# Online Appendix

# Entrepreneurial Learning and Strategic Foresight

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# A Online 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 Online 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*** ($p$   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.

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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 Online 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 Online 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* 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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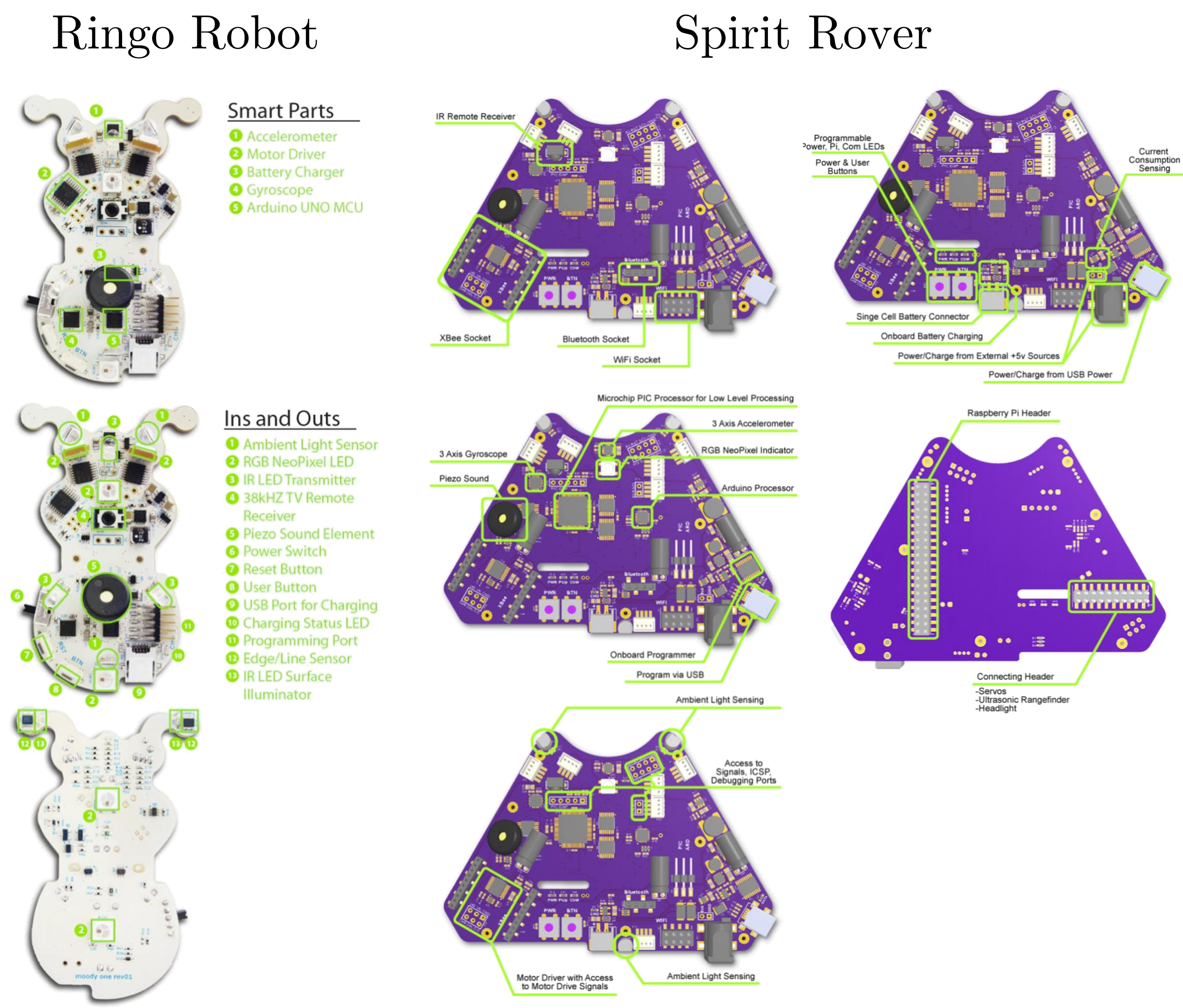
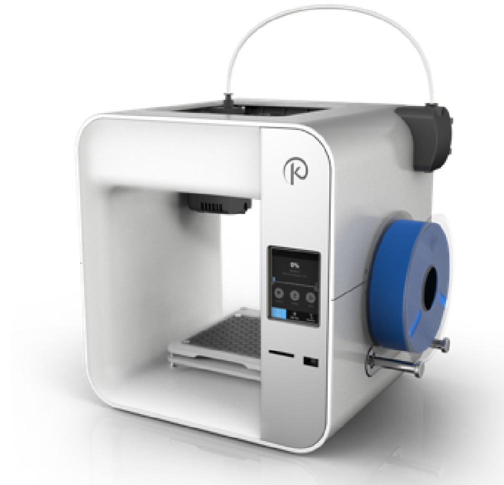



**Figure A.1: Plum Geek Robotics Product Features.** Reproduction of breakdowns of product features provided by Plum Geek Robotics on its company website. Ringo Robot was its first Kickstarter project, launched on February 25, 2015. The Spirit Rover was its third project, launched on September 28, 2016.

| 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.

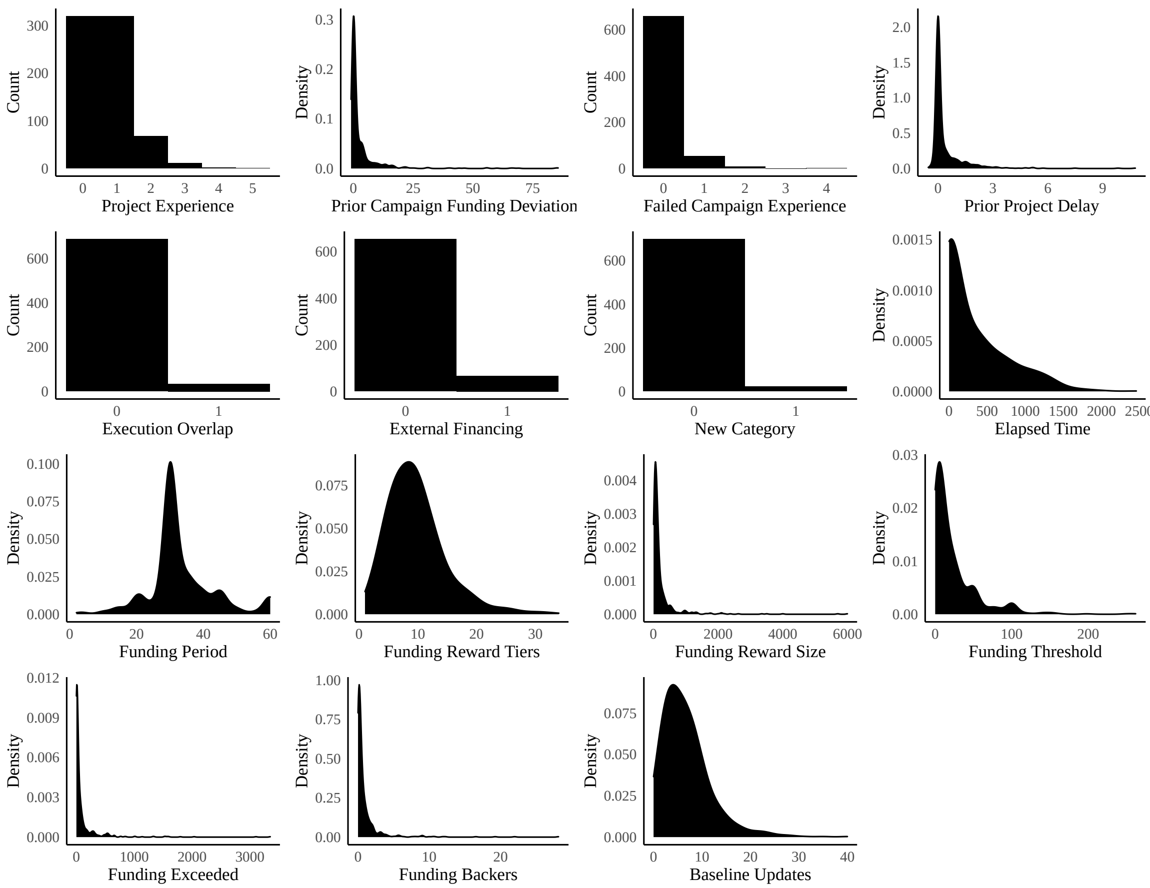



**Figure A.3: Variable Distributions.** Visualizations of the distributions of independent variables, with density plots for continuous measures and histograms for those with finite discrete values.

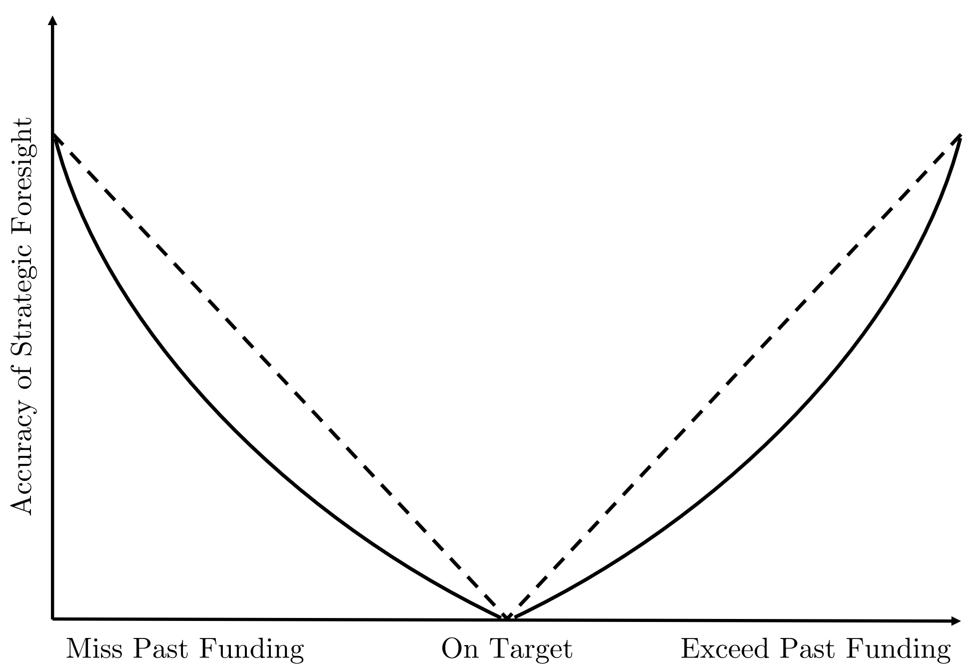



**Figure A.4: Outcome–Aspiration Gap and Accuracy of Strategic Foresight.** In our context, we operationalize the accuracy of strategic foresight as *Unforeseen Interdependencies* and *Delay Duration*.

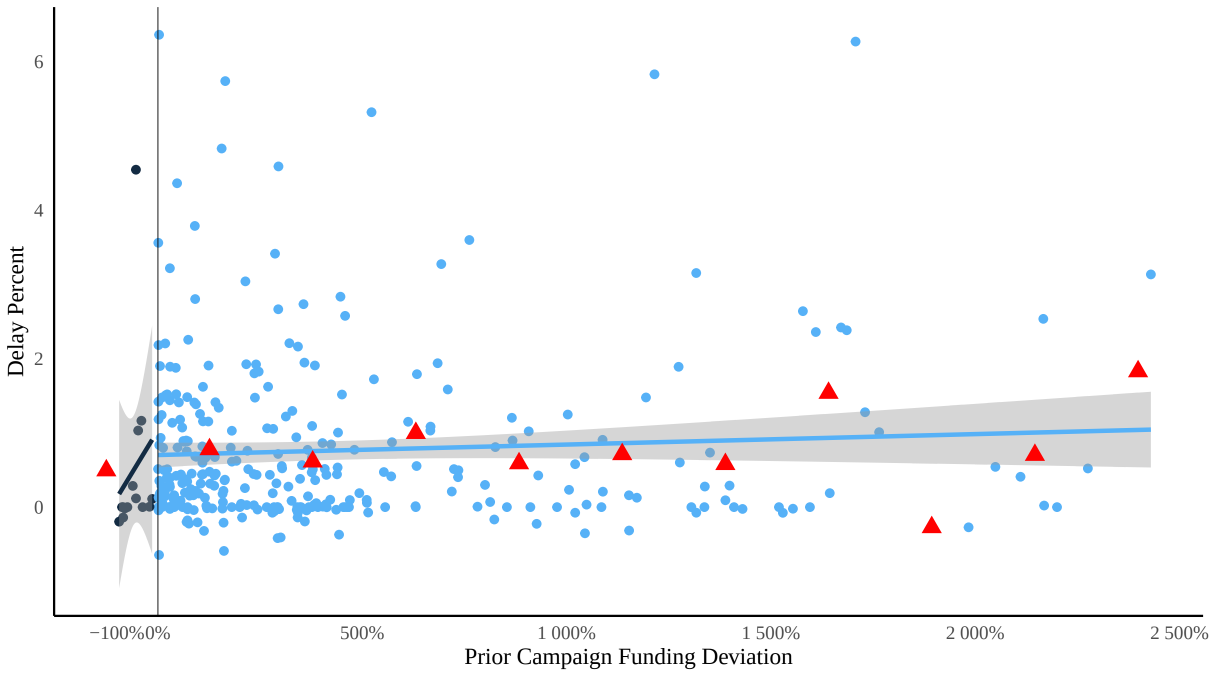



**Figure A.5: Deviation and Delay.** The binned scatter and linear fit to the left of 0% *Prior Campaign Funding Deviation* show the relationship with *Delay Percent* on the current project and the extent to which the entrepreneur failed to meet her funding threshold on the prior project. To the right,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

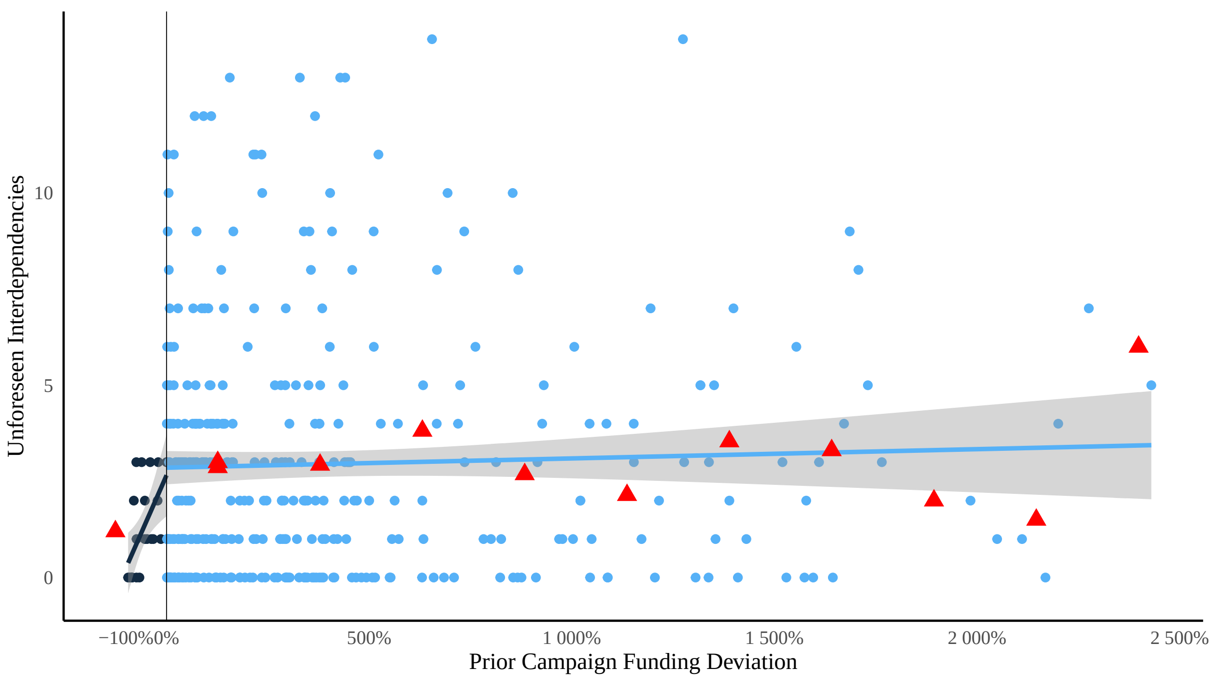



**Figure A.6: Deviation and Unforeseen Interdependencies.** The binned scatter and linear fit to the left of 0% *Prior Campaign Funding Deviation* show the relationship with *Unforeseen Interdependencies* on the current project and the extent to which the entrepreneur failed to meet her funding threshold 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 |