign Funding Deviation	−0.008	−0.003
	(0.068)	(0.051)
Prior Project Delay	−0.045	−0.029
	(0.041)	(0.032)
Execution Overlap	0.022	0.012
	(0.788)	(0.756)
External Financing	−0.120	−0.085
	(0.620)	(0.549)
New Category	0.124	0.064
	(0.112)	(0.069)
Elapsed Time	0.000	0.000
	(0.893)	(0.366)
Funding Period	0.001	0.002
	(0.872)	(0.236)
Funding Reward Tiers	0.003	0.001
	(0.559)	(0.689)
Funding Reward Size	−0.000	−0.000
	(0.991)	(0.914)
Ln Funding Threshold	0.047	0.018
	(0.161)	(0.289)
Ln Funding Exceeded	0.090	0.050
	(0.009)	(0.011)
Ln Funding Backers	−0.022	−0.030
	(0.753)	(0.292)
Baseline Updates	−0.004	
	(0.537)	
Ln Baseline Updates		−0.005
		(0.796)
Entrepreneur FE	Yes	Yes
Product Subtype FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
R^2	0.502	0.560
Entrepreneurs	314	314
Observations	722	722

Table A.6: Non-Linear Analysis of Complexity and Unforeseen Interdependencies. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Features Most	Features Rank	Features Percentile	Unforeseen Interdependencies	Ln Unforeseen Interdependencies
Project Experience: Second	0.266	0.417	0.302	1.457	0.270
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Project Experience: Third	0.188	0.541	0.234	2.721	0.420
	(0.133)	(0.011)	(0.048)	(0.000)	(0.002)
Project Experience: Fourth or More	0.508	1.468	0.457	4.116	0.738
	(0.024)	(0.000)	(0.026)	(0.000)	(0.003)
Failed Campaign Experience	0.091	0.184	0.103	0.632	0.184
	(0.432)	(0.214)	(0.291)	(0.086)	(0.056)
Prior Campaign Funding Deviation	−0.001	0.000	−0.002	0.003	−0.001
	(0.831)	(0.984)	(0.653)	(0.888)	(0.740)
Prior Project Delay	−0.004	−0.038	−0.015	−0.710	−0.133
	(0.917)	(0.475)	(0.665)	(0.000)	(0.000)
Execution Overlap	−0.440	−0.488	−0.412	−0.295	0.063
	(0.005)	(0.012)	(0.006)	(0.651)	(0.591)
External Financing	0.332	0.244	0.321	1.087	0.135
	(0.010)	(0.113)	(0.011)	(0.336)	(0.559)
New Category	−0.013	0.179	0.075	1.686	0.272
	(0.937)	(0.450)	(0.663)	(0.074)	(0.211)
Elapsed Time	−0.000	0.000	−0.000	0.004	0.001
	(0.435)	(0.900)	(0.776)	(0.009)	(0.000)
Funding Period	0.005	0.008	0.005	0.028	0.006
	(0.228)	(0.141)	(0.158)	(0.189)	(0.196)
Funding Reward Tiers	0.007	0.008	0.008	−0.024	−0.004
	(0.345)	(0.505)	(0.254)	(0.502)	(0.634)
Funding Reward Size	0.000	0.000	0.000	−0.000	0.000
	(0.002)	(0.000)	(0.001)	(0.796)	(0.814)
Ln Funding Threshold	0.035	0.043	0.028	0.745	0.156
	(0.429)	(0.424)	(0.503)	(0.004)	(0.000)
Ln Funding Exceeded				0.679	0.080
				(0.008)	(0.093)
Ln Funding Backers				−0.032	0.069
				(0.929)	(0.299)
Baseline Updates				0.175	
				(0.001)	
Ln Baseline Updates					0.283
					(0.000)
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	0.301	0.442	0.299	0.745	0.775
Entrepreneurs	314	314	314	314	314
Observations	722	722	722	722	722

Table A.7: Non-Linear Analysis of Delivery and Delay. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. *p*-values are shown in parentheses.

	Delay Indicator	Delay Duration	Delay Percent	Predicted Time	Actual Time
Project Experience: Second	0.115	44.858	0.717	6.082	49.112
	(0.038)	(0.003)	(0.000)	(0.151)	(0.004)
Project Experience: Third	0.262	75.369	1.109	18.816	89.149
	(0.013)	(0.006)	(0.001)	(0.010)	(0.004)
Project Experience: Fourth or More	0.362	145.106	1.581	30.063	169.153
	(0.010)	(0.002)	(0.001)	(0.028)	(0.001)
Failed Campaign Experience	0.134	−5.134	−0.053	14.622	7.842
	(0.132)	(0.766)	(0.810)	(0.047)	(0.739)
Prior Campaign Funding Deviation	−0.003	0.034	−0.004	0.127	0.361
	(0.074)	(0.939)	(0.620)	(0.450)	(0.464)
Prior Project Delay	−0.041	−21.968	−0.129	4.629	−19.659
	(0.050)	(0.023)	(0.640)	(0.021)	(0.037)
Execution Overlap	−0.050	8.015	1.124	−3.411	6.427
	(0.474)	(0.839)	(0.248)	(0.687)	(0.883)
External Financing	0.140	91.972	0.317	22.198	121.857
	(0.198)	(0.254)	(0.548)	(0.358)	(0.217)
New Category	0.086	41.691	0.477	5.572	48.525
	(0.596)	(0.109)	(0.091)	(0.576)	(0.149)
Elapsed Time	−0.000	−0.096	−0.001	−0.022	−0.112
	(0.448)	(0.100)	(0.285)	(0.271)	(0.078)
Funding Period	0.009	1.272	0.003	0.190	1.739
	(0.000)	(0.072)	(0.899)	(0.448)	(0.023)
Funding Reward Tiers	0.003	0.765	0.000	−0.165	0.968
	(0.479)	(0.489)	(0.989)	(0.692)	(0.459)
Funding Reward Size	0.000	−0.011	0.000	0.005	−0.009
	(0.792)	(0.707)	(0.680)	(0.525)	(0.814)
Ln Funding Threshold	0.006	22.322	−0.081	19.326	40.085
	(0.842)	(0.107)	(0.582)	(0.000)	(0.011)
Ln Funding Exceeded	0.035	29.877	0.205		29.323
	(0.194)	(0.003)	(0.081)		(0.010)
Ln Funding Backers	0.007	−35.697	−0.183		−33.133
	(0.852)	(0.006)	(0.265)		(0.031)
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	0.663	0.719	0.657	0.753	0.738
Entrepreneurs	306	303	303	314	303
Observations	686	644	644	722	644

Table A.8: Funding Deviation and Performance. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. *p*-values are shown in parentheses.

	Delay Percent		Unforeseen Interdependencies	
Prior Campaign Funding Deviation	0.519	−7.227	1.249	5.071
	(0.569)	(0.356)	(0.468)	(0.498)
Prior Project Funding Success	−0.110	1.665	0.991	0.108
	(0.898)	(0.247)	(0.420)	(0.954)
Prior Campaign Funding Deviation × Prior Project Funding Success	−0.524	7.238	−1.260	−5.010
	(0.565)	(0.356)	(0.465)	(0.503)
Prior Campaign Funding Deviation^2		−6.814		3.835
		(0.351)		(0.572)
Prior Campaign Funding Deviation^2 × Prior Project Funding Success		6.814		−3.836
		(0.351)		(0.572)
Project Experience	−0.045	−0.037	−0.106	−0.136
	(0.806)	(0.841)	(0.769)	(0.713)
Failed Campaign Experience	0.081	0.135	0.647	0.651
	(0.736)	(0.580)	(0.230)	(0.228)
Prior Project Delay	0.662	0.663	0.193	0.203
	(0.023)	(0.022)	(0.238)	(0.222)
Execution Overlap	1.431	1.427	0.734	0.765
	(0.210)	(0.213)	(0.168)	(0.155)
External Financing	−0.238	−0.264	0.917	0.799
	(0.550)	(0.500)	(0.167)	(0.228)
New Category	−0.765	−0.640	2.876	3.213
	(0.196)	(0.263)	(0.100)	(0.072)
Elapsed Time	−0.000	−0.000	0.000	0.000
	(0.277)	(0.285)	(0.987)	(0.955)
Funding Period	0.012	0.012	0.003	0.005
	(0.343)	(0.328)	(0.875)	(0.790)
Funding Reward Tiers	0.008	0.009	0.077	0.083
	(0.565)	(0.515)	(0.053)	(0.042)
Funding Reward Size	0.000	0.000	0.000	0.000
	(0.303)	(0.309)	(0.618)	(0.630)
Ln Funding Threshold	−0.069	−0.065	0.762	0.761
	(0.440)	(0.473)	(0.000)	(0.000)
Product Subtype FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
R^2	0.205	0.206	0.262	0.271
Sample	2+ Proj	2+ Proj	2+ Proj	2+ Proj
Observations	342	342	402	402

Table A.9: Predicted Time and Peer Group Comparison. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. *p*-values are shown in parentheses.

	Predicted Time
Project Experience	7.671
	(0.031)
Peer Group Predicted Time	0.042
	(0.736)
Failed Campaign Experience	18.161
	(0.030)
Prior Campaign Funding Deviation	0.169
	(0.304)
Prior Project Delay	4.035
	(0.028)
Execution Overlap	−4.249
	(0.608)
External Financing	14.281
	(0.589)
New Category	9.998
	(0.310)
Elapsed Time	−0.017
	(0.435)
Funding Period	0.229
	(0.356)
Funding Reward Tiers	−0.089
	(0.834)
Funding Reward Size	0.004
	(0.583)
Ln Funding Threshold	19.965
	(0.000)
Entrepreneur FE	Yes
Product Subtype FE	Yes
Year FE	Yes
Month FE	Yes
R^2	0.757
Entrepreneurs	314
Observations	712

Table A.10: Funding and Peer Group Comparison. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Ln Funding Exceeded		Funding Positive Deviation	
Peer Group Deviation	0.002	0.002	0.019	−0.002
	(0.131)	(0.085)	(0.013)	(0.822)
Project Experience	0.045	0.049	1.792	1.394
	(0.668)	(0.644)	(0.009)	(0.053)
Prior Campaign Funding Deviation	−0.155	−0.167	−2.693	−1.204
	(0.306)	(0.262)	(0.002)	(0.100)
Failed Campaign Experience	−0.024	−0.024	−0.422	−0.449
	(0.000)	(0.000)	(0.000)	(0.000)
Prior Project Delay	0.039	0.037	0.132	0.367
	(0.498)	(0.525)	(0.622)	(0.189)
Execution Overlap	−0.363	−0.376	0.645	2.313
	(0.113)	(0.094)	(0.638)	(0.190)
External Financing	0.835	0.838	2.277	1.914
	(0.286)	(0.282)	(0.264)	(0.327)
New Category	−0.098	−0.110	0.783	2.279
	(0.739)	(0.709)	(0.606)	(0.258)
Elapsed Time	0.001	0.001	0.001	0.003
	(0.417)	(0.417)	(0.834)	(0.677)
Funding Period	0.016	0.016	0.094	0.067
	(0.002)	(0.002)	(0.004)	(0.047)
Funding Reward Tiers	0.030	0.031	0.126	0.019
	(0.036)	(0.030)	(0.103)	(0.818)
Funding Reward Size	0.000	0.000	0.002	0.000
	(0.219)	(0.195)	(0.040)	(0.897)
Ln Funding Threshold	0.032		−4.043	
	(0.671)		(0.000)	
Entrepreneur FE	Yes	Yes	Yes	Yes
Product Subtype FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
R^2	0.850	0.850	0.813	0.783
Entrepreneurs	314	314	314	314
Observations	712	712	712	712

Table A.11: Consequences of Delay. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level and are shown in parentheses. *p*-values are shown in parentheses.

	Total Comments	Negative Comments	
Delay Duration	1.710	0.016	0.007
	(0.002)	(0.000)	(0.197)
Project Experience			0.145
			(0.846)
Delay Duration × Project Experience			0.011
			(0.022)
Failed Campaign Experience	55.540	1.479	1.896
	(0.572)	(0.144)	(0.065)
Prior Campaign Funding Deviation	−4.176	−0.005	−0.004
	(0.491)	(0.933)	(0.955)
Prior Project Delay	23.430	0.951	0.621
	(0.319)	(0.008)	(0.067)
Execution Overlap	−377.799	−1.741	−3.133
	(0.143)	(0.201)	(0.024)
External Financing	−518.389	4.748	4.202
	(0.041)	(0.202)	(0.251)
New Category	−150.405	−1.322	−1.031
	(0.191)	(0.510)	(0.614)
Elapsed Time	−0.632	0.006	0.003
	(0.086)	(0.052)	(0.356)
Funding Period	−1.006	0.047	0.058
	(0.834)	(0.382)	(0.279)
Funding Reward Tiers	−6.520	−0.190	−0.205
	(0.365)	(0.042)	(0.022)
Funding Reward Size	−0.174	−0.004	−0.004
	(0.048)	(0.025)	(0.026)
Ln Funding Threshold	−43.482	0.735	0.713
	(0.415)	(0.184)	(0.191)
Ln Funding Exceeded	151.209	−0.039	−0.023
	(0.046)	(0.952)	(0.971)
Ln Funding Backers	283.235	5.226	5.258
	(0.015)	(0.000)	(0.000)
Baseline Updates	−12.661	0.087	0.080
	(0.153)	(0.402)	(0.448)
Entrepreneur FE	Yes	Yes	Yes
Product Subtype FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
R^2	0.779	0.857	0.860
Entrepreneurs	303	303	303
Observations	644	644	644

Table A.12: Features and Negative Comments. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Negative Comments					
Features Most	0.537			1.436		
	(0.441)			(0.071)		
Features Rank		0.597			1.236	
		(0.181)			(0.028)	
Features Percentile			0.722			1.729
			(0.309)			(0.029)
Delay Duration				0.016	0.018	0.017
				(0.019)	(0.062)	(0.015)
Features Most × Delay Duration				−0.002		
				(0.849)		
Features Rank × Delay Duration					−0.001	
					(0.743)	
Features Percentile × Delay Duration						−0.003
						(0.706)
Project Experience	2.221	2.063	2.184	0.501	0.213	0.428
	(0.059)	(0.078)	(0.063)	(0.585)	(0.812)	(0.640)
Failed Campaign Experience	1.522	1.461	1.504	−0.042	−0.285	−0.182
	(0.532)	(0.549)	(0.539)	(0.970)	(0.803)	(0.873)
Prior Campaign Funding Deviation	−0.126	−0.126	−0.126	−0.106	−0.107	−0.106
	(0.115)	(0.115)	(0.116)	(0.170)	(0.164)	(0.172)
Prior Project Delay	0.994	1.020	0.998	1.019	1.071	1.034
	(0.103)	(0.095)	(0.103)	(0.036)	(0.027)	(0.033)
Execution Overlap	−5.064	−4.993	−5.016	−2.685	−2.623	−2.622
	(0.006)	(0.006)	(0.006)	(0.101)	(0.123)	(0.104)
External Financing	7.285	7.313	7.219	5.528	5.645	5.596
	(0.039)	(0.037)	(0.040)	(0.198)	(0.177)	(0.190)
New Category	−0.745	−0.873	−0.793	−1.232	−1.551	−1.346
	(0.730)	(0.684)	(0.712)	(0.586)	(0.485)	(0.546)
Elapsed Time	0.005	0.005	0.005	0.008	0.008	0.008
	(0.392)	(0.375)	(0.400)	(0.231)	(0.189)	(0.246)
Funding Period	0.098	0.096	0.096	0.089	0.086	0.087
	(0.083)	(0.087)	(0.089)	(0.139)	(0.154)	(0.148)
Funding Reward Tiers	0.011	0.010	0.009	−0.052	−0.051	−0.054
	(0.913)	(0.919)	(0.931)	(0.664)	(0.671)	(0.654)
Funding Reward Size	−0.006	−0.006	−0.006	−0.008	−0.008	−0.008
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Ln Funding Threshold	2.067	2.052	2.069	1.878	1.875	1.892
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)
Entrepreneur FE	Yes	Yes	Yes	Yes	Yes	Yes
Product Subtype FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.776	0.776	0.776	0.814	0.815	0.815
Entrepreneurs	314	314	314	303	303	303
Observations	722	722	722	644	644	644

Table A.13: Creator Engagement. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. *p*-values are shown in parentheses.

	Creator Engagement
Project Experience	1660.434
	(0.021)
Failed Campaign Experience	1510.288
	(0.019)
Prior Campaign Funding Deviation	9.544
	(0.653)
Prior Project Delay	−462.340
	(0.023)
Execution Overlap	−1931.397
	(0.237)
External Financing	687.536
	(0.508)
New Category	719.917
	(0.219)
Elapsed Time	−2.272
	(0.241)
Funding Period	4.890
	(0.820)
Funding Reward Tiers	−79.848
	(0.072)
Funding Reward Size	−1.240
	(0.067)
Ln Funding Threshold	1247.513
	(0.071)
Ln Funding Exceeded	1187.129
	(0.011)
Ln Funding Backers	−836.528
	(0.284)
Baseline Updates	215.579
	(0.034)
Entrepreneur FE	Yes
Product Subtype FE	Yes
Year FE	Yes
Month FE	Yes
R^2	0.720
Entrepreneurs	306
Observations	626

Table A.14: Incentive to Overpromise. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Ln Funds Raised	Ln Funding Exceeded
Predicted Time	0.001	0.002
	(0.102)	(0.247)
Features Rank	0.111	0.169
	(0.026)	(0.053)
Failed Campaign Experience	−0.097	−0.196
	(0.319)	(0.149)
Prior Campaign Funding Deviation	−0.022	−0.026
	(0.001)	(0.000)
Prior Project Delay	0.024	0.044
	(0.454)	(0.435)
Execution Overlap	−0.163	−0.349
	(0.212)	(0.125)
External Financing	0.137	0.302
	(0.680)	(0.660)
New Category	0.023	−0.172
	(0.906)	(0.559)
Project Experience	0.082	0.044
	(0.182)	(0.665)
Elapsed Time	0.001	0.001
	(0.509)	(0.477)
Funding Period	0.012	0.014
	(0.002)	(0.005)
Funding Reward Tiers	0.023	0.031
	(0.004)	(0.025)
Funding Reward Size	0.000	0.000
	(0.198)	(0.328)
Ln Funding Threshold	0.405	0.015
	(0.000)	(0.843)
Entrepreneur FE	Yes	Yes
Product Subtype FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
R^2	0.923	0.840
Entrepreneurs	314	314
Observations	722	722

Table A.15: Exiting After VC Financing. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Does Another Project
External Financing	0.033
	(0.819)
Failed Campaign Experience	0.052
	(0.617)
Prior Campaign Funding Deviation	−0.004
	(0.124)
Prior Project Delay	−0.028
	(0.132)
Execution Overlap	−0.081
	(0.408)
New Category	−0.199
	(0.042)
Project Experience	−0.394
	(0.000)
Elapsed Time	−0.001
	(0.001)
Funding Period	−0.003
	(0.237)
Funding Reward Tiers	0.008
	(0.195)
Funding Reward Size	0.000
	(0.217)
Ln Funding Threshold	−0.035
	(0.254)
Ln Funding Exceeded	0.030
	(0.354)
Ln Funding Backers	−0.005
	(0.921)
Entrepreneur FE	Yes
Product Subtype FE	Yes
Year FE	Yes
Month FE	Yes
R^2	0.770
Entrepreneurs	304
Observations	641

Table A.16: Exiting After Delay. Ordinary least squares (OLS) estimation. Robust standard errors are clustered at the entrepreneur level. p-values are shown in parentheses.

	Does Another Project
Delay Duration	−0.0003
	(0.194)
Failed Campaign Experience	0.235
	(0.116)
Prior Campaign Funding Deviation	−0.004
	(0.159)
Prior Project Delay	−0.024
	(0.337)
Execution Overlap	−0.034
	(0.785)
New Category	−0.266
	(0.049)
Project Experience	−0.344
	(0.000)
Elapsed Time	−0.001
	(0.016)
Funding Period	−0.003
	(0.352)
Funding Reward Tiers	0.008
	(0.238)
Funding Reward Size	0.000
	(0.527)
Ln Funding Threshold	−0.042
	(0.259)
Ln Funding Exceeded	0.045
	(0.280)
Ln Funding Backers	−0.014
	(0.821)
Entrepreneur FE	Yes
Product Subtype FE	Yes
Year FE	Yes
Month FE	Yes
R^2	0.780
Entrepreneurs	294
Observations	581