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Abstract. In uncertain environments, project reviews provide an opportunity to make "continue or abandon" decisions and thereby maximize a project's expected payoff. We experimentally investigate continue/abandon decisions in a multistage project under two conditions: when the project is reviewed at every stage and when review opportunities are limited. Our results confirm findings in the literature that project abandonment tends to be delayed; yet, we also observe premature termination. Decisions are highly path dependent; in particular, subjects are more likely to abandon after observing reduced project value, and abandonment rate is higher near the middle—rather than near the beginning or end—of a project. Interestingly, when reviews are limited, subjects are *less* likely to continue a project that should be abandoned. At the same time, subjects are more inclined to review again after receiving negative (rather than positive) news. Our data are explained well by a model that incorporates three behavioral concepts—gains or losses from comparing the project value with an internal adaptive reference point, sunk cost bias, and status quo bias. Our work suggests that more frequent reviews need not lead to better project performance, and it also identifies contexts in which outside intervention is most valuable in project decision making.

1. Introduction

In uncertain environments, the manager of a project monitors its progress and, at each review, decides whether to continue or abandon the project. This process enables decision makers to evaluate and respond to new information and plays an important role in managing project risk. However, project managers often fail to make optimal decisions given the information available. There is a tendency to delay termination of projects, often at considerable costs. For example, Guler (2007) studies sequential investment decisions in the U.S. venture capital industry and finds that venture capitalists tend to continue investing in companies even when prospects of success are declining. New products that fail in the market are often continued longer than is optimal (Power 1993, Simester and Zhang 2010). A similar tendency is observed in controlled experiments, where subjects who have made a previous investment in a project are significantly more

likely to continue that project (Staw and Ross 1989, Garland 1990).[1]

Although project termination delay is well documented in the literature, there have been few systematic studies on how the project manager (PM) makes continue/abandon decisions *over multiple stages* or the behavioral drivers behind these decisions at different points in a project's duration. Real-world projects typically involve many stages and reviews, wherein the PM's decision may be affected by the project's history, its performance trend, and the timing of reviews. It is crucial to understand the effect of these factors to devise policies for inducing correct continue/abandon decisions.

The frequency of reviews is also important in project management. In new product development (NPD) projects, the number of reviews can vary significantly across different projects with different risk levels (Schmidt et al. 2009). It is widely recognized that the number of reviews may be limited by

transaction costs or resource constraints (Bergemann et al. 2009) and that more reviews increase the economic value of projects by increasing flexibility (Huchzermeier and Loch 2001, Santiago and Vakili 2005). Yet, little is known about the *psychological* effect of review frequency on the PM's continue/abandon decisions. Specifically, whereas more frequent reviews provide the PM with more opportunities to abandon the project, they may also induce the PM to postpone the termination of an unprofitable project. If so, then more frequent reviews may not lead to better project outcomes.

In this paper, we experimentally investigate continue/abandon decisions in a multistage project under two conditions: when the project is reviewed at every stage and when review opportunities are limited. We pose three research questions. First, how does the information obtained at a project review affect continue/abandon decisions? Second, how do continue/abandon decisions change over time in a project? Third, if review opportunities are limited and if the PM can decide when to review, then what is the effect of limited reviews on continue/abandon decisions?

We formulate a simple dynamic programming model to capture the key characteristics of a multistage project in an uncertain environment: (i) the expected project payoff evolves stochastically over time; (ii) a continuation cost is incurred at each stage; (iii) the PM may review the project and abandon it before its completion; and (iv) payoff is received only upon the project's completion (Roberts and Weitzman 1981). The theoretical model allows us to identify payoff-maximizing decisions and therefore disentangle the economic and behavioral factors behind observed continue/abandon decisions.

To predict actual decisions, we then build a behavioral model based on the well-established concept of reference dependence, which is commonly used to model choice behavior over time (Karlsson et al. 2009, Kőszegi and Rabin 2009). More specifically, we posit that if the project is continued, then the PM compares the observed project value with an internal reference point and, accordingly, experiences a gain or loss in utility. We assume that the reference point reflects the PM's *expectation* of the project's payoff and that it is updated (albeit imperfectly) over time. We also incorporate two common explanations for termination delay into our model: sunk cost bias and status quo bias. The former describes the incentive to continue a project to recoup the sunk cost (Thaler 1999), and the latter refers to a preference for following the "default" option (Samuelson and Zeckhauser 1988). We capture these biases by assuming that a PM who abandons a project experiences a constant negative utility (status quo bias) in addition to a negative utility that is proportional to the amount of sunk cost. Our

behavioral model predicts that the decision maker tends to delay project abandonment, but there may also be cases of premature abandonment. In particular, decisions are history dependent. That is, as a result of reference dependence, the decision maker may be more likely to continue after observing recent increases (rather than decreases) in project value even when the optimal payoff-maximizing decision is the same. Further, because of reference dependence and sunk cost bias, the abandonment rate may be highest near the middle (rather than beginning or end) of a project.

To test these predictions, we design an experiment in which participants make continue/abandon decisions in each stage of a multistage project after a review reveals the current value of the project. We refer to this experiment as the *full review* (FR) experiment. We observe systematic deviations from the optimal policy[2] consistent with our behavioral model's predictions. Structural estimation results further show that our behavioral model describes the data well and accounts for the patterns of history dependence. The parameter estimates reveal that participants are gain seeking rather than loss averse. Overall, our estimation results show that, aside from the sunk cost bias, the status quo bias and gain-seeking preferences are also important drivers of termination delay.

In a second experiment, we further explore the role of reviews in project decisions and investigate whether limiting the number of review opportunities could be conducive to better continue/abandon decisions. Specifically, unlike the FR experiment, we limit the number of reviews and let the PM decide when to review. We refer to this experiment as the *limited review* (LR) experiment. Although for a rational agent limiting the number of reviews always hurts the project because it reduces flexibility (i.e., the PM's chance to respond to updated information), our behavioral model suggests that limited reviews may, in fact, lead to better project outcomes by inducing better abandonment decisions. That is, the abandonment rate may be higher under LR than under FR because of changes in the reference point when reviews are less frequent. Comparing the results from the two experiments, we confirm that participants are, indeed, less likely to make continuation errors when review opportunities are limited. Moreover, we find that participants review again sooner after receiving bad news than after good news and are more likely to review early (rather than late) in a project. This rules out information avoidance as a major driver of project termination delay. Finally, comparing the behavioral model estimates for the two experiments, we find that limiting the number of reviews results in smaller status quo bias and sunk cost bias, which—combined with the reference effects

predicted by the behavioral model—lead to an overall greater willingness to abandon.

Our study complements current project management literature and helps develop a better understanding of how project managers make continue/abandon decisions in multistage projects. By validating our behavioral model with data, we find that project termination delay is driven by different behavioral factors—and may require different intervention strategies—at different stages of a project. Our results also suggest that more reviews are not necessarily better, that is, limiting a "behavioral" PM's access to information by limiting the number of reviews can reduce continuation errors and alleviate project termination delay. This insight has important implications for practice. With recent technology advances, it has become increasingly common for project managers to monitor the progress of projects in real time. Whereas it may be intuitive to assume that more information and flexibility lead to better decision making, our results suggest otherwise: There is, in fact, a trade-off between the flexibility of having more review points in a project and the danger of exacerbating termination delay biases.

The paper proceeds as follows. After reviewing the literature in Section 2, in Section 3 we formulate the base model for a project and present our behavioral model. Section 4 describes the FR experiment and reports the experimental results. Section 5 describes the LR experiment and compares the experimental results and behavioral model estimates in the LR and FR experiments. In Section 6, we discuss the key insights, robustness checks, and directions for future research.

2. Literature Review

Our work relates to two research domains: (i) escalation of commitment and (ii) behavioral studies in project management.

2.1. Escalation of Commitment

There is extensive research on the escalation of commitment, which describes the tendency of decision makers to persist in failing courses of action (Staw and Ross 1989). Escalation behavior has been studied in various contexts: new product development (Schmidt and Calantone 2002), venture capital investment (Guler 2007), and firms' capital budgeting (Denison 2009). Researchers have identified many factors that influence escalation behavior, such as responsibility for the initial decision, sunk cost, overconfidence, and social norms (Sleesman et al. 2012).

We are particularly interested in studies on escalation over time. For example, Staw and Fox (1977) find that over three successive decision points after the initial investment, participants invest the most in

the first period and reduce the investment in later periods. McCain (1986) conducts a similar experiment and argues that decision makers escalate in early investment rounds, but deescalate later. Schmidt and Calantone (2002) find that managers become increasingly less likely to fund NPD projects as the project progresses and more negative feedback is generated. They conclude that escalation of commitment is a more serious problem in the earlier stages of the NPD process. In contrast, studies by Garland (1990) and Arkes and Blumer (1985) suggest that the *later* into a project (and the more money spent), the higher the escalation tendency. Finally, He and Mittal (2007) manipulate the project completion information while keeping sunk cost constant and find that participants are least likely to continue investing when the project is "half complete," compared with barely started (10% progress) or almost done (90% progress). They propose that this is due to the interactive effect of the need for more information at the beginning of a project and the psychological need for goal completion near its end.

The mixed results from previous studies may be due to the confounding of economic and behavioral factors in the experiment design. Because these studies usually employ a case study approach and do not specify the information structure of the project (e.g., potential benefits and costs, future decision points, social environment), what is presented as incorrect escalation behavior may, in fact, be the economically rational response (Bowen 1987, Heath 1995, Berg et al. 2009). For example, as a project's performance deteriorates over time, a decision maker may rationally infer that the project's likelihood of success is low and thus become less likely to invest in the project. Similarly, the decision to continue a project in its early stages could be due to the "real options" value of investment (Dixit and Pindyck 1994, McAfee et al. 2010). That is, the decision maker may expect to have another decision point in the future when more updated information is available, making "escalation" the correct decision in the current stage. Therefore, the question of when people are most likely to make *incorrect* escalation or deescalation decisions—and what are the psychological determinants of these decisions at different stages of a project—remains unanswered. Disentangling the rational and behavioral factors behind escalation behavior is crucial because, as Heath (1995, p. 39) points out, "advice on how to limit escalation is only appropriate when escalation should be limited." Although a few studies on escalation behavior have controlled for economic factors (Heath 1995, Berg et al. 2009, Denison 2009), none of them considers projects with more than two stages (including the initial launch stage).

Our incentivized experiment controls for multiple confounding factors (project state, future payoff expectations, and options value) and identifies the psychological effects of project history and development stage on continue/abandon decisions. Our results support the conjecture by Staw and Ross (1989) that different factors may contribute to escalation at different times in a project. Specifically, we find that the status quo bias and gain-seeking preferences are important drivers of project escalation near the beginning of a project, whereas the sunk cost bias dominates later on. We also find that after accounting for the "real options" value of reviews, participants still exhibit incorrect escalation behavior, but this tendency is reduced when the number of reviews is limited.

Our work complements existing research on policy recommendations to improve project decision making. Boulding et al. (1997) designed a two-stage experiment on product development (involving one launch decision and one continue/abandon decision) and tested the effectiveness of different decision aids. They find that escalation of commitment is alleviated by masking the project's "history" (e.g., having different individuals make the first and second decisions). However, this recommendation has been called into question recently by Boulding et al. (2017), who find that by framing a project in terms of a real option, the decision maker who is involved in the initial decision actually exhibits less escalation tendency. Our results add further nuance to this debate. We find that retaining the same decision maker is useful because observing a negative performance trend may induce more timely abandonment, especially near the middle of a project. However, this strategy may also lead to incorrect abandonment of profitable projects. Finally, whereas Denison (2009) and Boulding et al. (2017) show that the framing of review points (i.e., explicitly discussing the option of abandonment in a future review) can induce better abandonment decisions, we find that the design of the review process also matters. In particular, in contrast to the conventional advice that "a higher level of monitoring may curb escalation" (Schmidt and Calantone 2002, p. 114), our study shows that fewer reviews may, in fact, lead to better abandonment decisions.

2.2. Behavioral Studies in Project Management
There is limited research on human behavior in the study of new product development and project management (Sommer et al. 2008, Kavadias 2014). Oraiopoulos and Kavadias (2008) study the behavioral reasons behind delayed or premature termination of innovation projects and show analytically that diverse perspectives among group members, as well as social conformity, may lead to systematically biased termination decisions. Wu et al. (2014) analyze the optimal compensation scheme when project members are prone to procrastination. Kavadias and Sommer (2009) consider behavioral issues in analyzing the effectiveness of different team structures in creative processes. In an empirical study, Calvo et al. (2019) find that decreasing the intensity of government oversight can reduce a project's delay time and cost overrun.

The variety and complexity of projects have recently led to the application of experimental methods that afford more control to isolate a few key variables and study their interactions. Katok and Siemsen (2011) show that career concerns cause agents to choose more difficult tasks than necessary. Kagan et al. (2017) find that teams perform worse when they can decide when to transition from ideation to execution in NPD projects. Our paper contributes to this growing literature by experimentally investigating project continue/abandon and review decisions. In particular, whereas operations management (OM) researchers have focused on normatively analyzing the value of flexibility (i.e., review points) in multistage projects (Huchzermeier and Loch 2001, Santiago and Vakili 2005), we identify the biases of human decision makers in these settings and the potential *cost* of flexibility.

The impact of information on abandonment behavior has been studied in contexts other than project management. For example, some papers study customers' decisions to join or leave queues in service systems and the optimal design of delay announcements in the presence of customer bounded rationality/behavioral biases (e.g., Huang et al. 2013; Yu et al. 2016, 2017). Our work takes a similar approach in considering the design of information accessibility to influence continue/abandon decisions in projects.

3. Project Setup and Behavioral Model
In this section we describe the base model for a project and then present the behavioral model.

3.1. Project Setup
A project has T stages and its "state" at stage t is x_t. The state is the expected value of the project upon completion. The project state, or value, is stochastically evolving: $x_{t+1} = x_t + w_t$, where w_t is independent and identically distributed (i.i.d.) for $t = 1, 2, \ldots, T - 1$.

We assume there is no time discounting. We also assume that $w_t = \delta$ with probability p and $w_t = -\delta$ with probability $1 - p$. The initial assessment of project value, x_1, is known to the PM. Projects in our experiments have no drift (i.e., $p = 1/2$) and yield a

Figure 1. Example of a Project with $T = 4$
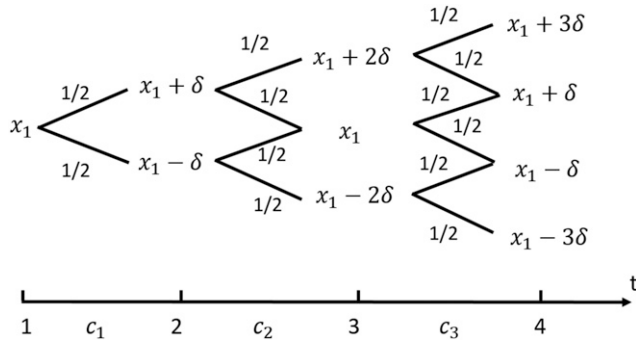
positive payoff $(x_1 - (T-1)\delta \geq 0)$. Figure 1 illustrates the model when $T = 4$.

At each stage t, the PM reviews the project, observes x_t, and decides whether to continue or abandon the project. In Section 5, we consider the case where review opportunities are limited and the PM decides when to review. The cost of continuing the project at stage t is c_t. Let the project payoff at time T be x_T; this payoff is zero if the PM abandons the project before stage T.

Our model lends itself to a laboratory experiment; yet, it captures the key characteristics of a multistage project in an uncertain environment. First, uncertainties become resolved over time. For example, observe from Figure 1 that at stage 3, even if the project value is the same as that in stage 1 (i.e., $x_3 = x_1$), the variance in the final project outcome is smaller. Second, project costs are incurred incrementally. Third, at a review, the PM receives information about the performance of the project and may adjust the distribution of final project value accordingly. The PM may also abandon the project before its completion at a review. For similar project models, we refer to Roberts and Weitzman (1981), Huchzermeier and Loch (2001), and Santiago and Vakili (2005). By modeling the project's value as a random walk and allowing the PM to observe x_t, we obtain a clean platform to investigate systematic effects of path and review frequency on continue/abandon decisions. However, this model does not entail situations where reviews yield imperfect information and the PM has to subjectively update his belief (i.e., "learn") about the underlying uncertainties.

Lemma 1 states that the rational PM's continue/abandon decisions follow a threshold policy.

Lemma 1. At stage t, there exists a threshold a_t such that the rational PM continues the project if and only if $x_t > a_t$.

All proofs are given in Online Appendix C.

3.2. Behavioral Model
To predict actual decisions, we propose a behavioral model with three components: reference-dependent

utility, sunk cost bias, and status quo bias. Below we describe these components and how they impact the decision maker's utility.

We posit that the PM who reviews a project and observes its value experiences a "gain-loss utility" by comparing the project value with an internal reference point. The PM experiences a gain if the project value exceeds his expectation and experiences a loss otherwise. We express this formally as $m(x_t - r_t)$, where r_t denotes the PM's reference point at time t. Specifically, let $m(x) = \gamma x$ for $x \geq 0$ and let $m(x) = \gamma \lambda x$ for $x < 0$, where $\gamma \geq 0$ is the weight of the reference-dependent utility and λ is the loss aversion parameter. If $\lambda \neq 1$, then the PM perceives gains and losses of the same size differently. Suppose the reference point is updated through exponential smoothing. That is, let $r_{t+1} = \theta r_t + (1 - \theta)x_t$; the parameter $\theta \in [0, 1]$ captures the speed with which the PM assimilates information. At the extremes, if $\theta = 1$, then the PM's reference point remains constant regardless of incoming information, and if $\theta = 0$, then the PM updates his reference point to fully reflect the latest information. Let $r_1 = x_1$.

Our formulation of the reference point captures the decision maker's internal expectation of the project's value and how it adjusts to new information—albeit imperfectly—over time.[3] This corresponds to Kahneman and Tversky (1979, p. 286) in that "there are situations in which gains and losses are coded relative to an expectation or aspiration level that differs from the status quo." Modeling the reference point as an expectation of a future outcome and assuming that it adapts to information over time are common in the literature (e.g., Popescu and Wu 2007, Post et al. 2008, Karlsson et al. 2009).

The gain-loss utility in our behavioral model represents the PM's psychological reaction to changes in the project value and is consistent with the literature in economics and psychology, which posit that people derive utility from information and beliefs. Karlsson et al. (2009) propose that information not only updates the reference point but also causes a direct psychological impact. Kőszegi and Rabin (2009, p. 913) suggest that "news is the central source [of reference-dependent utility]."

In the case that the PM abandons the project, we assume that two other psychological effects also impact his utility: the sunk cost and status quo effects. Thaler (1999) proposes that an initial investment opens a "mental account" and that abandonment would feel as a "loss" proportional to the amount in the account (i.e., sunk cost). To avoid this loss, people tend to continue the project—and more so as the sunk cost increases. Alternatively, Samuelson and Zeckhauser (1988) suggest that the preference to continue a project may be due to the status quo bias:

the tendency to stick with the default option or one's "current or previous decision." Specifically, we assume that the utility of abandoning is $m(x_t - r_t) - A - B \sum_{i=1}^{t-1} c_i$ for $A, B \geq 0$. The parameter A captures the PM's aversion to abandoning the project given that continuing the project seems like the default option. The parameter B is the sunk cost parameter that measures how strongly the sunk cost $\sum_{i=1}^{t-1} c_i$ affects the PM.

We write the value function as

$$V_t(x_t, r_t) = \max\{U_t^C(x_t, r_t), U_t^A(x_t, r_t)\}$$

for $t = 1, \ldots, T-1$ and $V_T(x, r) = x + m(x - r)$. The expected utility from continuing the project is

$$U_t^C(x_t, r_t) = -c_t + m(x_t - r_t) + \mathbb{E}V_{t+1}(x_{t+1}, r_{t+1});$$

here $r_{t+1} = \theta r_t + (1-\theta)x_t$ and $x_{t+1} = x_t + w_t$, and $\mathbb{E}V_{t+1}(x_{t+1}, r_{t+1})$ is the expected value of $V_{t+1}(x_{t+1}, r_{t+1})$ with respect to x_{t+1}. The utility from abandoning the project is $U_t^A(x_t, r_t) = m(x_t - r_t) - A - B \sum_{i=1}^{t-1} c_i$. The PM continues the project at stage t if and only if $U_t^C(x_t, r_t) > U_t^A(x_t, r_t)$.

The reference-dependent PM's continue/abandon decision depends not only on the project value x_t but also on his reference point r_t. This case contrasts with that of the rational PM, who makes decisions based on x_t only; see Lemma 1.

Proposition 1. *At stage t, (i) for a given r_t, there exists a threshold $\bar{a}_t$ such that the PM continues if and only if $x_t > \bar{a}_t$; (ii) for a given x_t, there exists a threshold $\bar{r}_t$ such that the PM continues if and only if $r_t < \bar{r}_t$.*

Proposition 1 states that, given x_t, the reference-dependent PM with a higher r_t has a higher likelihood of abandonment. We can expand the reference point as $r_2 = x_1$ and

$$r_t = \theta^{t-1}x_1 + (1-\theta)(\theta^{t-2}x_1 + \theta^{t-3}x_2 + \ldots + x_{t-1})$$

$$\text{for } t > 2. \quad (1)$$

On the one hand, suppose that the PM observes a high initial value but that the project's value decreases over time. Then, by Equation (1), the PM would have a reference point r_t that is higher than x_t; this entails a feeling of loss if he continues the project in stage t. And because the PM's current reference point is high, he is likely also to frame future outcomes as losses; that is, $\mathbb{E}m(x_{t+1} - r_{t+1})$ is decreasing in r_t. On the other hand, suppose the PM starts the project at a low initial value but observes increasing values over time. Then, the PM would have a low reference point r_t as compared with x_t, which means that he experiences a gain from continuing the project in stage t and also anticipates future gains. This example illustrates how, given x_t, the path may affect the likelihood of project abandonment.

Our model predicts two systematic effects of project path on abandonment decisions. First, Equation (1) implies that, given x_t and T, a PM who observes a downward (rather than an upward) history will have a higher r_t, which by Proposition 1 implies a greater likelihood of abandonment. Second, Proposition 1 suggests that, all else constant, a longer history of decreasing values should make the PM more likely to abandon the project owing to a higher r_t[4]; yet, a longer history also means a larger sunk cost, which makes the PM more likely to continue the project. Thus, we may observe a peak in abandonment rate as project length increases: In the early stages of a project, gain-loss utility dominates and so makes the PM more likely to abandon a project as project length increases. In later project stages the sunk cost dominates, making the PM more likely to continue the project. We then formulate the following two hypotheses.

Hypothesis 1. *At the same decision point, the likelihood of abandonment is higher after recent decreases of the project value.*

Hypothesis 2. *At the same decision point and given a history of decreasing values, the likelihood of abandonment is highest near the middle of a project.*

4. Study 1: Full Review

To test our behavioral model's predictions, we design a laboratory experiment in which each participant plays the role of an investor in a series of projects. Upon a project review, the participant observes the current forecast of the project value and decides whether to continue or abandon the project. At the start of each project, we inform the participant of the project's initial value, number of stages, and the continuation cost, which is constant over time. Once a project is either completed or abandoned, the participant is informed of the project payoff and moves on to the next project.

All participants are given the same 32 projects in random order. In all projects, we fix the continuation cost at $c = 11$ and set $\delta = 10$. We choose projects with different number of stages ($T = 4, 6, 8, 10$) and different initial values. We predetermine the project paths to ensure that there is sufficient variation—with some paths going up, some going down, and some staying around the initial value. Table 1 shows the paths of the 32 projects.

Our design has three key aspects. First, the projects differ in initial value, $x_1 = (T-1)\delta$ or $x_1 = (T+1)\delta$, and the optimal policy depends on the initial value. Specifically, if the initial value is high (i.e., if $x_1 = (T+1)\delta$), then the project should be started and continued at every subsequent stage. We refer to these as *profitable* projects. If, however, the initial value is low ($x_1 = (T-1)\delta$), then the PM should abandon the

Table 1. Project Paths

Project	T	Path	Project	T	Path
1	4	30-20-30-20	9	6	50-40-30-40-50-40
2	4	50-40-50-60	10	6	50-60-70-80-90-100
3	4	30-20-10-20	11	6	50-40-50-40-50-60
4	4	30-40-30-20	12	6	50-60-70-60-70-80
5	4	50-60-70-80	13	6	70-80-70-80-90-100
6	4	30-40-50-60	14	6	70-60-50-40-50-60
7	4	30-40-30-40	15	6	50-60-50-40-50-60
8	4	30-20-30-40	16	6	50-40-30-20-30-40
17	8	70-80-70-80-90-100-110-120	25	10	90-80-70-60-50-60-70-60-70-80
18	8	70-80-90-100-110-100-90-80	26	10	90-100-90-100-110-120-130-140-150-160
19	8	90-80-70-80-70-80-90-100	27	10	90-100-90-80-90-100-90-100-90-100
20	8	90-80-70-60-50-60-70-80	28	10	90-80-70-80-90-100-110-100-90-80
21	8	70-60-50-60-70-60-70-80	29	10	90-80-90-100-110-120-130-140-150-140
22	8	70-60-50-40-50-40-50-60	30	10	90-80-70-60-50-40-30-20-30-40
23	8	90-100-90-80-90-80-90-100	31	10	90-100-110-100-90-100-110-120-110-120
24	8	70-60-50-40-30-20-30-40	32	10	90-100-90-100-90-100-110-100-110-120

project at stage 1 or at any subsequent stage that is on a strictly decreasing path ($x_t = (T - t)\delta$) and continue otherwise. We refer to these projects as *unprofitable* projects. Figure 2 illustrates the optimal policy when $x_1 = 50$ and $T = 6$. Detailed formulation and analyses of the optimal policy are in Online Appendix A. Of the 32 projects, 7 (22%) are profitable and 25 (78%) unprofitable with an optimal policy such as the one illustrated in Figure 2. The larger number of unprofitable projects ensures that we collect enough data for decision points where it is optimal to abandon the project.

In a follow-up experiment (see Section 6.2), we consider the alternative setup where the continuation cost increases over time. This leads to situations where it is optimal to start the project but to abandon it if the value deteriorates. We find that our main insights remain robust.

Second, for projects with the same length (T), project paths may overlap. This allows us to study

path dependence while keeping sunk cost constant. For example, compare projects 1 and 4 in Table 1. They present the same decision problem at stage 3 with $x_3 = 30$ and $T = 4$. So even though their respective previous-stage values differ ($x_2 = 20$ in project 1 and $x_2 = 40$ in project 4), the rational PM's decision at stage 3 should be the same in both projects. Any observed difference would reveal that a behavioral factor *other than* sunk cost affects the PM's behavior.

Third, paths may overlap also for projects of different lengths (T). For instance, the first two stages of project 1 are identical to stages 3 and 4 of project 16, to stages 5 and 6 of project 24, and to stages 7 and 8 of project 30. A rational PM's decision at either of these two decision points should be independent of the project path observed up to that stage.

We implemented the experiment via an online platform. Each participant was assigned to a cubicle with a computer and instructed to log into the experiment platform. We read the instructions (which also appeared on the participant's computer screen) out loud and answered any questions privately. The participants then completed a short test to ensure that they understood the instructions. After answering the test questions correctly, each participant was given three practice projects before starting the actual experiment. All participants received a cash payoff proportional to the sum of their respective earnings (project payoff *minus* total incurred cost) from the projects in addition to a fixed participation fee. Payoffs were given to participants at the end of the experiment. We also collected some demographic information about each participant and recorded the time taken to finish the 32 projects. The instructions and platform screenshots are presented in Online Appendix D.

Figure 2. Optimal Abandonment Policy
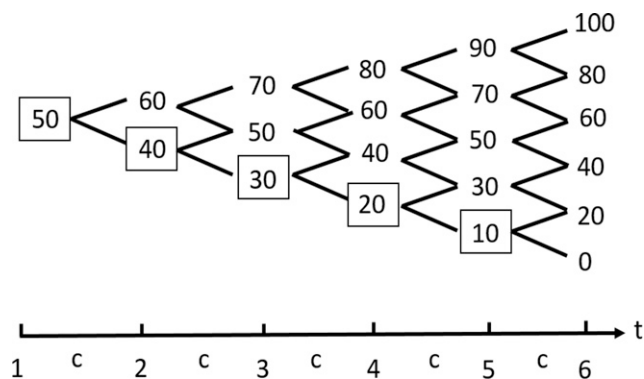
Note. The PM should abandon a project at any of the states highlighted by a box but should continue otherwise.

Table 2. Abandonment Rates Under Full Review When the Optimal Decision Is
to Abandon

	Abandonment rate	N		Abandonment rate	N		Abandonment rate	N
$T = 4$			$T = 8$			$T = 10$		
$x_1 = 30$	14%	222	$x_1 = 70$	11%	185	$x_1 = 90$	13%	296
$x_2 = 20$	13%	98	$x_2 = 60$	8%	99	$x_2 = 80$	7%	130
$x_3 = 10$	3%	31	$x_3 = 50$	18%	91	$x_3 = 70$	16%	92
$T = 6$			$x_4 = 40$	20%	50	$x_4 = 60$	18%	51
$x_1 = 50$	10%	222	$x_5 = 30$	23%	22	$x_5 = 50$	7%	42
$x_2 = 40$	6%	98	$x_6 = 20$	0%	17	$x_6 = 40$	10%	21
$x_3 = 30$	20%	60				$x_7 = 30$	16%	19
$x_4 = 20$	19%	26				$x_8 = 20$	0%	16

Notes. FR, full review. We use N to denote the number of observations, which are grouped by the same path up to the current stage. At $x_4 = 60$ and $T = 10$; for example, there are 51 observations of the continue/abandon decision (which consist of the observations from stage 4 of projects 25 and 30 being reached). Among these 51 observations, 18% are decisions to abandon the project.

A total of 37 undergraduate students at a large public university participated in the experiment. All payments were made in the local currency. The average payment was equivalent to $13.77 (USD), and the average time for participants to finish the experiment was 25 minutes.

4.1. Results: Preliminary Analysis
Preliminary analysis shows no significant effect of age, gender, or time spent on a participant's payoff.[5] We report participants' continue/abandon decisions in two cases: when the rational decision is to abandon or instead to continue.

Suppose that the rational decision at a given stage is to abandon the project; in that case, a decision to continue the project is a deviation from the rational decision. Table 2 presents the actual abandonment rates in the FR experiment for those stages at which abandoning is the rational decision. In total, of the 1,888 observations at decision points where the rational decision is to abandon the project, 87.76% choose to continue. This result is in line with the evidence that PMs incorrectly continue the project even as project performance deteriorates.

Conversely, at decision points where the rational decision is to continue the project, we observe cases of abandonment. Table 3 shows the abandonment rate at each stage of a profitable project whose value decreases over time. Although the abandonment error rate for the entire set of FR data are only 1.46%, the abandonment error rate is 10% on projects with decreasing values. This difference suggests that decisions are path dependent, which we discuss extensively in Section 4.2.

4.2. Results: Path-Dependent Continue/ Abandon Decisions
To test Hypothesis 1, we consider whether downward paths lead to a greater likelihood of project

abandonment. Recall from Section 4.1 that participants may wrongly abandon a profitable project when its value decreases. The abandonment rate is significantly lower at the same decision point given a different path. For example, at stage 2 of a four-stage project and with $x_2 = 40$, the abandonment rate is 8% if that value is lower than the initial value ($x_1 = 50$) but is 0% if the (same) value is higher than the initial value ($x_1 = 30$). The difference is significant[6] ($p < 0.05$). Similar comparisons can be made at all decision points where the paths of different projects overlap. As another example, consider the abandonment rates on decreasing paths and compare them with the abandonment rates at the same decision points but given paths that do not strictly decrease (Table 4); the former rates are higher in all cases. Using observations at the decision points presented in Table 4, we estimate a logistic regression model for the continuation decision on path type (decpath = 1 if path is strictly decreasing, decpath = 0 otherwise) while controlling for project length T and stage number.[7] Our regression results (see Table 1 in Online Appendix E) show that a decreasing path corresponds to a significantly lower likelihood of continuing the

Table 3. Abandonment Rates Under FR When the Optimal Decision Is to Continue

	Abandonment rate	N		Abandonment rate	N
$T = 4$			$T = 8$		
$x_1 = 50$	4%	74	$x_1 = 90$	2%	111
$x_2 = 40$	8%	36	$x_2 = 80$	6%	72
$T = 6$			$x_3 = 70$	18%	68
$x_1 = 70$	3%	74	$x_4 = 60$	13%	30
$x_2 = 60$	3%	36	$x_5 = 50$	23%	26
$x_3 = 50$	6%	35			
$x_4 = 40$	9%	33			

Note. N, number of observations, which are grouped by the same path (of decreasing values) up to the current stage.

Table 4. Abandonment Rates Corresponding to Different Paths

	Strictly decreasing path?			Strictly decreasing path?	
	Yes	No		Yes	No
$T = 4$			$T = 8$		
$x_2 = 40$	8%	0%	$x_2 = 80$	6%	0%
	$(N = 36)$	$(N = 92)$		$(N = 72)$	$(N = 66)$
$T = 6$			$x_3 = 70$	18%	6%
$x_2 = 60$	3%	0%		$(N = 68)$	$(N = 35)$
	$(N = 36)$	$(N = 101)$	$x_4 = 60$	13%	0%
$x_3 = 50$	6%	0%		$(N = 30)$	$(N = 25)$
	$(N = 35)$	$(N = 66)$	$x_5 = 50$	23%	0%
$x_4 = 40$	9%	2%		$(N = 26)$	$(N = 18)$
	$(N = 33)$	$(N = 88)$			

Note. N, number of observations.

project (coefficient < 0, $p < 0.01$). Finally, consistent with our behavioral model, more recent declines in project value induce a higher likelihood of abandonment. For instance, at decision point $x_4 = 80$ when $T = 8$, the abandonment rate given path (up to stage 4) 90-100-90-80 is 8%; this is significantly higher than the 0% abandonment rate given path 70-80-70-80 or 90-80-70-80 ($p < 0.05$). The same pattern holds throughout the data.

To test Hypothesis 2, we examine the effect of project length on the abandonment rate when project value decreases over time. Figure 3 shows the abandonment rates corresponding to different project lengths for the same decision point. If the decision were path independent, then, for a fixed project value and fixed time to completion, the abandonment rate would be the same irrespective of T. Yet, we consistently observe an inverted U-shaped pattern in Figure 3, where the likelihood of abandonment is highest when the decision stage is near the middle of a project and is lower both in earlier stages and in

later stages. To test this observation rigorously, we separate the relevant decision points[8] into two parts depending on whether t is near the middle of a project. We define "middle of a project" (mid = 1) as $t = 3, 4$ for a $T = 6$ project and as $t = 3, 4, 5$ for a $T = 8$ or $T = 10$ project; these values are chosen based on the peaks observed in Figure 3.[9] Let mid = 0 otherwise. We fit a logistic regression for the decision to continue the project on mid while controlling for both the number of stages left and the project value (results are reported in Table 2 in Online Appendix E). We find that the coefficient for mid is negative and significant ($p = 0.018 < 0.05$), which confirms that participants are less likely to abandon a project near its beginning or end.

Overall, our data support both Hypotheses 1 and 2. This suggests that the participants' decisions are driven by both reference-dependent preferences and the sunk cost bias.

4.3. Maximum Likelihood Estimation

To further validate the fit of our behavioral model and determine the strengths of the biases, we estimate our behavioral model using the maximum likelihood estimation (MLE) method. In this section we describe the estimation procedure.

At each stage t, participant j chooses to continue project i if and only if $U_t^C - U_t^A + w_{itj} > 0$. Here, w_{itj} is the noise term and an i.i.d., normally distributed random variable with mean 0 and variance $1/(s_1)^2$. The terms U_t^C and U_t^A are as given in Section 3.2 (we suppress the variables to ease the exposition). It follows that the probability of the participant choosing to continue or abandon is

$$P_{itj}(\text{continue}) = \Phi(s_1(U_t^C - U_t^A)),$$
$$P_{itj}(\text{abandon}) = \Phi(s_1(U_t^A - U_t^C)), \qquad (2)$$

where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal random variable.

Figure 3. Proportion of Abandonment in Project on a Decreasing-Value Path
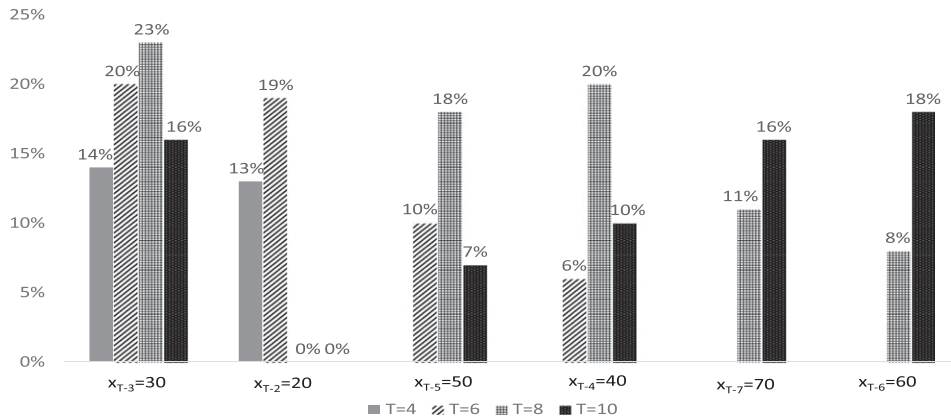
Note. T represents the total number of project stages.

The log-likelihood (LL) function is then

$$LL_{FR} = \sum_{i=1}^{32} \sum_{t=1}^{T_i} \sum_{j=1}^{N_1} \left(a_{itj} \log P_{itj}(\text{continue}) \right.$$
$$\left. + (1 - a_{itj}) \log P_{itj}(\text{abandon}) \right).$$

Here $N_1 = 37$ is the number of participants in the FR experiment. Let $a_{itj} = 1$ if participant j continues project i at stage t, with $a_{itj} = 0$ otherwise.

The unknown parameters in our behavioral model (θ, γ, λ, A, B, and s_1) are selected to maximize the log-likelihood LL_{FR}. To determine whether our model describes behavior significantly better than either the rational model or the behavioral model without gain-loss utility, we perform likelihood ratio tests.

4.4. Estimation Results

Table 5 reports estimation results for the full model as well as for the nested model with $\gamma = 0$ and the rational model with only noise parameter s_1. The p values from the likelihood ratio tests, which test the nested models against the full model, are very small in all cases ($p = 0.000$). We conclude that the full behavioral model provides the best fit to our data.

The parameter estimation in the full behavioral model yields some interesting insights. We find that the loss aversion parameter is less than 1 ($\lambda < 1$), which means that the participants have gain-seeking preferences.[10] This result does not align with the descriptions of prospect theory (Kahneman and Tversky 1979). However, it is instructive to compare our setting with those of existing works that report loss-neutral or gain-seeking behavior. For example, Novemsky and Kahneman (2005) find that

loss aversion disappears when people intend to trade. Ert and Erev (2008) replicate well-known experiments testing preferences between mixed gambles and a safe option and find that, if context is abstracted away (i.e., if the safe option is no longer presented as the status quo), then loss aversion is no longer evident. They conclude that context is a driver of asymmetric preferences with regard to gains versus losses. This is consistent with our observation of gain-seeking behavior in a setting where the risky option (continue), rather than the safe option (abandon), is the status quo. Ert and Erev (2013) further point out that gain-seeking preferences typically arise in situations involving betting behavior. For example, Sonsino et al. (2001) find that participants are highly likely to participate in betting games even when the expected returns are negative. Erev et al. (2010) similarly find that, in a market entry game, more participants choose entry over the safe option even when expected profits are unspecified. It is possible that the nature of our project management task induces a betting mindset that likewise leads to gain-seeking behavior.

Our estimation results confirm the existence of both status quo bias and sunk cost bias (estimates for both A and B are significant). The status quo parameter represents the part of utility from abandoning that does not change over time, whereas a positive sunk cost parameter implies that the PM is more likely to continue the project at later stages. Thus, our results show the important role played by status quo bias in termination delay during a project's early stages. Furthermore, we simulate the abandonment rates on a decreasing path to find that eliminating the status quo bias (sunk cost bias) can increase the abandonment rate by as much as 43% (18%).

Table 5. Estimation Results for Full Behavioral Model and Nested Models (FR)

Behavioral parameters	Only noise	No gain–loss utility	Full model
θ	—	—	0.52***
			(0.01)
γ	—	—	2.30***
			(0.53)
λ	—	—	0.86***
			(0.07)
A	—	49.39***	71.42***
		(3.83)	(14.43)
B	—	0.00	0.58***
		(0.08)	(0.21)
s_1	0.065***	0.027***	0.018***
	(0.002)	(0.002)	(0.003)
$-LL$	2025.2	993.4	963.7
Likelihood ratio test and p-value	$\chi^2(5) = 2{,}123$	$\chi^2(3) = 59.4$	
	$p = 0.000$	$p = 0.000$	

Notes. Standard errors are reported in parentheses. The likelihood ratio test is against the full model.
  *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Finally, we estimate that $\theta = 0.52$, which implies that participants' choices can be affected by project values from as many as three previous observations.

Overall, the results show that the status quo bias, gain-seeking preferences, and sunk cost bias are all important drivers of project termination delay, with the first two explaining the continuation errors in a project's early stages. Reference dependence explains the higher tendency to abandon on a downward path, and the reference-dependent utility and sunk cost bias combined can explain the observed tendency to abandon near the middle of a project.

From a managerial perspective, our results show that the tendency to delay project termination has different behavioral drivers—and may require different intervention strategies—at different stages of a project. Specifically, to reduce the status quo bias and gain-seeking preferences, the firm should emphasize the value of good abandonment decisions and ensure the PM considers all future scenarios in the early stages of a project. In contrast, near the end of a project, it may be more effective to involve a new decision maker who is not subject to psychological effects of the project's sunk costs. Further, our behavioral model provides systematic predictions (validated by data) on how the project's history affects the PM's decisions. PMs may overreact to any increasing or decreasing trends in project value, and they are especially sensitive to recent changes. Therefore, it may be beneficial to supplement the decision-making process to prevent incorrect project continuation or abandonment by having outside experts assess the project after steady decreases or increases in project value.

5. Study 2: Limited Review

Study 1 and its estimation results establish that decision makers have a strong tendency to delay project termination and that their decisions are described well by our behavioral model. In this section, we study whether it is possible to devise a simple remedy to improve decisions by managing the information accessible to PMs and in particular, whether reviewing the project *less often* could reduce continuation errors. From a rational perspective, reducing the number of reviews always hurts the project because it limits flexibility; that is, the PM loses the chance of responding to updated information. However, our behavioral model suggests that limiting the number of reviews may, in fact, lead to better project outcomes by inducing the PMs to make better abandonment decisions.

To illustrate, consider a PM who reviews only once in a four-stage project and the project value decreases over time. After the PM starts the project, he decides whether to review in stage 2 or stage 3. We will show that in both cases, he may be more likely (than a PM

under full review) to abandon the project upon receiving bad news.

Result 1. *If the PM reviews in stage 3 of a four-stage project (under LR) and observes $x_3 < x_1$, he is more likely to abandon the project than a PM under FR at the same decision point.*

The detailed formulations of the behavioral model for LR and proofs of results are in online Appendices B and C. To see why Result 1 arises, consider the PM's marginal utility from continuing the project at stage 3:

$$U_3^C - U_3^A = x_3 - c_3 + \frac{1}{2}m(\theta(x_3 - r_3) + \delta)$$
$$+ \frac{1}{2}m(\theta(x_3 - r_3) - \delta) + A + B(c_1 + c_2).$$

Because stage 3 is the last stage before project completion, the utility functions for the PMs under LR and FR are identical except for the reference point (r_3), which is higher under LR. That is, compared with the PM under FR who observes two subsequent small reductions in project value, the PM under LR observes one large value reduction and assimilates less of this new information into his reference point. As a result, the PM under LR anticipates more losses in the future if he continues and becomes more likely to abandon the project ($U_3^C - U_3^A$ is decreasing in r_3).

On the other hand, if the PM reviews in stage 2, we can prove the following result.

Result 2. *If the PM reviews in stage 2 of a four-stage project (under LR) and observes $x_2 < x_1$, he is more likely to abandon the project than a PM under FR when λ is sufficiently small.*

In this case, the reference points at stage 2 are the same under FR and LR, but the expected future gains and losses are different owing to the difference in future review points. Specifically, looking forward, the PM prefers the possibility of multiple gains to one big gain and prefers the possibility of one big loss to multiple losses. The former dominates when the loss parameter λ is sufficiently small and thus the PM derives a higher utility from continuing an FR project than an LR project.

These predictions are not limited to four-stage projects. We simulate abandonment rates in a six-stage project whose value decreases over time and where only one review opportunity is available. Figure 4 shows that for a wide range of behavioral parameter values (λ, θ), the simulated abandonment rates are higher under LR (than under FR) at every review stage. Simulation for projects of other lengths and different number of reviews yields similar results.

We test this prediction—that the abandonment rate is different depending on the frequency of review—by designing a new experiment with limited reviews.

Figure 4. (Colour online) Comparison of Simulated Abandonment Rates under FR and LR ($\gamma = 2.3$, $A = 71.42$, $B = 0.58$, $s_1 = 0.018$, $s_2 = 0.05$, $x_1 = 50$, $c = 11$, $\delta = 10$)

FR vs. LR at stage 2   FR vs. LR at stage 3   FR vs. LR at stage 4
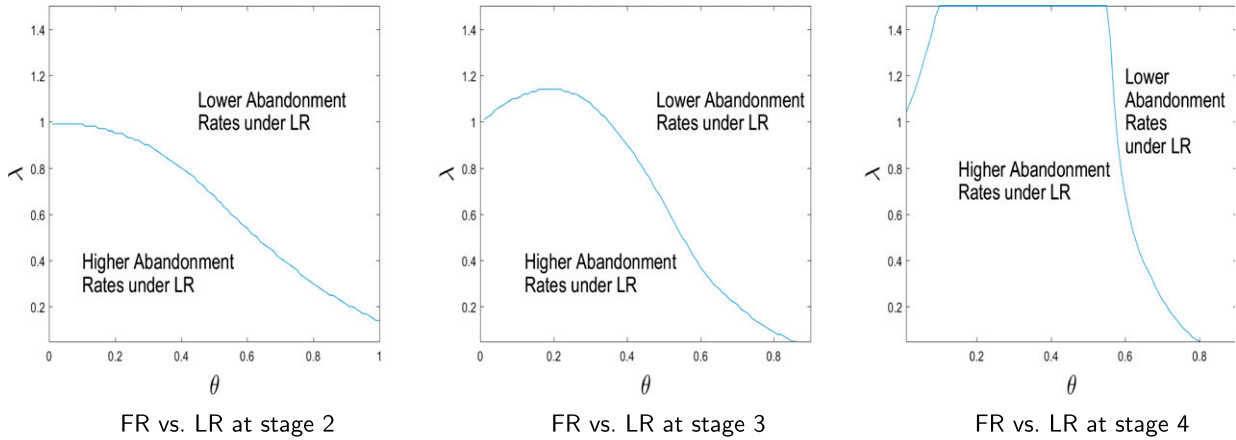
Notes. The simulation is based on the stochastic choice model in Section 4.3 and Online Appendix B. We change λ (from 0.01 to 1.50 in increments of 0.01) and θ (from 0.01 to 1 in increments of 0.01). Stage 5 is omitted because the simulated abandonment rates are always higher under LR.

We use the same setup as in Section 3 with the following difference: In each project, the number of reviews are limited and the participants can decide when to review. Specifically, the number of reviews in a four-stage project is limited to 1 and in a six-, eight-, or 10-stage project to 2. Participants are always informed of the initial value of each project. In other words, they start to make review decisions at stage 2. If the participant reviews the project, then he observes the current project value and decides whether to continue or abandon the project; in the absence of a review, the project is continued to the next stage. In this experiment setup, the rational continuation policy is the same regardless of how many review opportunities are available (see Corollary EC.2 in Online Appendix A). Therefore, any observed difference indicates a deviation from rationality. On the basis of our behavioral model's predictions, we consider two competing hypotheses:

Hypothesis 3. (a) *The likelihood of abandonment is higher in LR than in FR.* (b) *The likelihood of abandonment is lower in LR than in FR.*

We are also interested in the timing of reviews by participants. Project abandonment could be delayed if the participants avoid reviews in the early stages of a project. However, the behavioral model suggests that a gain-seeking decision maker may be more likely to review in the early stages of a project (see Example 1 and discussion in Online Appendix B). We again consider two competing hypotheses:

Hypothesis 4. (a) *PMs prefer to review early (rather than late) in a project.* (b) *PMs prefer to review late (rather than early) in a project.*

There were 38 participants in the LR experiment. The average payment to participants was equivalent to $14.27 (USD). The average time for participants to finish the experiment was 33 minutes.

5.1. Results: Effect of Limited Reviews on Continue/Abandon Decisions

Table 6 reports the error rates in FR and LR experiments. Upon a review at stage $t > 1$, an LR participant's average likelihood of wrongly continuing the project is 72.84% as compared with 87.85% for an FR participant. The difference is significant ($p < 0.01$) and suggests that limiting the opportunities to review increases the participant's likelihood of abandoning an ongoing project. Similarly, the LR participant's likelihood of wrongly abandoning the project is significantly higher than that of the FR participant.

Using observations at decision points where the rational decision is to abandon, we fit a logistic regression model for the continuation decision on the binary variable FR and the number of stages left,[11] with robust variance clustered by subject (see Table 3 in Online Appendix E). We find that FR participants are more likely than LR participants to continue a project once it has been launched ($p < 0.01$); the predicted difference in the likelihood of continuing is 13%. As a further illustration of this point, Table 7 presents a node-by-node comparison of abandonment rates in FR versus LR. At almost every node for $t > 1$, LR participants demonstrate a higher likelihood of abandonment. Therefore, Hypothesis 3b is rejected and Hypothesis 3a supported. Overall, we find that limiting the number of reviews can effectively reduce continuation errors in an ongoing project.

Table 6. Comparison of Error Rates

	Full review	Limited review
Error of continuing	87.76% ($N = 1{,}888$)	86.35% ($N = 1{,}414$)
Error of continuing*** (excluding stage 1)	87.85% ($N = 963$)	72.84% ($N = 464$)
Error of abandoning***	1.46% ($N = 4{,}039$)	2.91% ($N = 1{,}686$)
Error of abandoning*** (excluding stage 1)	1.376% ($N = 3{,}780$)	3.098% ($N = 1{,}420$)

Notes. N, number of observations. The statistical test used is Fisher's exact test for comparing the error rates of FR vs. LR.
    *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

5.2. Results: When Do Participants Review?

In this section, we test Hypothesis 4 by examining participants' first review decisions. We then investigate whether the second review decision is affected by receiving good or bad news in an earlier review.

Our results show that the participants distribute their reviews to span the duration of the project, with a higher preference for early reviews (see Table 8). For example, of the 199 observations when a project with $T = 4$ and $x_1 = 30$ is launched, 65% review in stage 2, compared with 31% in stage 3 ($p < 0.01$). For longer projects, the likelihood of making the first review in stages 2 or 3 is higher than that of reviewing in later stages ($p < 0.01$ for $T = 6, 8$). This supports Hypothesis 4a and rejects Hypothesis 4b.

Furthermore, we find that the second review's timing is significantly affected by the information received in the first review. We fit an ordered logistic model for the number of stages between the first and the second review on whether the news in the first review is good or bad (r1sign = 1 if the value in the first review is lower than the initial value; r1sign = 0 otherwise). The regression results (Table 4 in Online Appendix E) show that the coefficient for r1sign is negative and significant ($p < 0.01$).

In summary, participants tend to review early in a project, and they are more likely to seek out information after observing a decrease (rather than increase) in project value. These results suggest that review avoidance is not likely a major cause of termination delay.

5.3. Behavioral Model Estimation

Our results confirm that abandonment rates are higher under LR than under FR, which is consistent with the behavioral model's prediction that decisions differ when the frequency of reference point updating changes. However, it is possible that the limit on review opportunities also changes the strengths

Table 7. Abandonment Rates (Under FR vs. LR) When the Optimal Decision Is to Abandon

	Abandonment rate			Abandonment rate			Abandonment rate	
	FR	LR		FR	LR		FR	LR
$T = 4$			$T = 8$			$T = 10$		
$x_1 = 30$	14% ($N = 222$)	13% ($N = 228$)	$x_1 = 70$	11% ($N = 185$)	5% ($N = 190$)	$x_1 = 90$	13% ($N = 296$)	6% ($N = 304$)
$x_2 = 20$	13% ($N = 98$)	37% ($N = 62$)	$x_2 = 60$	8% ($N = 99$)	23% ($N = 31$)	$x_2 = 80$	7% ($N = 130$)	17% ($N = 36$)
$x_3 = 10$	3% ($N = 31$)	15% ($N = 13$)	$x_3 = 50$	18% ($N = 91$)	40% ($N = 55$)	$x_3 = 70$	16% ($N = 92$)	19% ($N = 37$)
			$x_4 = 40$	20% ($N = 50$)	23% ($N = 30$)	$x_4 = 60$	18% ($N = 51$)	36% ($N = 25$)
$T = 6$								
$x_1 = 50$	10% ($N = 222$)	5% ($N = 228$)	$x_5 = 30$	23% ($N = 22$)	20% ($N = 10$)	$x_5 = 50$	7% ($N = 42$)	38% ($N = 21$)
$x_2 = 40$	6% ($N = 98$)	17% ($N = 59$)	$x_6 = 20$	0% ($N = 17$)	38% ($N = 8$)	$x_6 = 40$	10% ($N = 21$)	29% ($N = 7$)
$x_3 = 30$	20% ($N = 60$)	33% ($N = 45$)				$x_6 = 40$	10% ($N = 21$)	29% ($N = 7$)
$x_4 = 20$	19% ($N = 26$)	7% ($N = 15$)				$x_7 = 30$	16% ($N = 19$)	17% ($N = 6$)
						$x_8 = 20$	0% ($N = 16$)	25% ($N = 4$)

Note. N, number of observations.

Table 8. Proportion of First Review by Stage

Project length and initial value	N	Proportion of first review decision							
		Stage 2	Stage 3	Stage 4	Stage 5	Stage 6	Stage 7	Stage 8	Stage 9
$T = 4$									
$\quad x_1 = 30$	199	65%	31%						
$\quad x_1 = 50$	74	61%	32%						
$T = 6$									
$\quad x_1 = 50$	217	49%	37%	12%	1%				
$\quad x_1 = 70$	76	50%	41%	9%	0%				
$T = 8$									
$\quad x_1 = 70$	181	31%	35%	22%	9%	1%	1%		
$\quad x_1 = 90$	111	23%	36%	26%	13%	0%	0%		
$T = 10$									
$\quad x_1 = 90$	286	24%	26%	23%	13%	10%	2%	0%	0%

Note. N, number of observations.

of participants' behavioral biases under LR. Such framing effects are often observed and used by researchers to alleviate decision biases. For example, Ho et al. (2010) manipulate the salience of participants' reference-dependent preferences in newsvendor experiments and find this strategy effective in generating better inventory decisions. Heath (1995) shows that people's response to sunk costs depends on the relative saliency of past/future costs and the budget. Using both laboratory and field experiments, Mullainathan and Shafir (2013) find that people make more myopic decisions when the scarcity of monetary or time resources is salient.

To identify any difference in the strengths of behavioral biases when reviews are limited, we conduct structural estimation of the behavioral model using LR data and compare the parameter estimates under FR and LR. Table 9 presents the estimation results for the full behavioral model as well as the nested model with $\gamma = 0$ and the rational model with only noise parameters s_1 and s_2. As in the FR case, the full model provides the best fit for the data.

The comparison of FR and LR estimates shows that both the status quo parameter A and sunk cost parameter B are smaller in LR. In fact, the estimate for B is not statistically different from zero. This suggests that limiting the number of review opportunities weakens both the status quo and sunk cost biases. It is possible that, when review opportunities are limited, the "decision-making value" of reviews becomes more salient. Therefore, the decision maker may become more cognitively attentive to the information revealed at a review and be more willing to choose the abandonment option. This is consistent with the finding of Mullainathan and Shafir (2013) that when the resources for implementing a task are scarce, the decision maker focuses more on that task. Furthermore, existing research suggests that the sunk cost bias is driven by individuals' desire to justify their previous investment decisions (Sleesman et al. 2012). When review opportunities are limited, this bias may be weaker because participants have made fewer investment decisions.

Further, we find that the estimates for θ and γ are fairly consistent across the two experiments, whereas λ is smaller (and not statistically different from zero) in LR. The smaller λ in LR suggests that participants are less averse to losses when review opportunities are limited. This is consistent with studies that show that gain-loss preferences vary with the frequency of potential gains and losses and that people dislike frequent small losses more than infrequent large ones (Lambrecht and Skiera 2006).

Overall, estimation results show that participants are more gain seeking but have smaller sunk cost and status quo biases under LR. These changes, combined with the reference effects as predicted by the behavioral model, lead to an overall higher willingness to abandon when review opportunities are limited.

6. Discussion and Conclusion

In this section we summarize our results and contribution. We then describe results from two additional experiments to show the robustness of our key insights. Finally, we discuss the limitations of our work and directions for future research.

6.1. Results and Contribution

Sequential investment decision making is a crucial component of managing projects in uncertain environments. Our study sheds light on the behavioral regularities in such decisions and their psychological drivers. Decision makers exhibit a strong tendency to delay project termination, but they are less likely to do so after observing decreases in project value or near the middle (rather than beginning or end) of a project. These observations are consistent with the predictions of our behavioral model. Specifically, reference

Table 9. Estimation Results for Full Behavioral Model and Nested Models (LR)

Behavioral parameters	Only noise	No gain-loss utility	Full model
θ	—	—	0.48***
			(0.05)
γ	—	—	2.22***
			(0.11)
λ	—	—	0.00
			(0.17)
A	—	58.88	11.02***
		(74.36)	(1.62)
B	—	0.00	0.01
		(0.99)	(0.20)
s_1	0.053***	0.021***	0.032***
	(0.003)	(0.006)	(0.008)
s_2	0.000	0.499	0.092***
	(0.021)	(1.582)	(0.015)
−LL	4,146.4	3,469.9	3,259.4
Likelihood ratio test and p-value	$\chi^2(5) = 1{,}774$	$\chi^2(3) = 421$	
	$p = 0.000$	$p = 0.000$	

Notes. Standard errors are reported in parentheses. The likelihood ratio test is against the full model.
   *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

dependence explains the higher tendency to abandon on a downward (versus upward) path, while reference dependence and sunk cost bias combined explain the higher abandonment rate near the middle of a project. Finally, our structural estimation results reveal that, aside from the sunk cost bias, the status quo bias and gain-seeking preferences are also important drivers of termination delay, especially at the early stages of a project.

To alleviate termination delay, we conducted a new experiment whereby we limited the number of review opportunities and allowed the participants to choose when to review. We find this strategy effective to reduce the continuation errors. The reduction is due to a combination of reference effects (as predicted by our behavioral model) and smaller status quo and sunk cost biases. In particular, we propose that the status quo and sunk cost biases are alleviated for two reasons. First, the limit on review opportunities makes the "decision-making value" of reviews more salient, and hence participants become more cognitively attentive to information and more willing to abandon the project. Second, when reviews are limited, participants feel less "committed" to the project because they have made fewer investment decisions.

Our work is indicative of policies that might improve the quality of decisions in project management. First, it may be possible to counteract the effect of path dependence by periodically introducing new personnel (e.g., outside experts or upper level managers)—who are not familiar with the project's history—to assess its current situation (McNamara et al. 2002). This intervention is especially useful when a project's value has been steadily decreasing or increasing. Second,

different policies may be effective at different stages of a project. Specifically, during the early stages of a project, the firm should focus on alleviating the PM's status quo bias and gain-seeking preferences. For example, the firm may change the decision procedure from "opt out" to "opt in" by making abandonment the default option and requiring the PM to provide justifications for continuing a project. An alternative approach to alleviate the status quo bias is to promote a culture that values appropriate abandonment decisions; for example, the firm can evaluate the PM based more on the quality of the decision process rather than the final decision outcome (Simonson and Staw 1992). Further, to suppress the PM's gain-seeking preferences, the firm can mandate detailed reports of worst-case scenarios in order to draw attention to the potential downside risks in the project. When a project is nearing completion, however, a more effective policy may be to change the decision maker to reduce the prominence of sunk costs (Boulding et al. 1997). Finally, limiting the number of reviews is a potential remedy for termination delay. Our results show that there is a trade-off between the economic value of reviews and the "psychological cost" of reviewing too frequently. The firm should take this trade-off into account when designing the review process of a project. For instance, the firm should be careful about employing IT systems that allow the PM to monitor projects in real time since frequent reviews may actually exacerbate project termination delay. In this regard, a "rotating" team of decision makers who take turns reviewing the project may be best positioned to make correct continue/abandon decisions.

6.2. Robustness Checks

It is plausible that the specific design of our experiments drives the insights we summarize above. To address this issue, we conducted two additional experiments that we describe succinctly here. The related details are in online Appendices F and G.

6.2.1. Cost Saliency.
The path-dependent behavior and high continuation error rates we observe may be due to the saliency of project value relative to cost. Therefore, if we make project costs more salient, participants may avoid making these decision errors. To test this, we changed the experiment interface and instructions to emphasize cost (see a complete list of changes and detailed results in Online Appendix F). The new data show that our key insights from the original experiments continue to hold. In particular, participants are still highly likely to make continuation errors (the continuation error rates in both FR and LR are above 70%) and decisions are influenced by path and review frequency.

6.2.2. Increasing Cost Profile.
In our original experiments, continuation cost is constant and, by design, projects should be continued to completion or abandoned at the first stage. In reality, however, a profitable project may turn into an unprofitable one. To check the robustness of our results in this more realistic setting, we ran a new experiment in which continuation cost increases over time. For example, in a six-stage project with $x_1 = 50$, we set the continuation costs as $c_1 = 8, c_2 = 9, c_3 = 10, c_4 = 11,$ and $c_5 = 12$. In this case, it is optimal to start the project in stage 1 but to abandon it in the second stage if project value deteriorates (i.e., at $x_2 = 40$). Our main insights remain robust in this setting. In particular, participants still exhibit a tendency to delay project termination, make path-dependent decisions, and are less likely to make continuation errors when review opportunities are limited; see Online Appendix G for details about the experiment setup and data analysis.

6.3. Future Research

There are several directions for future research. First, we consider a simple sequential investment setting and do not include interactions among different parties. In reality, projects are complex endeavors that involve multiple parties with different (and sometimes conflicting) incentives. It would be interesting to study the investment decisions in a principle–agent setting or in a setting where the project is managed by multiple decision makers. Second, though we have assumed a zero payoff for the project manager's outside option, in reality, the PM often has several alternative options. For example, an investor may be investing in multiple projects at once or a manager who invests in the development of a new product may have the option of focusing instead on an existing product. Third, project reviews, in practice, often yield imperfect information and project managers have to interpret the information to update their beliefs about the uncertainties involved. There is no such subjective updating of beliefs in our model. It is possible that our key insights carry over to these alternative settings, i.e., the PM may overreact to project performance trends and become more willing to abandon when reviews are limited. Finally, our work is a first step to build a theory on how the frequency of project reviews and evaluations affects the PM's decisions. The theory may incorporate the project context (e.g., exploration versus exploitation) and decision-making hierarchy among other factors. We leave it to future research to examine these issues.

Endnotes

[1] This phenomenon is often referred to as *escalation of commitment*, or "throwing good money after bad"; see Staw and Ross (1989) and Sleesman et al. (2012).

[2] We refer to rational decisions as "optimal" in this paper.

[3] We can also formulate the reference point as an internal expectation for the *net* project value (project value minus total cost). Specifically, consider the initial reference point $r_1 = x_1 - \sum_{i=1}^{T-1} c_i$, and the updating scheme $r_{t+1} = \theta r_t + (1 - \theta)(x_t - \sum_{i=1}^{T-1} c_i)$. Suppose the decision maker compares the current net project value with his reference point and experiences a gain-loss utility, i.e., $m(x_t - \sum_{i=1}^{T-1} c_i - r_t)$. It is easy to see that the cost terms cancel out and we obtain the same model as that provided here.

[4] A history of decreasing values means that $x_{t-1} = x_t + \delta, x_{t-2} = x_t + 2\delta, \ldots, x_1 = x_t + (t-1)\delta$. It follows from Equation (1) that in this case, for a given $x_t = x$, a larger t corresponds to a higher r_t.

[5] Multiple regression with robust variance clustered by subject. The cluster-robust variances adjust for potential correlation in errors between decisions from the same individual (Greene 2012, Section 17.3.1).

[6] Fisher's exact test.

[7] Controlling for T and t effectively controls for the project value because the only decision points we use are $x_t = (T - t + 2)\delta$ for $t > 1$.

[8] We use decision points in projects with decreasing values; that is, $x_t = (T - t)\delta$ for unprofitable projects and $x_t = (T - t + 2)\delta$ for profitable projects.

[9] In a $T = 10$ project, using $t = 3, 4, 5, 6$ or $t = 4, 5, 6$ for mid = 1 in the analysis yields similar significant results.

[10] We also estimate the behavioral model using alternative formulations for the reference point and find that $\lambda < 1$ is robust.

[11] Because we focus on decision points at which the optimal decision is to abandon (i.e., $x_t = (T - t)\delta$), controlling for the number of stages left also controls for the project value.

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