Initiating and Sustaining Supplier Involvement in Development Projects: a Behavioral Investigation

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While suppliers are often an excellent source of product innovation for buyers, their propensity to undertake or continue an innovation project is often elusive. This study examines what factors, including characteristics of the innovation project or the supplier’s decision environment, influence the decision to accept and subsequently continue an innovation project involving significant financial investment and cost uncertainty. Through a series of controlled human experiments motivated by behavioral theory, we find that acceptance rates increase when projects are characterized by low real options value or represent entirely new (versus replacement) revenue. While these factors have less influence on the supplier’s decision to continue the project, once accepted, continuation rates do increase if acceptance and continuation decisions are made by the same person. We also find that the buyer’s choice of contract frame for sustaining supplier engagements (penalty versus reward) has a significant impact on acceptance rates.

Key words: supplier innovation, supply chain contracts, buyer-supplier relationship, behavioral operations

1. Introduction

Buyers increasingly rely on their suppliers to engage in new product development. For highly technical products, such as those residing within the electronics, pharmaceutical, or automotive industry, suppliers often have access to unique knowledge and resources that are integral to successful product innovation. For example, Goodyear Tire & Rubber reported that it faced seventeen specific product development challenges which it could
not solve on its own (Hannon 2009). Goodyear’s CEO was able to solve many of these challenges successfully by turning to the company’s suppliers and asking them to develop new technologies. Shifting product development responsibilities to suppliers has the added benefit of engaging them in the product development process early, enabling them to design for manufacturability, which ensures better speed to market and quality at launch (Petersen et al. 2005).

Even if product development projects are off to a good start and all parties agree on contract parameters, they can still fail during execution (Lhuillery and Pfister 2009). Consider the case of a U.S. based firm selling gardening products. The firm had a strong brand name and distribution network, but relied on Asian original design manufacturers to develop and manufacture the next generation of their products. Technological change allowed upgrading one of their products – a development project taking almost two years. The company selected a Chinese supplier to develop and ultimately manufacture this new version of their product. Yet despite initial enthusiasm and agreement on both sides, the relationship soured. Technical difficulties amounted in the project, and the buyer soon perceived a lack of effort among their supplying company. Due to the challenges of the project, and due to massive growth in other areas, the Chinese firm apparently lost economic interest in the project. After two years of development, the project was finally canceled, leaving the buying firm with no new product to sell to their customers. The buying firm had to select a new supplier and start a new development project, which would take another 1-2 years of development time with an uncertain outcome.

The multi-phased nature of such innovation projects can make it challenging for a supplier to assess their profitability. This, in turn, makes it difficult for the buyer to predict whether the supplier will accept and continue to invest in the innovation through its successful completion. As Reuer and Zollo (2005) report in their study on high-tech research alliance termination, only 15% of terminated alliances were successful, with over 51% experiencing either a natural contract expiration or unilateral withdrawal by a partner. Collaboration failures are costly to buyers and put them at risk of falling behind the innovation advances of competitors. Understanding what factors contribute to a supplier passing over, or later terminating, an innovation contract is an important step towards reducing the
incidence of collaboration failures. In this paper, we seek to advance this understanding by taking a behavioral perspective and examining how the structure of innovations, as well as the supplier’s decision environment and buyer’s contract frame, can lead suppliers to stray from profitable decisions.

Bhaskaran and Krishnan (2009) characterize innovations in terms of two factors, project uncertainty and project revenue. An important characteristic of project uncertainty in a phased decision environment is how uncertainty is resolved over time. Specifically in this context, whether cost uncertainty reduces significantly before additional R&D investment must be made. Previous behavioral research finds that decision makers often fail in estimating the real options value of such information updating, with the direction of the error depending on the decision context (Delquié 2008). Our research sheds light on how the real options value is perceived by suppliers in the context of distributed product development.

The type of project revenue, which Bhaskaran and Krishnan (2009) characterize as either new or replacement, also has the potential to influence acceptance decisions. New revenue projects are usually evaluated independently against the default of adding no additional revenue. In contrast, replacement revenue projects are evaluated relative to existing revenue. This difference in the framing of the default option could conceivably make one type of revenue more attractive to the supplier, even when both provide the same profit potential. Our research provides a platform for testing these effects.

The supplier’s decision environment, particularly linkages between acceptance and continuation decisions, may also influence the supplier’s decisions. From a normative perspective, once an innovation contract is accepted, the decision of whether to continue investing in the project should be independent of the level of investment already incurred. However, behavioral studies have found that a “sunk cost bias” can cause decision makers to continue projects that should be abandoned (Arkes and Blumer 1985). Acceptance and continuation decisions are also potentially linked by decision authority. Previous behavioral research suggests that having authority for both the acceptance and continuation decisions may change the resulting continuation rate (Cialdini et al. 1978), which could have implications for how the supplier’s R&D process should be organized. We examine
whether either of these decision linkage biases (sunk cost or continuation) exists in this innovation context.

We also examine how the buyer’s choice of contract frame can further influence contract decisions. To this end, we examine the supplier’s decisions first using a penalty contract frame, where the buyer offers a bonus to the supplier for accepting the contract, but later invokes a penalty if the supplier chooses not to continue the R&D investment. This penalty can be understood as a breach remedy which explicitly specifies the consequences of a unilateral contract termination. The use of breach remedies, where a charge is incurred when a supplier fails to meet specific contractual terms, is commonly stipulated by contract law (Plambeck and Taylor 2007). Setting specific penalties occurs frequently in relation to innovation contracts, for instance in the cases of Rolls-Royce, Bombardier, and Hitachi (Visnjic et al. 2013). In our study we consider the case where penalties relate to specific product innovation targets. This is then compared to a reward frame where the buyer offers only a smaller initial revenue to the supplier for accepting, but then also promises a second reward for seeing the project to completion. Such a reward structure is typically used in the pharmaceutical industry for compensating suppliers as they reach predetermined project milestones (Bhattacharya et al. 2014). Daimler also uses rewards in response to successful innovations within its automotive component network (Wood 2011).

In summary, we investigate three research questions: (1) how do innovation factors, such as the type of project uncertainty and project revenue, affect the supplier’s propensity to enter into an innovation contract? (2) how do linkages between the acceptance and continuation decision influence the innovation project’s completion rate? (3) how does the contract frame further contribute to the supplier’s propensity to enter into and complete the innovation? These questions are addressed by developing a series of behavioral hypotheses, and testing them through a set of laboratory experiments.

We find that the level of project uncertainty, specifically the real options value of the R&D project, does influence the suppliers acceptance rate. Suppliers generally underestimate this real options value, leading them to prefer projects where the real options value is a small percentage of the overall innovation valuation. This finding is particularly relevant for buyers who seek to incentivize radical innovations which are often marked by higher
real options value. We also find that new revenue projects yield a higher acceptance rate
than replacement revenue projects, confirming that the framing of the default revenue
option does influence contract decisions. In terms of potential decision linkage effects, we
find no evidence of sunk cost bias. However, giving authority over both decisions to one
individual does increase the project continuation rate. This highlights the importance of
buyers knowing how decision authority is structured within their supplier’s organization.
Finally, changing the contract frame from a penalty to a reward leads to higher acceptance
rates, but has little impact on the continuation decision. This suggests that buyers would
benefit from framing innovation contracts in terms of rewards whenever possible.

2. Related Literature

Our paper relates to the supply chain literature on product innovation, which high-
lights how differences in the capabilities of diverse supply chain entities can influence
new product-development outcomes (Bhattacharya et al. 2014, Kim and Netessine 2013,
2012). Like Cui et al. (2012), Wang and Shin (2012), and Wang and Shin (2013), we con-
sider cases where a supplier has the capability to develop an innovative product. Several
studies have shown that misalignment of incentives in such settings can lead to sub-optimal
levels of R&D efforts (Gilbert and Cvsa 2003, Xiao and Xu 2012, Plambeck and Taylor

Gilbert and Cvsa (2003) study trade-offs which arise when an upstream supply chain firm
can either commit to prices that stimulate downstream innovation, or remain flexible when
reacting to demand uncertainty. Xiao and Xu (2012) analyze the impact of royalty contract
revision on incentives and profits in a two-stage supply chain under information asymmetry.
They also propose a contingent royalty contract where the innovator obtains royalties
based on technical performance. Like us, they consider a reward contract, but assume
the technical performance to be dichotomous, i.e. the supplier finishes the development
project or resorts to a default version of a product. This is typical of products that can be
independently developed and allow the supplier to stop an ongoing development process.
Plambeck and Taylor (2007) consider a setting where one buyer reserves capacity for \(N\)
buyers who invest in innovation. Based on the state of the realized market, renegotiation may take place and capacities may be reassigned. Like their model, our setting considers breach remedies, which influence decisions in the second stage. However, in our setting the supplier is the innovator and there is no renegotiation. Kim and Netessine (2013) study collaboration of suppliers and buyers in new product development projects. Their focus is on the dilemma suppliers face as more collaboration implies lower risks and higher profits, but at the same time increases the risk of exposing a better estimate of her costs to the buyer who would in turn obtain a better bargaining position. Like their model, we assume the supplier faces uncertain costs but learns over time. While they consider uncertain unit costs, we consider uncertain development costs. Moreover, the dynamics between buyer and supplier are different in our setting.

The study by Bhaskaran and Krishnan (2009) is closest to our work. They analyze the impact of effort, revenue, and cost sharing mechanisms in a dyadic supply chain where both parties have the capability to engage in new product development. Bhaskaran and Krishnan (2009) introduce uncertainty in the forms of translational uncertainty, which reflects uncertainty of a firm’s ability to translate an innovation into a commercially viable product, and timing uncertainty, which captures stochastic costs and is similar to cost uncertainty in our model. They further analyze how the type of project uncertainty and the type of project revenue influence optimal contract decisions. Inspired by their work, we similarly study the impact of the structure of uncertainty and the type of project revenue, although the application of these factors are different given our different problem context. In our setting, suppliers make two binary decisions (accept and continue) while in theirs supplier make one continuous effort decision. Also, our dependent variable of interest is the supplier’s behavior rather than the profit-maximizing strategy. Two other papers who also study the impact of contracts on supplier innovation are Wang and Shin (2012) and Wang and Shin (2013). Both assume an innovative supplier and a buyer selling the innovation to his customers. Wang and Shin (2012) confirms that revenue-sharing contracts can coordinate supply chain decisions, including innovation. Wang and Shin (2013) focuses on the impact of downstream competition on upstream innovation. In contrast to these
papers, our model assumes two decision phases for the supplier and stochastic development costs.

The supply chain contracting literature has recently highlighted the importance of behavioral facets on contract design performance. Katok and Wu (2009) use experiments to show that, despite the mathematical equivalence of revenue sharing and buyback contracts, actual decision makers tend to react differently to each. Zhang et al. (2013) use laboratory studies to provide further explanations for why behavior is different between the two contracts, highlighting the role of the suppliers’ loss aversion. Cui et al. (2007) find analytically that even a simple wholesale price can achieve channel coordination, if channel members are fair-minded. Further behavioral factors related to operations decisions, such as anchoring and insufficient adjustment (Schweitzer and Cachon 2000, Katok and Wu 2009), bounded rationality (Su 2008), and misjudgements of the value of information (Kremer et al. 2013), indicate that supply chain models can often benefit from a more behavioral approach in order to understand how supply chain decisions are actually made. This motivated us to examine supplier innovation contracts from a behavioral perspective.

Our contractual setting is also related to the literature on forcing contracts among principals and agents. Under forcing contracts, the decision of an agent is non-contractible, but can be clearly inferred from the outcome of the decision. Contracts are then strongly tied to outcome, imposing strong benefits for reaching (or penalties for not reaching) target outcomes. This structure is often encountered in behavioral operations research; for example, the options contract studied by Davis and Leider (2015) allows a buyer to provide a fee to the supplier which he can withdraw from the supplier if she fails to deliver the according amount of product. Among the earliest papers to analyze forcing contracts is Harris and Raviv (1979). The authors consider a risk-neutral agent who must take an action which leads to a specific outcome given a random state of nature. They show that the principal may design an optimal contract which only depends on the outcome. As Holmstrom (1982) later showed, this class of contracts can potentially help to alleviate shirking problems in groups when individual actions are not observable. However, an inherent weakness of forcing contracts is the sensitivity of the agent’s utility to slight deviations in the target outcome (Eswaran and Kotwal 1984). Behavioral experiments examining productivity and
group incentives have shown that despite providing normatively strong incentives, forcing contracts may not induce individuals to find an efficient solution (Nalbantian and Schotter 1997). The penalty and reward contracts in our setting can be interpreted as forcing contracts. The action of abandoning all effort in the project is not directly observable, but the outcome of that (abortion/continuation of project) is, with the penalty contract imposing heavy fines for not obtaining the right outcome and the rewards contract creating benefits of obtaining that outcome. However, in contrast to Harris and Raviv (1979) we conceptualize uncertainty through a two-phase realization of the underlying project costs, where in phase one a random cost signal is observed before action in phase two is taken, and the uncertain outcome in phase 2 is correlated with this phase one signal. Risk in our model stems from development costs rather than strategic uncertainty as observed in the group incentives setting of Nalbantian and Schotter (1997). Moreover, our setting has a finer operational detail which allows us to focus on both project characteristics (structure of project uncertainty and type of revenue) as well as decision linkages (sunk costs and consistency).

3. Theory Development and Hypotheses

The model presented in this section is designed to capture the structure and fundamental trade-offs that suppliers face when deciding whether to initially accept an innovation contract, as well as whether to continue the associated R&D investment once the cost of the innovation becomes more apparent. Consider a two-stage supply chain with a buyer who can either sell an innovative product with revenue $r_I$ or receive revenue $r_0 < r_I$ without the innovation. While this assumption of dichotomous outcomes is stylized, it corresponds well to situations where the outcome of a development project depends on the successful adoption of a particular technology, the result of a drug trial or the ability to adhere to predefined specifications. For example, consider the battery type used in hybrid vehicles. Ni-MH batteries are commonly used (default version) for engines of hybrid vehicles such as the Toyota Prius (Serrao et al. 2005) whereas Li-Ion batteries (innovative version) could be more efficient. Yet, there is no intermediate solution such as a single battery that is 80% Li-Ion and 20% Ni-MH that can be used in the car. Similarly, in the introductory example...
of a garden tools manufacturer, the outcome of the project depended on whether a new technological standard could be adopted for the established product line; a half adoption was not possible, and the failed project led to no additional revenues.

The innovative product requires investment in R&D by the supplier which needs to be incentivized through a contract proposed by the buyer. If the supplier accepts this contract, she starts investing into R&D project consisting of two phases. During the first phase, the supplier incurs development costs $c_1$. Based on early design studies and prototypes, her information regarding further stochastic costs are updated, which we model through a signal $\xi$. For example, in the case of Li-Ion batteries it is known there are substantial technical challenges related to hybrid vehicles which may cause high development costs (Etacheri et al. 2011). So the supplier must begin the development project to understand whether she can handle them and to get a better estimate on actual costs. After observing this signal, the supplier has the opportunity to terminate or continue the R&D process. She will produce the innovative product only if she continues with R&D. So she has two choices: accept the contract proposed by the buyer ($A = 1$) or reject it ($A = 0$) and in the former case either to continue into the second phase ($C = 1$) or stop the development ($C = 0$). If the supplier rejects the contract or stops R&D her revenue is $w_0$.

The supplier’s (real) option to discontinue projects in the second phase may give rise to misalignment of incentives because the supplier might stop projects which should have been continued from the buyer’s perspective. To account for this, we assume the buyer’s contract consists of two parameters, namely revenue for the innovative product, $w_I$, and a breach penalty, $p$, which is charged if the supplier discontinues the project. This is typical of projects where the buyer can explicitly list requirements that the innovative product needs to satisfy such as using Li-Ion batteries instead of Ni-MH batteries. If the supplier develops the innovative version, she will receive $w_I$ and, if not, she is forced to pay $p$.

Please note that the restriction to binary choices will not change the structure of our results as the existence of Pareto optimal is ensured for any action spaces which are compact subsets of nonnegative reals (Harris and Raviv 1979). A detailed comparison of the binary choice model and a model allowing for continuous innovations can be obtained from the authors. However, we analyze this binary choice benchmark model as this is the setting we consider in the laboratory.
Without loss of generality, we assume the supplier’s production costs are the same, $k$, for both versions of the product\(^2\). We assume the first phase R&D cost, $c_1$, is deterministic since this cost is incurred almost immediately. In the second phase, costs are assumed to be stochastic, expressed by the random variable, $\zeta$, as the time-frame is longer and dependent on outcomes of the first phase. After the first phase, the supplier observes the signal, $\xi$, indicating which distribution of $\zeta$ is updated and the supplier makes her continuation decision based on that signal. For ease of exposition, let $\mu : \mathbb{R} \to \mathbb{R}$ be defined by $\mu(\xi) := \mathbb{E}[\zeta | \xi]$. We assume $\mu(\xi)$ increases strictly in $\xi$ and is differentiable. Let $f_1$ denote the probability density function of $\xi$ and $F_1$ the corresponding cumulative distribution function. Without restricting the analysis to any specific distribution, we only consider those distributions whose support is an interval, $I \subset \mathbb{R}$, with $f_1(z) > 0 \ \forall \ z \in I$. Figure 1 illustrates the sequence of events and associated profit outcomes for the buyer and supplier ($\pi_b$ and $\pi_s$, respectively).

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\(^2\)Capturing heterogeneous production costs simply requires adding another parameter to the model, with no impact on the results of Propositions 1, 2, or 3.
3.1. Normative Predictions

The supplier’s problem can be solved by backward induction as implied by Figure 1. Focusing first on the continuation decision in phase 2, a profit maximizing supplier should only continue the R&D investment if her cost signal is sufficiently low.

**Proposition 1.** The optimal continuation strategy for a profit-maximizing supplier in phase 2 is a threshold policy where the innovation investment should continue if $\xi \leq \xi^*$, with $\xi^* = \mu^{-1}(w_I - w_0 + p)$.

All proofs can be found in the appendix. The threshold for the cost signal depends on the breach penalty and the revenue difference between the innovative and default products. As either this revenue difference or breach penalty level increase, the continuation threshold for the cost signal increases as well. Turning now to the acceptance decision in phase 1, we define $c_2(\xi^*) := \int_{-\infty}^{\xi^*} \mu(z)f_1(z)dz/F_1(\xi^*)$ as the conditional expected costs in phase 2, which is helpful in stating the following result.

**Proposition 2.** The optimal acceptance decision for a profit-maximizing supplier is to choose the innovation contract when $(w_I - w_0)F_1(\xi^*) \geq p(1 - F_1(\xi^*)) + c_1 + c_2(\xi^*)F_1(\xi^*)$ and the default version otherwise.

This proposition implies that, in choosing whether to accept the innovation contract, the supplier has to take four terms into account and weigh them with their probability. Here $F_1(\xi^*)$ reflects the probability of continuing the innovation, as it is the probability of a cost signal below the threshold $\xi^*$ defined in Proposition 1. This probability plays a central role in the acceptance rule, which implies that the supplier should consider the likelihood of continuing in the phase 2 when making her phase 1 decision. As we see in Proposition 1, this likelihood is impacted by the margin $(w_I - w_0 + p)$.

The buyer’s optimal contract parameters, assuming the supplier behaves as predicted in Propositions 1 and 2, can then be determined as follows:

**Proposition 3.** A profit maximizing buyer should set contract parameters as follows when interacting with a profit maximizing supplier:
1. If the total expected value of an innovation $v \geq 0$ then

$$w^*_I = w_0 + c_1 + \mathbb{E}_\xi [\mu(\xi)] - \int_{\mu^{-1}(r_I - r_0)}^{\infty} (\mu(z) - (r_I - r_0)) f_1(z)dz$$

and

$$p^* = r_I - r_0 - \mathbb{E}_\xi [\mu(\xi)] - c_1 + \int_{\mu^{-1}(r_I - r_0)}^{\infty} (\mu(z) - (r_I - r_0)) f_1(z)dz$$

(1)

The profit-maximizing supplier will accept this contract and breach only if the observed signal $\xi > \mu^{-1}(r_I - r_0)$.

2. Otherwise, the buyer maximizes his profit by setting $w^*_I = w_0$ and $p^* = 0$ such that the supplier rejects the offer and produces the default version of the product.

While our model is stylized, the resulting contract structure possesses several desirable properties from the buyer’s perspective. First, the penalty contract is Pareto optimal and channel coordinating. Also, it allows the buyer to push all innovation risk onto the supplier. The buyer’s profit might appear to be a random variable since the supplier’s continuation decision depends on the realization of the random variable $\xi$. However, we learn from Proposition 3 that the optimal contract satisfies $p^* + (r_0 - w_0) = (r_I - w^*_I)$. The left side of this equality can be interpreted as the buyer’s revenue when the supplier accepts the contract but chooses not to complete it. The right side is the buyer’s profit when the supplier both accepts and completes the contract. Since both are equal, the buyer’s profit is independent of the continuation risk. It can also be shown that no single parameter contract exists that leads to the same results for the buyer. Finally, because the buyer cannot benefit by having the supplier breach the contract, the contract is court-enforceable.

Since the case of $v < 0$ is trivial we will focus our attention throughout the remainder of the paper on parameter values where $v \geq 0$. The variables within equation (1) reflect key features of R&D projects that motivate our behavioral predictions.

3.2. Behavioral predictions: influence of project characteristics

We next examine how different aspects of the project structure may cause the supplier’s acceptance behavior to deviate from Proposition 2. We focus on two important structural

$^3$Note that more complex contracts are possible. For instance, payment could be conditioned on the realization of the signal. However, in line with forcing contracts studied by Harris and Raviv (1979) we find that such contracts cannot increase the buyer’s profit.
characteristics: the type of project uncertainty (captured through the real options value) and type of project revenue (captured through \( w_0 \)).

### 3.2.1. Project uncertainty

In our model we distinguish between two types of R&D projects, namely incremental and radical innovations, following a typical characterization of innovation (Ettlie et al. 1984, Song and Thieme 2009). Incremental innovations are characterized by low to moderate upfront uncertainty, which is not substantially reduced over time. Radical innovations have higher initial uncertainty, but this uncertainty is often substantially reduced once initial design studies are conducted and prototypes are developed.

To differentiate between these two types of uncertainty, we decompose the innovation value for the project, \( v \), into two components. The first component, which we refer to as the core value \( (v_c) \), captures the difference between the buyer’s customers’ willingness to pay and the expected innovation costs assuming both phases of the R&D project are carried out. This is computed as
\[
v_c := (r_I - r_0) - c_1 - \mathbb{E}_\xi [\mu(\xi)].
\]

The second component, which we refer to as the real options value \( (v_r) \), emerges from the real option of stopping unattractive projects. This captures the maximal real options value that could be realized when both buyer and supplier act in their mutual interest and is computed as
\[
v_r := \int_{\mu^{-1}(r_I - r_0)} \infty (\mu(z) - (r_I - r_0)) f_1(z)dz.
\]

From a behavioral perspective, this real options value \( v_r \) is of particular interest as its estimation bears a large cognitive load. Related research on valuing options and information (e.g. Arrow and Fisher 1974, Rauchs and Willinger 1996) indicates that people generally understand the concept of option value. For example, individuals are willing to pay for the option to receive future information (Rauchs and Willinger 1996). However, previous studies indicate that decision makers often fail in estimating the value of \( v_r \) correctly (Delquié 2008, Rauchs and Willinger 1996, Schoemaker 1989). Kremer et al. (2013) provides a recent overview of value of information studies relevant to operations management settings.

Whether people tend to under- or overestimate the value of information depends on the decision context (Delquié 2008). Within an operations context, Kremer et al. (2013)
observed that decision makers in a two-stage newsvendor setting have a preference to avoid ex-post errors, which induces them to overvalue the option to decrease demand forecast uncertainty. If the signal in our context would completely resolve uncertainty, one would likely follow Kremer et al. (2013) by hypothesizing an overvaluation of $v_r$. However, three elements are fundamentally different in our context. First, even with a perfect signal there remains uncertainty since the realization of the signal itself is random. So, eliminating regret from ex-post errors, which underlies the reasoning of Kremer et al. (2013), does not apply here. In fact, rather the opposite seems to hold. The better the signal, the clearer an apparent error cristalizes, and the more suppliers may regret their acceptance decision. Second, by actualizing the real options value, i.e. discontinuing the R&D project, the supplier would incur a certain loss rather than having uncertain losses through a continuation. The question of whether people tend to over- or undervalue certain outcomes has been discussed in the realm of prospect theory, where there is consent that people tend to overweight certain outcomes relative to uncertain ones (Kahneman and Tversky 1979). Applying this same reasoning to our setting, a supplier may underestimate the real options value as this component is more uncertain.

In order to link the undervaluation of $v_r$ with the acceptance propensity of real suppliers, we can introduce a behavioral parameter $\alpha$ in our model such that the supplier overvalues $v_r$ if $\alpha > 0$ and undervalues $v_r$ if $\alpha < 0$. Assuming that an optimal offer according to Proposition 3 has been made, we can then derive a utility function for the supplier from Proposition 2. Her net utility from accepting the contract is

$$u_{s,v_r} = (w^*_I - w_0) - c_1 - \mathbb{E}_\xi [\mu(\xi)] + (1 + \alpha) v_r = \alpha v_r,$$

(2)

where we used Proposition 3 for the second equals sign. So, if the supplier’s acceptance propensity increases monotonically in her utility function, it follows that her propensity to accept an optimal offer will decrease in the real options value. This leads to the following prediction.

**Hypothesis 1.** Suppliers will exhibit a higher acceptance rate if the project’s real options value is a smaller (versus larger) fraction of the overall innovation.
3.2.2. Project revenue It is also common to characterize innovation projects according to the type of revenue they create, be it replacement revenue \( w_0 > 0 \) where an existing product is improved through R&D or new revenue \( w_0 = 0 \) where a completely new product is developed (Bhaskaran and Krishnan 2009). There are no strategic differences in optimal decisions with respect to different types of project revenue. This helps us to isolate behavioral effects from strategic ones, since we know that if real suppliers are sensitive to the type of revenue within our model framework, this represents a deviation from profit-maximizing behavior. In that regard, the implications of our model differ from Bhaskaran and Krishnan (2009) who found that the type of revenue impacted the type of contract that was most effective.

We draw from two competing theories in predicting whether new revenue projects have higher or lower acceptance rates. First, differences in the framing of the default option for the two types of revenue suggests that new revenue projects will have a higher acceptance rate. For a new revenue project the default is to produce nothing, while in the replacement revenue project the default is to revert back to producing the prior version of the product. Accepting a new revenue project, therefore, provides two benefits, allowing the supplier to engage in R&D and having the chance to produce something. Accepting a replacement revenue project provides only the first benefit, since the second is given whether or not the innovation is accepted. This may make the innovation opportunity appear more attractive under a new revenue setting, leading to the following prediction.

Hypothesis 2A. Suppliers will exhibit a higher acceptance rate if the type of revenue is new.

The other theory relates new revenue with decreasing acceptance rates and results in a competing hypothesis. Clearly, a supplier is more likely to make overall losses if she faces a new revenue project rather than a replacement revenue project. In this sense, the supplier’s choices could be interpreted as lotteries. A new revenue lottery implies gambling where the supplier could end up with a loss, while a replacement revenue lottery means gambling to gain a slightly lower expected profit but no loss (provided \( w_0 \) is sufficiently high). Since people are often loss averse according to prospect theory (Kahneman and Tversky 1979),
their propensity to accept a contract may be smaller if the type of revenue is new revenue. Loss aversion has been shown to have strong effects in multiple context (e.g. Tversky and Kahneman 1991, Kahneman et al. 1991, Jervis 1992). This leads to a competing prediction.

**Hypothesis 2B.** Suppliers will exhibit a lower acceptance rate if the type of revenue is new.

### 3.3. Behavioral predictions: influence of decision linkages

The remaining parameter of interest relates to development costs in the first phase. They are decision linkages as they result from the first decision and seem to inform the second. From Proposition 1 we know that the continuation decision is independent of $c_1$, which can be viewed as a sunk costs that should not be taken into account when making future decisions. However, previous empirical evidence indicates that sunk costs may lead to escalated commitment (Arkes and Blumer 1985, Staw 1976). A series of studies has been conducted to understand reasons for the sunk cost fallacy (Arkes and Blumer 1985, Thaler 1980, Staw 1976, Garland 1990, Garland and Newport 1991, Heath 1995). These researchers found that the psychological reasons for sunk costs are often related to prospect theory and framing of outcomes. When decision makers face the continuation decision, they essentially have the choice between a certain loss, by stopping a project, and an uncertain negative outcome, by continuing. Since it has been shown in other contexts that people overweigh certain outcomes over uncertain ones (Kahneman and Tversky 1979), the continuation propensity of decision makers in our context may be increased (Arkes and Blumer 1985). In our model, $\frac{c_1}{\mu(\xi)+c_1}$ indicates the fraction of expected costs that occurred in phase one. Transferring the above reasoning it seems plausible that the continuation propensity increases in this fraction.

**Hypothesis 3.** Suppliers will exhibit a higher continuation rate if sunk costs are higher.

Our normative model has implicitly assumed that the acceptance and continuation decisions are made by the same supplier. While this is typical of many firms, there are also cases where these decisions are made by two different people. For instance, a sales manager could decide on the acceptance of a contract while an R&D manager decides on the
continuation. While combining or separating these decisions does not matter in terms of the normative model, it may from a behavioral perspective. Different outcomes may arise when one person makes both decisions due to the so-called consistency effect (Cialdini 2007). Several experiments have shown that people are likely to pursue a certain set of actions once they have voluntarily committed to them. Even if new information becomes available, information which would normally change this same decision maker’s actions, consistency might prevent such people from doing so (Freedman and Fraser 1966, Cialdini et al. 1978). This leads to the following prediction.

**Hypothesis 4.** Suppliers will exhibit a higher continuation rate if they are responsible for both the innovation project acceptance and continuation decisions rather than only the continuation decision.

### 3.4. Behavioral predictions: influence of framing

So far we have examined the influence of different structural characteristics of the supplier’s decision context, some of which are inherent to the type of project or organization and so difficult to change. In this final subsection we consider whether changing the contract frame, something that may be relatively easy to do from the buyer’s perspective, could also influence the supplier’s behavior. Previous studies on supply chain contracting have shown that framing matters, i.e. mathematically equivalent contracts have different implications for supply chain performance (Katok and Wu 2009, Zhang et al. 2013, Ho and Zhang 2008). In the case of incentivizing supplier innovation this leads to the question of whether buyers should use penalties as stipulated by contract law (Plambeck and Taylor 2007) or follow recent industry examples relying on rewards.

It is straightforward to construct a rewards contract equivalent to the penalty contract. Consider the following contract consisting of two parameters proposed by the buyer. The first parameter, $w_{I1}$, represents guaranteed revenue, which the supplier would obtain if she accepts the contract, independent of $C$. If $C = 1$, the supplier would get, in addition to the guaranteed revenue, a reward of $w_{I2}$, the second parameter specified in the contract.

**Proposition 4.** A profit maximizing buyer will set reward-contract parameters as follows:
1. If $v \geq 0$ then

$$w_{I1}^* = w_0 - p^* \quad \text{and} \quad w_{I2}^* = p^* + w_I^* - w_0$$

2. Otherwise, the buyer maximizes his profit by setting $w_{I1}^* = w_0$ and $w_{I2}^* = 0$ such that the supplier rejects the offer and produces the default version of the product.

This contract is equivalent to the contract defined in Proposition 3.

To compare these two frames in behavioral terms, consider first the central tenet of Kahnemann and Tversky’s prospect theory, namely, that people tend to be risk-averse in the gain domain but risk-taking in the loss domain when making decisions under uncertainty (Kahneman and Tversky 1979). Based on this tenet, the theory argues that changes in perspective often influence decision making (Tversky and Kahneman 1981). Such changes include whether an unfavorable outcome is framed as an uncompensated loss or as a necessary investment. The penalty frame in our study implies uncompensated losses. If the supplier enters the contract but fails to continue, she incurs a loss and the game is over. In contrast, in the reward contract, the supplier may perceive the reduced guaranteed-revenue as a necessary investment in order to obtain the later reward when the innovation is completed. Following prospect theory, uncompensated losses can cause higher disutility than investments. Hence, the utility drawn from penalty contracts may be lower than the utility from reward contracts.

Second, both contracts emphasize different possible costs (penalties) and rewards. Social exchange theory reasoning (Blau 1964, Homans 1958, Emerson 1976) helps to infer possible implications of these differences. In our setting, we consider agreeing to the contract as engaging in (additional) social exchange. Social exchange theory argues that people engage in social exchange if they expect more rewards than costs from the relationship (Emerson 1976). While the rewards and costs are the same quantitatively in both contracts (cf. Proposition 4), qualitatively they differ. The penalty contract accentuates negative outcomes by explicitly stating the potential punishment. The reward contract, on the other hand, emphasizes the benefits of entering into this innovation-relationship. Together prospect theory and social exchange theory lead to the following prediction.
Hypothesis 5. Suppliers will exhibit a higher acceptance rate if a reward frame is used instead of a penalty frame.

The contract frame could also affect the continuation decision through the application of prospect theory and, in particular, loss aversion. Being mathematically equivalent, the reward might be perceived as a gain, whereas the penalty seems perceptually closer to a loss. For loss averse decision makers, the threat of a loss is a stronger incentive to continue than a foregone profit. This indicates higher continuation rates under the penalty frame. There is also empirical evidence from the employee incentivization literature supporting this idea. While employees tend to prefer reward contracts over penalty contracts in the acceptance decision (Luft 1994, Hannan et al. 2005, Frederickson and Waller 2005), they exhibit higher effort under the penalty frame (Hannan et al. 2005). In our setting, higher effort maps to higher continuation rates, leading to our last prediction.

Hypothesis 6. Suppliers will exhibit a lower continuation rate if a reward frame is used instead of a penalty frame.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Normative Predictions</th>
<th>Behavioral Predictions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure of project uncertainty</td>
<td>no impact</td>
<td>Higher acceptance rates if the real options value is a smaller fraction of the overall innovation (H₁)</td>
</tr>
<tr>
<td>Type of project revenue</td>
<td></td>
<td>Higher acceptance rate if the type of revenue is new (H₂a)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lower acceptance rate if the type of revenue is new (H₂b)</td>
</tr>
<tr>
<td>Sunk cost</td>
<td></td>
<td>Higher continuation rate if sunk costs are higher (H₃)</td>
</tr>
<tr>
<td>Consistency</td>
<td></td>
<td>Higher continuation rate if same decision maker is responsible for both tasks (H₄)</td>
</tr>
<tr>
<td>Reward</td>
<td></td>
<td>Higher acceptance rate if a reward frame is used instead of a penalty frame (H₅)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lower continuation rate if a reward frame is used instead of a penalty frame (H₆)</td>
</tr>
</tbody>
</table>

Table 1 Comparison of normative and behavioral predictions
4. Experimental Design and Implementation

To test our six hypotheses, summarized in Table 1, we conducted a controlled laboratory experiment involving various treatments. The experiment was run with human subjects acting in the role of a supplier and using a computer-interface written in Google script (see Appendix B for instructions and sample screen-shots). Participants took part in two different tasks. In one task, suppliers made both acceptance and continuation decisions. In the other task, suppliers were informed that a colleague had already accepted the contract but they were responsible for the continuation decision. After finishing 20 repetitions of each task, participants responded to a demographic survey and gave a qualitative description of their strategies. This descriptive data was coded and used to control for heterogeneity in individuals’ understanding of the tasks (see Appendix D).

Even though we do not have any hypotheses on risk-preferences related to the innovation, we measured risk-attitudes in the post-experiment survey for control purposes. We used three sub-scales of the DOSPERT scale (Domain-specific-risk-taking) which was developed by Weber et al. (2002) and refined by Blais and Weber (2006). We measured the preferences toward financial risks in terms of investment and gambling, and toward social risk. By framing decisions as investment problems we expect financial risk (particularly investment) to be task-related and we follow de Véricourt et al. (2013) by including social risk as a discrimination check. In particular we used these risk measures for three purposes: (1) to test whether subjects across different treatments differed significantly in their risk preferences, (2) as control variables, and (3) to test specifically whether there was an interaction effect of risk preferences and treatment effects related to project uncertainty.

The experiment was run in a large public university in the American Midwest, using participants recruited through the business school’s subject pool. In total, 238 students participated in this experiment, each assigned to only one treatment. 61.7% of the students were undergraduates and 82% had taken at least one college-level business class. The use of students as subjects in our research is appropriate since the decision biases we are testing do not depend on domain specific knowledge. However, we did also run a smaller

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4 The total number of subjects participating in this and the subsequent studies outlined in Table 5 was 402.
version of this experiment with professional subjects, which is reported as a robustness check in section 5.5. Subjects were paid according to their outcome with a participation fee of $10.00. The maximum payoff was $20 and the average payoff was $13.04.

The requirement of our experimental design was to facilitate hypotheses testing. More specifically, we needed to test the impact of (1) low versus high real options value, (2) replacement versus new revenue, (3) low versus high sunk costs, (4) decision authority (both decisions or only continuation), and (5) contract frame (penalty versus reward). To meet this objective we used a $4 \times 2$ design with four effects (baseline/high real options value/new revenue/high sunk costs), two frames (penalty/reward) and the two distinct tasks for each subject ($A$ - $C$ - $C$, $C$). Having each subject do both tasks enabled us to test the decision authority hypothesis. To control for possible task ordering effects, the order of the tasks was also varied across subjects within each treatment. Table 2 provides an overview of the treatment design and number of subjects.\(^5\)

<table>
<thead>
<tr>
<th>Treatment Design</th>
<th>Penalty Contract</th>
<th>Reward Contract</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline (BASE1)</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>Baseline* (BASE2)</td>
<td>14</td>
<td>15</td>
</tr>
<tr>
<td>High real options value (HROV)</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>New revenue* (NREV)</td>
<td>18</td>
<td>16</td>
</tr>
<tr>
<td>High sunk costs (HSUNK)</td>
<td>0</td>
<td>18</td>
</tr>
<tr>
<td>Total</td>
<td>53</td>
<td>68</td>
</tr>
</tbody>
</table>

Table 2: Treatment design with number of participants. * = run with higher incentives

In our parameterization of the treatments, we followed two general guidelines. First, we opted for values that reflected the magnitude of costs, penalties, and rewards experienced in actual innovation projects. This was informed based on feedback from 10 managers (primarily in the supply chain field) who took part in prototype testing of the experiment. Second, when possible, we chose parameterizations that helped control the cognitive load of participants. For example, this led to choosing distributions for the cost outcomes that were

\(^5\)Note that treatment sets BASE2 and NREV were run a year later than the other treatments and used a higher incentives (show up fee of $5 and reward of up to an additional $15) in response to reviewer suggestions.
continuous and smooth with a clear mode. Appendix C provides details on the distribution assumptions and parameter values for the baseline treatment and how these were varied across treatments.

It is important to note that in testing our hypotheses we are interested in measuring relative acceptance or continuation rates, rather than profit outcomes that would be more sensitive to parameter scaling effects. The contract parameters presented to participants in the acceptance task were randomized in an interval around the optimum defined by Proposition 3. Therefore, suppliers could make two types of errors relative to the normative prediction in Proposition 2: accepting an unprofitable contract (type-I error) or failing to accept a profitable contract (type-II error). Only optimal contract parameters were used in the continuation-only decision task in order to focus exclusively on type-I and -II errors relative to Proposition 1.

Our theory targets human decision makers who have the intention to maximize profit but do not act optimally due to underlying, systematic biases. A further source of deviations in the lab stems from subjects who ignore underlying figures and other parametrizations of our specific R&D context and instead follow strategies independent of this information, such as claiming they always chose to innovate no matter the underlying costs because it seems more exciting. In order to capture whether subjects reacted to data or not, we coded the qualitative descriptions of their acceptance decision into categories and used this as a control variable (Strategy Code) as further elaborated in Appendix D.

5. Empirical Analysis
Since subjects made 20 acceptance decisions and up to $2 \times 20$ continuation decisions, we modeled our data in a random effects probit framework. All estimations were completed in Stata 13 using the ‘xtprobit’ procedure on subject level. Detailed results can be found in Appendix E in Tables 8 and 9. Independent variables were the different experimental treatments and their interactions, as well as control variables for order effects, individual risk measures, management experience, business experience, strategy code (as defined in

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6We also ran probit models clustered on supplier level as a robustness check, which yielded similar results
Appendix D) and the natural log of the time period of the decision to control for learning effects.

We tested for order effects among all treatments, but found no evidence that the ordering of tasks mattered (cf. Tables 8 and 9 in Appendix E). Therefore, we were able to pool the data but kept the variable “order” as a control variable. We also found no significant differences between the BASE1 and BASE2 datasets and so pooled these together into one BASE. We also tested whether subjects across different treatments differed significantly with respect to their risk preferences; they did not. Nevertheless, we kept the risk measures as control variables.

As a manipulation check, we also estimated the model without any treatment effects but with the contract parameters used in each actual decision, to see whether subjects were reacting to these parameters as predicted. Specifically, we examined acceptance decisions as a function of the added revenue of the innovation \((b=1.1 \cdot 10^{-4}, p<0.0001)\) and the breach penalty \((b=-0.87 \cdot 10^{-5}, p<0.0001)\) imposed. The variable ‘breach penalty’ refers to the difference between default version revenue and guaranteed revenue in the rewards frame. In both cases, subjects reacted to the underlying values as predicted, and the effect sizes of these two regression effects are statistically different from each other \((p < 0.05)\) with added revenue having a slightly greater effect size. Further, we examined continuation decisions as a function of revenue \((b = 4 \cdot 10^{-5}, p<0.01)\), breach penalty \((b = 3 \cdot 10^{-5}, p < 0.01)\), and cost signal \((b = -1.1 \cdot 10^{-4}, p<0.001)\). Collectively, these results imply that subjects reacted to changes in revenue, the breach penalty involved, and cost signal information in the direction that is normatively predicted.

5.1. Descriptive statistics

Table 3 reports the observed percentages of acceptance and continuation decisions across treatments, as well as the percentages of total errors and errors that were of type-I. In case of acceptance decisions, these percentages are calculated over task (A-C) in the experiment. In case of the continuation decisions, these percentages are only calculated over task (C) (ignoring the continuation decisions from task (A-C)). Interestingly, the absolute acceptance error rates were the same in each study (at about 40%). While this number may
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Table 3 Acceptance and continuation decisions with means, mean error rates, and mean type-I error rates of all studies

<table>
<thead>
<tr>
<th></th>
<th>acceptance decision (first task)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>decision = accept</td>
<td>% total error (type I + II)</td>
<td>% of total error that are type I</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>pen. frame rew. frame</td>
<td>pen. frame rew. frame</td>
<td>pen. frame rew. frame</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BASE</td>
<td>67 %</td>
<td>40%</td>
<td>66%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HROV</td>
<td>54 %</td>
<td>42%</td>
<td>48%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NREV</td>
<td>78 %</td>
<td>39%</td>
<td>77%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOTAL</td>
<td>68 %</td>
<td>40%</td>
<td>66%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>continuation decision (second task)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>decision = continue</td>
<td>% total error (type I + II)</td>
<td>% of total error that are type I</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>pen. frame rew. frame</td>
<td>pen. frame rew. frame</td>
<td>pen. frame rew. frame</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BASE</td>
<td>77%</td>
<td>15%</td>
<td>39%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HROV</td>
<td>71%</td>
<td>11%</td>
<td>41%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NREV</td>
<td>74%</td>
<td>13%</td>
<td>36%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HSUNK</td>
<td>75%</td>
<td>16%</td>
<td>45%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOTAL</td>
<td>75%</td>
<td>14%</td>
<td>39%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

appear large, participants clearly did not make random decisions \(t = 12.5, p < 0.0001\), as also supported by our earlier manipulation check. When acceptance errors were committed, participants erred on the side of action by entering into unprofitable contractual relationships (70%). The absolute error rates were much lower for the continuation decision (on average 14%). When continuation errors were committed, participants erred on the side of caution and predominantly abandoned projects that were still profitable (65%).

5.2. Influence of project characteristics

5.2.1. Project uncertainty Our first hypothesis relates a project’s inherent real options value to its acceptance rate. We argued that subjects in our context were likely to undervalue the real option, and thus accept fewer contracts whose value depended more strongly on an underlying real options value. The descriptive statistics in Table 3 support this idea, as the acceptance rates in HROV lie below their BASE counterparts. For a more rigorous test, we estimated the random effects probit models described in the previous section with acceptance as the dependent variable, and treatment direct effects and interactions as independent variables (and further controls). The average marginal effect of HROV is significant \(p < 0.05\), as presented in Table 4, supporting Hypothesis 1.
While the acceptance decision is the primary unit of analysis, it could potentially be distorted by the random assignment of different contract parameters for each participant. Estimating error rates helps control for this random effect. While our results in Table 4 show no significant change in total error rates between BASE and HROV, there is a shift in the type of errors incurring across treatments. HROV had fewer type-I errors relative to type-II errors compared with BASE ($p < 0.01$). This further supports Hypothesis 1 by confirming that even profitable projects are less likely to be accepted when they have a high real options value.

To explore whether the effect of high real options value can be explained by risk preferences, we reestimated the model by allowing for interaction of effect (real options value) and risk measured on the DOSPERT scale. All interaction terms were insignificant, indicating that the effect of high real options value seems is the same effect irrespectively of the subject’s risk preferences. Therefore, we conclude that the difference in acceptance rates between low versus high real options value projects cannot be explained by individual risk preferences.

5.2.2. Project revenue Hypotheses 2 consists of two competing hypotheses relating acceptance rates to the project’s revenue type, whether new or replacement. From Table 3 we see that acceptance rates are on average 79% for NREV versus 69% for BASE, providing initial support for Hypothesis 2A. To test the significance of this difference, we re-estimated our random effects probit model, with results reported in Table 4. The acceptance rate and propensity to commit a type-I error both significantly increase under NREV compared to BASE ($p < 0.001$), while the overall error rate is roughly the same. Together these results show strong support for Hypothesis 2A, and allow us to reject Hypothesis 2B. Subjects

<table>
<thead>
<tr>
<th></th>
<th>Effect of $v_r$ (HROV vs. BASE)</th>
<th>Effect of $w_0$ (NREV vs. BASE)</th>
<th>Frame effect (reward vs. penalty)</th>
</tr>
</thead>
<tbody>
<tr>
<td>accept decision</td>
<td>$-0.38^*$ (0.16)</td>
<td>$0.55^{***}$ (0.16)</td>
<td>$0.24^*$ (0.11)</td>
</tr>
<tr>
<td>accept errors</td>
<td>$0.05$ (0.08)</td>
<td>$0.005$ (0.08)</td>
<td>$0.03$ (0.06)</td>
</tr>
<tr>
<td>type-I-errors</td>
<td>$-0.66^{**}$ (0.23)</td>
<td>$0.85^{***}$ (0.23)</td>
<td>$0.3^+$ (0.17)</td>
</tr>
</tbody>
</table>

Table 4 Marginal effect post-estimation random effects probit models on acceptance decisions. $^{***}p < 0.001; ^{**}p < 0.01; ^{*}p < 0.05; ^{+}p < 0.1$
are, on average, 55% more likely to accept a project with new revenue compared to one with replacement revenue.

When introducing Hypothesis 2A, we argued that such behavior could be driven by perceived differences in the default options for the two project types. Since the default option for the new revenue project was to produce nothing, compared to the default of producing a prior version of the product for the replacement revenue project case, a supplier might be inclined to accept the new revenue project more often just so some form of production could take place. To test whether this propensity to produce something is driving the result, we designed a follow-on study labeled NREV-P which was run with 46 subjects (see Table 5 for subject breakdown). NREV-P was identical to NREV except that subjects were told their firm would also produce an unrelated product, with profit of $25,000, whether or not they accepted the new revenue project. The average acceptance rate for this study decreased to 68%. Tested in a random effects model we find that both acceptance rate and type-I errors are significantly lower for NREV-P compared with NREV \( (p < 0.001) \). However, there is no significant difference between NREV-P and BASE. This additional study suggests that the propensity to produce something is indeed contributing to the relative attractiveness of new revenue projects.

### 5.3. Influence of decision linkages

HSUNK was used to understand the effect of the relative monetary value of sunk costs on the continuation rate, as stated in Hypothesis 3. Parameters of HSUNK implied that 55% of total cost was sunk in the first phase as opposed to only 4% in BASE. So, if the relative monetary value that is lost matters, the continuation rate should be higher in HSUNK. We find that the continuation rate is actually similar across BASE and HSUNK, as reported in Table 3. A more careful assessment through a random effects probit model, as presented in Table 6, confirms there are no significant differences between the two treatments. Hypothesis 3 is not supported by the data.

A potential explanation for this surprising result can be derived from a series of studies conducted by Heath (1995) and Friedman et al. (2007), who also found absence of escalated commitment as a response to increased monetary sunk costs. According to their research,
a necessary condition for escalating commitment due to sunk costs is a certain intransparency, i.e. people often vaguely guess how a project might continue instead of relying on precise predictions. In our setting, however, decision makers have full information regarding the distribution of $\zeta|\xi$, and therefore, can estimate future costs. So, they are less likely to escalate their commitment. A further potential explanation for the insignificance of the effect are opportunity costs. When constructing the high sunk cost treatments we used a clearly distinguishable average sunk cost levels (55% versus 4% in the baseline treatments). However, this clear separability dilutes when individuals classify opportunity costs, such as forgone profits or potential breach penalty, in the same mental account as sunk costs.

To test whether consistency in decision authority has an impact on the continuation decision, as suggested by Hypothesis 4, we compared continuation rates between (A-C) tasks and (C-only) tasks. To do this, we introduced the variable ‘both’, which denotes whether or not both decisions were made by the same subject, and then re-estimated our random effects probit model with this new variable. This variable is significant (cf. Table 9 in the Appendix) and implies that making both decisions increases the continuation likelihood by around 10% ($p < 0.01$). The propensity to commit type-I-errors increases even more, by 54% ($p < 0.001$). Splitting the sample by the two types of tasks (A-C versus C-only) confirms that making both decisions leads to significantly more type-I errors ($\mu = 0.55, p < 0.01$), while making only the continuation decision, leads to more type-II errors ($\mu = 0.34, p < 0.0001$). Together these results support Hypothesis 4.

### 5.4. Influence of framing

Hypothesis 5 related the frame used in the experiment to the acceptance decision. A simple comparison of our descriptive statistics aggregated across all studies is supportive of this idea (cf. Table 3); the percentage of accepted contracts is generally higher under the rewards (versus penalty) frame. Again, using the random effects probit model, we find that subjects are on average 23% ($p < 0.05$) more likely to accept offers under the reward frame. Likewise, the propensity to commit type-I errors increases by 30% ($p < 0.1$).

To test this hypothesis further, we re-estimated the model without using direct treatment effects. This time, we estimated the effects of the reward and the breach penalty involved.
We found that the effect on revenue is consistent across frames. However, the effect of the actual breach penalty is quite different across frames. We compared the effect of breach penalty in the penalty frame with its equivalent in the rewards frame, namely lower guaranteed revenue and higher rewards (cf. Eq. (3)). We find the impact on the acceptance propensity in the penalty frame to be significantly more negative (\(p = 0.04, p = 0.0004\), and \(p = 0.01\), respectively). This provides further evidence for the strong negative effect of the breach penalty on the acceptance rate when a penalty frame is used.

Interestingly, the rewards frame did not influence the overall rate of errors, despite enticing participants to accept more contracts. We re-estimated our random effects probit model using the occurrence of a non-optimal acceptance as the dependent variable. The average marginal effect of the rewards frame here was not statistically significant. We do, however, see a shift in the type of errors being made in the rewards frame. A similar estimation, using error type as the dependent variable, reveals that an error in the rewards frame is more likely to be a type-I error. This result is consistent across all treatments. In other words, the rewards frame enticed people to accept more contracts than they were otherwise prone to erroneously reject; however, more of the former contracts that were correctly rejected were incorrectly accepted, and at nearly equal rates. The rewards frame is therefore not a ‘trick’ to get suppliers to accept bad contracts per se, but also leads them to accept good contracts they would have otherwise turned down.

Turning to the impact of the contract frame on the continuation decision, Hypothesis 6 suggests that we should expect lower continuation rates under the reward frame. However, as reported in Table 6, the reward frame appears to have only an insignificant negative impact on the continuation rate. The percentage of type-1 continuation errors is also not significantly different across frames. Hypothesis 6 is not supported. While we cannot conclusively say that the frame does not matter for the continuation decision, it does appear that the typical adverse effects of rewarding high effort (continuation) instead of punishing low effort (discontinuation) as witnessed in employee incentivization (Hannan et al. 2005), is less evident in incentivizing supplier innovation.
5.5. Robustness checks

One intriguing aspect of the empirical analysis was the emergence of an “over-acceptance” bias despite the risks associated with the acceptance. While applying normative predictions based on Propositions 1 and 2 suggests an average acceptance rate of 54% for our dataset, the actual acceptance rate of 71% was significantly greater (paired t-test, \( t = 16.8, p < 0.0001 \)). This made us wonder if this phenomenon is inherent to the structure of the task or also impacted by the innovation context. In other words, whether there was a pro-innovation bias driving the acceptance. To tease this out, we conducted an additional study with 43 subjects, labeled as NULL (see Table 5 for subject breakdown). This study was identical to BASE except that we described the tasks as a series of gambles rather than as part of an innovation proposal. The results suggest that the high acceptance rate is not due to a possible pro-innovation bias. Neither acceptance rates nor type-I error rates are significantly different between NULL and BASE (\( p = 0.35 \) and \( p = 0.14 \), respectively).

While we originally chose to use student subjects since the decision biases we are testing do not depend on domain specific knowledge, we did also run the BASE and HROV treatments with executives which are labeled as BASE-E and HROV-E in Table 5. The purpose of this repetition was to test whether the behavior of student subjects differed significantly from that of executives, in particular to examine whether the acceptance and continuation rates of executives as well as the amount and types of errors committed are distinct. We made several changes to the protocol to facilitate executive participation. These included having participants sign into a website to conduct the experiment (rather than coming to a lab), and providing no monetary compensation (although a “winner” was announced). We began by comparing BASE and BASE-E. In order to test whether being an executive has a significant impact, we added a variable called ‘executive’ and reestimated the random effects probit models described in the previous section. In terms of the acceptance decision, we find that no rates differed significantly from students, including acceptance rate, total error rate, or type of errors (\( p = 0.4, p = 0.9, p = 0.4 \), respectively). Also, in terms of the continuation decision, we find no significant difference in continuation rate, rate of errors and type of errors (\( p = 0.9, p = 0.9, p = 0.4 \), respectively). We also estimated effect of ‘executive’ comparing HROV and HROV-E. We find that acceptance
rates are about the same \((p = 0.2)\) as well as accept error rate \((p = 0.8)\) and types of acceptance errors \((p = 0.2)\). In terms of the continuation decision we find that the error rate of executives is weakly significant lower \((b = -0.5, p < 0.1)\), but this does neither appear to impact the continuation rate \((p = 0.4)\) nor the type of continuation errors \((p = 0.5)\). Overall, we conclude that there are not significant differences between the two subjects pools in terms of their performance in these innovation tasks.

A further robustness check of the theory relates to the economic relevance of deviations from normative predictions. For each contract we evaluated the gap between expected profits resulting from decisions of suppliers in the lab versus decisions of hyper-rational decision makers as defined in Section 3.1 and examine how project project characteristics, decision linkages, and the frame affect these gaps. Looking first at some aggregate statistics, it is not surprising that suppliers perform significantly worse than optimal in terms of profit \((t = 22.3, p < 0.0001)\). Interestingly for the buyers, the suppliers’ behavior led to higher profit relative to the normative solution \((t = 26.7, p < 0.0001)\). This was primarily driven by the suppliers’ tendency to accept a significant percentage of unprofitable contracts.

The performance gaps were partially affected by project characteristics. In HROV, supplier profits were significantly worse than in BASE \((t = 2.4, p < 0.01)\). This translated also to lower profits for the buyer in HROV versus BASE \((t = 2.4, p < 0.01)\). In NREV, supplier profits were not significantly different from BASE, but buyer profits benefited significantly with higher profits compared to BASE \((t = 4.8, p < 0.0001)\).

The decision linkages are also potentially important predictors of performance. Looking at the continuation decision and comparing BASE with HSUNK we see that suppliers had a slightly better performance under HSUNK \((p < 0.1)\). Table 6 indicates a potential explanation for this phenomenon. While neither the reduction in error rates nor the types of error committed differed significantly from the BASE treatment, both are in the favorable direction in HSUNK. We also find that having one individual make both acceptance and continuation decisions positively impacts performance. The profit gap between suppliers and normative predictions was significantly lower when subjects made both decisions \((t = 7.3, p < 0.0001)\).
We also found that the use of rewards increases the acceptance propensity significantly. For suppliers this leads to even greater losses relative to the normative optimum \((t = 3.0, p < 0.001)\). For buyers it lead to significantly more profit \((t = 3.2, p < 0.001)\). These results corroborate our findings indicating that buyers would benefit from offering a contract with a reward rather than penalty frame.

<table>
<thead>
<tr>
<th></th>
<th>Penalty Contract</th>
<th>Reward Contract</th>
</tr>
</thead>
<tbody>
<tr>
<td>NREV-P</td>
<td>11</td>
<td>13</td>
</tr>
<tr>
<td>NULL</td>
<td>14</td>
<td>9</td>
</tr>
<tr>
<td>BASE-E</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>HROV-E</td>
<td>11</td>
<td>7</td>
</tr>
<tr>
<td><strong>total</strong></td>
<td><strong>47</strong></td>
<td><strong>38</strong></td>
</tr>
</tbody>
</table>

Table 5  Treatment design with number of participants of additional studies

Finally, while we did not hypothesize a relationship between project characteristics (either uncertainty or revenue types) and the continuation rate, our data allows us to test whether any such relationships exist. We reestimated the probit model with the continuation decision, total error, and type-I-error rates as dependent variables, respectively. The real option value does not affect the types of errors committed nor the amount of erroneous decisions in the lab (cf. Table 6). Even when the signal is better predicts potential outcomes, suppliers deviate from the optimal prediction at about the same frequency with about the same tendencies. The same holds true for NREV and NREV-P, except for a significantly greater continuation error rate in NREV-P versus BASE \((p < 0.001)\). The observation of about the same propensity to commit type-I errors is important to buyers because it implies that the desirable effect of higher acceptance rates in NREV is not countered by a significantly lower continuation rate.

6. Discussion, insights, and conclusion

In this study we examined the initiation and continuation decision of a supplier engaging on a product development project on behalf of a buyer. In contrast to previous studies on new product development in supply chains (such as Kim and Netessine 2013, Gilbert and Cvsu 2003, Xiao and Xu 2012, Plambeck and Taylor 2007, Bhaskaran and Krishnan
Table 6  Marginal effect post-estimation random effects probit models on continuation decisions.  

<table>
<thead>
<tr>
<th>Effect of $v_i$ (HROV vs. BASE)</th>
<th>Effect of $w_0$ (NREV vs. BASE)</th>
<th>Effect of $c_1$ (HSUNK vs. BASE)</th>
<th>Frame effect (reward vs. penalty)</th>
</tr>
</thead>
<tbody>
<tr>
<td>continue dec.</td>
<td>$-0.11$ (0.07)</td>
<td>$0.05$ (0.07)</td>
<td>$-0.1$ (0.1)</td>
</tr>
<tr>
<td>continue errors</td>
<td>$-0.12$ (0.08)</td>
<td>$-0.08$ (0.07)</td>
<td>$-0.27^*$ (0.12)</td>
</tr>
<tr>
<td>type-I-errors</td>
<td>$0.18$ (0.22)</td>
<td>$0.07$ (0.2)</td>
<td>$-0.05$ (0.3)</td>
</tr>
</tbody>
</table>


decisions. $^{***}p < 0.001;^{**}p < 0.01;^*p < 0.05;^{+}p < 0.1$

2009, Gupta and Loulou 1998, Wang and Shin 2012, 2013), our study takes a behavioral approach. Starting from a game theoretical model as the normative benchmark, we derived a series of behavioral hypotheses predicting how R&D project characteristics, decision linkages, and different contract frames could trigger deviations from profit maximizing behavior.

The two focal R&D project characteristics in our study are structure of project uncertainty and type of project revenue (Bhaskaran and Krishnan 2009). We capture the structure of project uncertainty through the real options value of innovation projects. This value arises as suppliers may initiate innovation projects but later abandon them if cost estimates turn out to be unfavorable. Our results show that human decision makers understand the idea of real options which is in line with former behavioral studies (Kremer et al. 2013, Arrow and Fisher 1974, Rauchs and Willinger 1996). However, whereas decision makers in Kremer et al. (2013) overvalued the real option, the subjects in our study undervalued the real option. The acceptance rates of decision makers facing a high real options value project were about 33% lower than the acceptance rates of decision makers facing a low real options value project.

The second R&D project characteristic in our study is the type of revenue. While Bhaskaran and Krishnan (2009) studied how the type of revenue affects the optimal choice of strategies, we constructed a model where the type of revenue is inconsequential for profit maximizing suppliers. This enables us to tease out the behavioral implications. Even though new revenue opposed to replacement revenue increases the probability of losses, we find that loss aversion is not strong enough to drive down the acceptance rates of suppliers facing new revenue projects. In our study subjects made decisions on behalf of suppliers.
which would result in losses for the supplier, but not immediately for the subject (due to our protocol no participant in our study could incur a real loss). As recent results show, deciding for others reduces loss aversion (Andersson et al. 2014). This might explain the ineffectiveness of loss aversion in this treatment. Instead, we find a competing hypothesis confirmed, namely that new revenue increases the acceptance rate by 50%. However, this is not always the case. In a further study we show that the existence of an outside production opportunity seems crucial for the supplier. Only if the supplier faces new revenue projects, which imply that by rejecting she would not produce at all, do her acceptance rates increase. For buyers seeking to incentivize their suppliers this is good news. Not only are acceptance rates of new revenue projects at least as high as replacement revenue projects, but acceptance increases further if no alternative production option exists.

Both types of decisions (acceptance and continuation) are linked by the consequences in terms of costs resulting from the acceptance decision. We find no support for the hypothesis that the actual monetary amount of sunk costs matters. While this seems to contradict studies on the sunk cost fallacy (Arkes and Blumer 1985, Staw 1976), there have been related studies indicating that transparency of cost updates can help induce more normative behavior (Heath 1995, Friedman et al. 2007). However, our data reveals that individuals are more likely to escalate commitment to a research project if they were responsible for the initial acceptance decision. This leads to an average increase in continuation propensity of about 10%. Translating this observation into practice, procurement managers should be aware of their supplier’s decision authority. If they can encourage the same person to make both decisions, they should expect higher commitment and so could potentially offer lower penalties.

Finally, like the pharmaceutical company Merck (Bhattacharya et al. 2014), some firms prefer to use rewards to incentivize the achievement of targets or milestones. To understand the efficacy of this approach we constructed an equivalent frame which allows buyers to reward continuation rather than to penalize contract breaches. We find support for the hypothesis that the penalty contract leads to lower acceptance rates than the reward contract. From studies on employee incentivization it is known that employees tend to exert higher effort if they are afraid of being penalized instead of rewarded (Hamman et al.
Initiating and Sustaining Supplier Involvement in Development Projects

2005). Interestingly, this does not seem to be the case in the case of supplier innovation. Our results suggest that sourcing managers should consider rewards rather than penalties as a way to motivate their suppliers to undertake innovation projects. From a legal point of view, this implication is positive as it is usually easier to withhold rewards than it is to enforce penalties.

Our study also enabled us to estimate the significance of behavioral factors in terms of bottom line impact. We find that suppliers earn significantly less compared to normative predictions. This is mainly driven by higher acceptance rates, particularly when facing new revenue projects without an outside production option or when presented with a reward frame. Overall, this over-acceptance bias leads to significantly higher buyer profit compared to normative predictions. While it is outside the scope of this paper, it seems evident that considering these behavioral tendencies when drafting contracts could further increase the buyer’s profit.

Our study has some limitations. The setting had to be kept parsimonious, which excludes more elaborate mechanisms such as cost sharing or innovation sharing (Bhaskaran and Krishnan 2009). We assume an extreme case of bargaining in the Stackelberg game. While this captures the essentials of more difficult non-cooperative bargaining, the implications of cooperative agreements on the innovation continuation would be interesting. Specifically, suppliers in our study have only the ability to abandon the innovation if projects turn out more costly than expected; in reality, further options would be available, such as re-negotiating the contract with the buyer, or cutting corners ex-post in order to make the contract profitable again. Our study takes a first step in testing predicted directional deviations. However, we do not estimate specific parameters which would be necessary to derive optimal decisions.

There are several opportunities for future research. A possible extension consists of a repeated game where suppliers are penalized for not innovating, through lost sales in future periods, instead of an explicit penalty or withheld reward. One could also reverse the experiment and ask how procurement managers would deviate from normative predictions. Systematic analysis of biases would have direct practical implications. Finally, human-human interaction would be interesting. Effects such as fairness (c.f Katok and Pavlov
2012, Fehr and Schmidt 1999, Cui and Mallucci 2012) would certainly come into play. Particularly with repeated interaction, new forms of punishment would lead to further, maybe more natural, equilibria. Overall, our study contributes a first step towards better understanding the behavioral implications on the effectiveness of contract mechanisms when incentivizing supplier innovation.

Appendix A: Proofs

Proposition 1 The profit-maximizing supplier continues with the R&D project if the expected profit of a continuation is not below the expected profit associated with stopping as presented in Figure 1. More formally, we can transform this condition in a series of inequalities:

\[
E_\xi[\pi_s(w_I, p|A = 1, C = 1)] \geq E_\xi[\pi_s(w_I, p|A = 1, C = 0)]
\]

\[
\iff E_\xi[w_I - c_1 - \xi - k] \geq E_\xi[w_0 - c_1 - p - k]
\]

\[
\iff w_I - c_1 - k - E_\xi[\xi] \geq w_0 - c_1 - p - k
\]

\[
\iff w_I - \mu(\xi) \geq w_0 - p
\]

\[
\iff w_I + p - w_0 \geq \mu(\xi)
\] (4)

By assumption, \(\mu(\xi)\) increases strictly in \(\xi\) and is continuous. Hence \(\mu\) is bijective and \(\mu^{-1}\) exists, and is increasing, too. It follows that the inequality \(w_I + p - w_0 \geq \mu(\xi)\) holds if and only if

\[
\mu^{-1}(w_I + p - w_0) \geq \xi
\] (5)

Now we can define a critical value \(\xi^*\) in terms of the left hand side of the equation, i.e. \(\xi^* := \mu^{-1}(w_I + p - w_0)\). Note that this is the expression that we also use in the proposition. Hence, equation (5) can be re-written as \(\xi \leq \xi^*\), which proves the proposition.

Proposition 2 The profit-maximizing supplier accepts the contract if the expected profit of a accepting is not below the expected profit associated with rejecting. She takes her second decision
First, define $g : \mathbb{R} \to \mathbb{R}$ by

$$g(w_1, p) := (w_1 - w_0) F_1(\xi^*) - p(1 - F_1(\xi^*)) - c_1 - \int_{-\infty}^{\xi^*} \mu(z) f_1(z) dz = 0$$

Proposition 3 If the innovation does not have a positive value ($v < 0$) the buyer makes an offer which the supplier will reject because the buyer cannot force the supplier to accept an offer implying expected losses to the supplier. So we can assume $v \geq 0$. In this proof we will apply the Lagrange rule as first order condition and use the bordered Hessian matrix as second order condition to prove optimality. We then use the results in order to express the closed form solution as presented in the proposition.

But first, let us formally derive the buyer’s objective function,

$$\hat{\pi}_b(w_1, p) := F_1(\xi^*) \mathbb{E}[\pi_b(w_1, p|A = 1, C = 1) | \xi \leq \xi^*] + (1 - F_1(\xi^*)) \mathbb{E}[\pi_b(w_1, p|A = 1, C = 0) | \xi > \xi^*]$$

$$= F_1(\xi^*) \frac{\int_{-\infty}^{\xi^*} \pi_b(w_1, p|A = 1, C = 1) f_1(z) dz}{\int_{-\infty}^{\xi^*} f_1(z) dz} + (1 - F_1(\xi^*)) \frac{\int_{\xi^*}^{\infty} \pi_b(w_1, p|A = 1, C = 0) f_1(z) dz}{\int_{\xi^*}^{\infty} f_1(z) dz}$$

$$= \frac{F_1(\xi^*)}{\int_{-\infty}^{\xi^*} f_1(z) dz} \int_{-\infty}^{\xi^*} \pi_b(w_1, p|A = 1, C = 1) f_1(z) dz + \frac{(1 - F_1(\xi^*))}{\int_{\xi^*}^{\infty} f_1(z) dz} \int_{\xi^*}^{\infty} \pi_b(w_1, p|A = 1, C = 0) f_1(z) dz$$

$$= \int_{-\infty}^{\xi^*} \pi_b(w_1, p|A = 1, C = 1) f_1(z) dz + \int_{\xi^*}^{\infty} \pi_b(w_1, p|A = 1, C = 0) f_1(z) dz$$

$$= \int_{-\infty}^{\xi^*} (w_1 - w_0) f_1(z) dz + \int_{\xi^*}^{\infty} (r_0 - w_0 + p) f_1(z) dz$$

$$= (r_1 - w_1) F_1(\xi^*) + (r_0 - w_0 + p) (1 - F_1(\xi^*))$$

Step 1: First, define $g : \mathbb{R} \to \mathbb{R}$ by
Let \( \nabla \) denote the gradient. Note that the supplier’s optimal threshold rule \( \xi^* : \mathbb{R}^2 \to \mathbb{R} \) defined by equation (5) as \( \xi^*(w_1, p) = \mu^{-1}(w_1 + p - w_0) \) is a function of \( w_1 \) and \( p \). In the following we will write \( \frac{d}{dw_1} \xi^* := \frac{d}{dw_1} \xi^*(w_1, p) \) as a shorter way to express the derivative of \( \xi^* \) with respect to \( w_1 \). And likewise we use \( \frac{d}{dp} \xi^* := \frac{d}{dp} \xi^*(w_1, p) \). Then we can write

\[
\nabla \hat{\pi}_b(w_1, p) = \left( \frac{-F_1(\xi^*) + (r_1 - w_1 - r_0 + w_0 - p) \frac{d}{dw_1} \xi^* f_1(\xi^*)}{(1 - F_1(\xi^*))} + (r_1 - w_1 - r_0 + w_0 - p) \frac{d}{dp} \xi^* f_1(\xi^*) \right).
\]

Note that due to equation (5):

\[
\begin{align*}
\frac{d}{dw_1} \xi^* &= \mu^{-1'}(w_1 + p - w_0) \\
\frac{d}{dp} \xi^* &= \mu^{-1'}(w_1 + p - w_0) \\
\frac{d}{dw_1} \xi^* &= \frac{d}{dp} \xi^*.
\end{align*}
\]

And with this and some rearranging we have:

\[
\nabla \hat{\pi}_b(w_1, p) = \left( \frac{-F_1(\xi^*) + (r_1 - w_1 - r_0 + w_0 - p) \frac{d}{dw_1} \xi^* f_1(\xi^*)}{(1 - F_1(\xi^*))} + (r_1 - w_1 - r_0 + w_0 - p) \frac{d}{dp} \xi^* f_1(\xi^*) \right). \tag{9}
\]

To prepare the Lagrange multiplier, we apply the Leibniz rule to the implicit constraint function, \( g \), and we use from equation (5) that \( \mu(\xi^*) = w_1 + p - w_0 \).

\[
\begin{align*}
\nabla g(w_1, p) &= \left( (w_1 - w_0) \frac{d}{dw_1} \xi^* f_1(\xi^*) + f_1(\xi^*) + \mu(\xi^*) \frac{d}{dw_1} \xi^* f_1(\xi^*) \right) \\
&= \left( (w_1 - w_0) \frac{d}{dw_1} \xi^* f_1(\xi^*) + f_1(\xi^*) + \mu(\xi^*) \frac{d}{dw_1} \xi^* f_1(\xi^*) - (1 - F_1(\xi^*)) \right) \\
&= \left( -F_1(\xi^*) \right)
\end{align*}
\]

Let \( \lambda \in \mathbb{R} \). Then the Lagrange conditions are:

\[
\nabla \hat{\pi}_b(w_1, p) = \lambda \nabla g(w_1, p) \tag{11}
\]

From the first it follows

\[
\begin{align*}
(1 - F_1(\xi^*)) + (r_1 - w_1 - r_0 + w_0 - p) \frac{d}{dw_1} \xi^* f_1(\xi^*) &= \lambda \left( -F_1(\xi^*) \right) \\
(1 - F_1(\xi^*)) + (r_1 - w_1 - r_0 + w_0 - p) \frac{d}{dp} \xi^* f_1(\xi^*) &= \lambda \left( -F_1(\xi^*) \right) \tag{12}
\end{align*}
\]

\[
\begin{align*}
(1 - F_1(\xi^*)) + (r_1 - w_1 - r_0 + w_0 - p) \frac{d}{dw_1} \xi^* f_1(\xi^*) &= \lambda \left( -F_1(\xi^*) \right) \\
(1 - F_1(\xi^*)) + (r_1 - w_1 - r_0 + w_0 - p) \frac{d}{dp} \xi^* f_1(\xi^*) &= \lambda \left( -F_1(\xi^*) \right)
\end{align*}
\]
The only solution to this equation implies $\lambda = -1$, because $F_1(\xi^*) \neq -(1 - F_1(\xi^*))$, $\forall \xi^* \in \mathbb{R}$. As we assumed a strictly increasing signal, $\frac{d}{dw_I} \xi^* > 0$ and also $f_1(\xi^*) > 0$ because we assumed the density to be positive for all values within the support. This, in turn, implies $r_I - w_I - r_0 + w_0 - p = 0$. So for the optimal decisions we know now that

$$p^* + w_I^* = r_I - r_0 + w_0$$  \hspace{1cm} (13)

This relationship states that as $p^*$ increases, $w_I^*$ decreases. Finally, the third Lagrange-condition needs to hold, $g(w_I, p) = 0$. We will use the implicit function theorem on $g$ in order to show that even though there are some values of $p^*, w_I^*$ which would lead to $g(w_I^*, p^*) = 0$, there is only one that satisfies $p^* + w_I^* = r_I - r_0 + w_0$. More precisely, we show that along $g$ it is $\frac{dw_I^*}{dp} > 0$. This procedure can be pictured in the $w_I - p$ plain as follows: The condition $p^* + w_I^* = r_I - r_0 + w_0$ is a strictly decreasing line, the condition $g(w_I^*, p^*) = 0$ is increasing. Therefore, they have only one intersection. So, let us prove what is left, i.e. $\frac{dw_I^*}{dp} |_{g} > 0$. The theorem of implicit functions is applicable here, because $g$ is an implicit function and it is differentiable in $(w_I^*, p^*)$. This property follows from the observations that $g$ consists of the concatenation of differentiable functions. Finally, $\frac{\partial g(w_I, p)}{\partial w_I} = F_1(\xi^*) \neq 0$. Applying the theorem we have,

$$\frac{dw_I}{dp} |_{g(w_I, p)} = -\frac{\frac{\partial g(w_I, p)}{\partial p}}{\frac{\partial g(w_I, p)}{\partial w_I}} = -\frac{- (1 - F_1(\xi^*))}{F_1(\xi^*)} = 1 - \frac{1 - F_1(\xi^*)}{F_1(\xi^*)} > 0$$  \hspace{1cm} (14)

Hence, there is at most one extreme solution.

Step 2:

To prove the optimality of this candidate, we use the bordered Hessian, $\mathbf{H}$. The star (*) indicates that we focus on the value of the optimal solution as described in Eq. 13. This becomes very handy in the second derivative, as we know that $p^* + w_I^* - r_I + r_0 - w_0 = 0$ and thus several second order
terms are irrelevant. Also recall that we found $\lambda = -1$ above. With that we have:

$$
\mathbf{H}^* := \begin{bmatrix}
\frac{\partial^2 g}{\partial w^2_{ij}} & \frac{\partial^2 g}{\partial w_{ij} \partial \lambda} & \frac{\partial^2 g}{\partial \lambda^2} \\
\frac{\partial^2 g}{\partial w_{ij} \partial \lambda} & \lambda \frac{\partial^2 g}{\partial w_{ij}^2} + \lambda \frac{\partial^2 g}{\partial w_{ij} \partial \lambda} & \frac{\partial^2 g}{\partial \lambda^2} \\
\frac{\partial^2 g}{\partial \lambda^2} & \lambda \frac{\partial^2 g}{\partial \lambda^2} + \lambda \frac{\partial^2 g}{\partial \lambda^2} & \lambda \frac{\partial^2 g}{\partial \lambda^2}
\end{bmatrix}
$$

$$
= \begin{bmatrix}
0 & F_1(\xi^*) - (1 - F_1(\xi^*)) \\
F_1(\xi^*) & - (1 - F_1(\xi^*)) \\
- (1 - F_1(\xi^*)) & - 3 \frac{d}{dw_I} \xi^* f_1(\xi^*)
\end{bmatrix}
$$

To give an example of how we derive at the second derivatives, consider:

$$
\frac{\partial^2 (\pi - g)}{\partial w_I^2} = \frac{\partial}{\partial w_I} \left( -F_1(\xi^*) + (r_I - w_i^* - r_0 + w_0 - p^*) \frac{d}{dw_I} \xi^* f_1(\xi^*) - F_1(\xi^*) \right)
$$

$$
= -3 \frac{d}{dw_I} \xi^* f_1(\xi^*) + (r_I - w_i^* - r_0 + w_0 - p^*) \left( \frac{d^2}{dw_I^2} \xi^* f_1(\xi^*) + \left( \frac{d}{dw_I} \xi^* \right)^2 f_1(\xi^*) \right)
$$

$$
= -3 \frac{d}{dw_I} \xi^* f_1(\xi^*)
$$

because $(r_I - w_i^* - r_0 + w_0 - p^*) = 0$ under optimality. The other three second order partial derivatives are analog to this one. Note, that a real matrix, $M$, with the structure

$$
M := \begin{bmatrix}
0 & a & b \\
a & c & c \\
b & c & c
\end{bmatrix}
$$

Has the determinant $\text{det}(M) = 2abc - a^2c - b^2c = -(a-b)^2c$. With that it is

$$
\text{det}(\mathbf{H}) = - (F_1(\xi^*) + (1 - F_1(\xi^*)))^2 \left( -3 \frac{d}{dw_I} \xi^* f_1(\xi^*) \right)
$$

$$
= 3 \frac{d}{dw_I} \xi^* f_1(\xi^*) > 0
$$

because $\frac{d}{dw_I} \xi^* > 0$ as with $\xi^*$ increases obviously in $w_I$. From that it follows that the extreme point is indeed a maximum.

Step 3:

Finally, let us find the corresponding values of $w_I^*$ and $p^*$. Therefore, calculate the intersection of
both curves by inserting the former the latter. Moreover, note that by the first curve, i.e. \( p^* + w_I^* = r_I - r_0 + w_0 \) it is also \( \xi^* = \mu^{-1}(r_I - r_0) \). Thus,

\[
0 = g(w_I^*, p^*) = g(w_I^*, r_I - r_0 + w_0 - w_I^*) = (w_I^* - w_0)F_1(\xi^*) - \int_{-\infty}^{\xi^*} \mu(z)f_1(z)dz - (r_I - r_0 + w_0 - w_I^*)(1 - F_1(\xi^*)) - c_1 = w_I^*F_1(\xi^*) - w_0F_1(\xi^*) - \int_{-\infty}^{\xi^*} \mu(z)f_1(z)dz - (r_I - r_0 + w_0)(1 - F_1(\xi^*)) + w_I^*(1 - F_1(\xi^*)) - c_1,
\]

hence

\[
w_I^* = w_0 + c_1 + \int_{-\infty}^{\xi^*} \mu(z)f_1(z)dz + (r_I - r_0)(1 - F_1(\xi^*)).
\]

And correspondingly,

\[
p^* = r_I - r_0 + w_0 - w_I^* = (r_I - r_0)F_1(\xi^*) - c_1 - \int_{-\infty}^{\xi^*} \mu(z)f_1(z)dz,
\]

which proves the last assertion of the proposition.

**Proposition 4** The proof follows the logic of Propositions 1 through 3, with \( w_{I1} \) replaced by \( w_0 - p \) and \( w_{I2} \) replaced by \( p + w_I - w_0 \).
Appendix B: Experimental instructions and sample screenshots (penalty frame)

Supplier Innovation Experiment

Background

As a manager in a manufacturing firm you can choose between two versions of a product: a default and an innovative version. With the innovative version you receive higher revenue, but your firm would have to invest in research and development (R&D).

If you decide to invest in R&D your firm starts with a first phase, after which you have a better estimate of the total R&D costs. With this updated cost information in hand, you have an opportunity to either continue R&D or to stop it. If you stop R&D, you still produce the default version, but incur a penalty from your customer, whom your firm promised the innovative version after you started R&D.

From your R&D team you have been informed that the innovation will not be patentable. This means that its value to you is exactly the additional revenue you obtain from your customer.

To summarize, you have two decisions. First, you decide whether you want to begin investing in R&D (investment decision) and if you do so, you will decide later whether to continue R&D (continuation decision). An online-tool will provide you all required information in each round:

In this screenshot you see a red diagram. This diagram reflects the uncertainty of the R&D costs in the second phase and should be read as follows. The potential outcomes of R&D costs in the second phase are on the horizontal axis (i.e. between 30,000 EUR and 70,000 EUR). On the vertical axis you find their corresponding probability. This means, a realization of around 50,000 EUR is more likely than a realization of, for instance, 65,000 EUR. However, note that all values between 30,000 EUR and 70,000 EUR could be realized – this diagram only states that not all of them are equally likely.
Profit calculation
Your profit is the difference between your revenue and your costs. Production costs are the same in any case. There are three cases which have to be distinguished:

1. You choose the default option
   your profit = revenue (default version) - production costs

2a. You decide to invest in R&D and finish it
   your profit = revenue (innovative version) - production costs - R&D costs phase 1 - R&D costs phase 2

2b. You decide to invest in R&D but you stop it
   your profit = revenue (default version) - production costs - R&D costs phase 1 - penalty

R&D cost information update after first phase
As aforementioned, your R&D team will provide you with a cost update after the first stage, which will be presented in a diagram such as the following. Please note that this is only one illustrative example. Actual updates differ in each round. More examples can be found on the last page of this document.

As you see in this diagram, the estimate became more precise, as for instance certain values (above 65,000EUR) are very unlikely, whereas other values (around 42,000EUR) are more likely than before.

Your payoff
You will receive a participation fee of $10.00 if you finish the experiment and the survey.
In addition, you will be paid according to your performance. Your average profit per round in the simulation will be approximately between EUR 23,000 and EUR 28,000. For each 500 EUR that your average profit is above EUR 23,000, you will receive $1.00. For instance, if your profit in the simulation is EUR 25,000 you receive $4.00, i.e. in total $14.00. Your maximum payoff is $ 20.00.

Procedure
In 20 rounds of the experiment you will make both decisions: the investment and the continuation decision. In 20 further rounds, you will be informed that your company has already invested in R&D and you only make the continuation decision. The instructions on the screen will inform you, whether you start by making two decisions or by making one.

Good luck!
Appendix: Further examples of cost updates

These diagrams are examples to give you a better idea how cost and profit updates could look like. However, in each round you receive different updates.
You have two contract options.

1. Default Option
   If you choose the default version, your production costs will be 100,000 EUR and you will receive a revenue of 125,000 EUR from your customer.

2. R&D Investment Option
   If you choose the R&D investment option, you will have R&D costs of 2,000 EUR in the first phase. The costs of the second phase are unknown; however, they will be drawn from the distribution in the following diagram.

Once the second phase R&D costs are updated, you will have an opportunity to either continue or stop the R&D investment.

If you choose to continue the R&D investment, you will incur second phase R&D costs as well as production costs of 100,000 EUR and a revenue of 175,359 EUR.

If you stop the R&D investment, you will incur a penalty of 6,541 EUR from your customer as well as production costs of 100,000 EUR. Your revenue for the default version will be 125,000 EUR.

Which contract option do you choose?

- R&D Investment Option
- Default Option

Simulation screenshot on the acceptance decision

The first R&D phase has been completed.
Your company has invested 2,000 EUR for R&D in the first phase. You now have an updated R&D cost estimate for the second phase as given below.

You now must decide whether to continue the R&D investment or stop.

If you choose to continue the R&D investment, you will incur second phase R&D costs as expressed in the above diagram, as well as production costs of 100,000 EUR and revenue of 175,359 EUR for the innovative version.

If you choose to stop the R&D investment, your phase one R&D investment of 2,000 EUR cannot be recovered. You will incur a breach penalty of 6,541 EUR from your customer as well as production costs of 100,000 EUR and revenue of 125,000 EUR for the default version.

What is your decision?

- Continue R&D
- Stop R&D

Simulation screenshot on the continuation decision
Appendix C: Operationalization and parameterization

The parameters used in the BASE treatment were chosen in consultation with practitioners. The scale of $1000's was chosen to reflect that profits and costs in innovation decisions are not inconsequential, while also keeping the scale manageable for subjects to view. The parameters for the BASE treatment include: $r_0 = 180,000$, $r_I = 238,000$, $w_0 = 125,000$, $k = 100,000$, $c = 2,000$, $\zeta \in [30,000; 70,000]$. The core value of this innovation is $v_c = 6000$ and the real options value is $v_r = 541$. So the fraction of total value that was due to the real option was $\frac{v_r}{v_c + v_r} = 8.3\%$. The average amount of sunk costs was about 4%.

When the supplier made only the continuation decision, we assumed that the optimal theoretical offer had been previously accepted. While the aforementioned values were fixed among all rounds within one treatment, the offers varied each round so that $w_I$ was within an interval with a length of 9,000 that started 5,000 below the theoretically optimal $w_I^*$. The breach penalty was randomized and took values between 0 and two times the theoretically optimal $p^*$. Both variables were uniformly distributed. This procedure lead to a profit-maximizing strategy of accepting, on average, about 50% of the offers; the optimal acceptance rate given the actual realization of random numbers was 53.8%. We decided to use intervals of this magnitude because decreasing ranges substantially would lead to less randomization and offers would look very similar. On the other hand, much larger intervals could result in strong anchoring effects just because of the sequence in which orders are presented. To increase external validity, we used different random streams for different subjects. The benefit of this approach, as opposed to using the same random stream for all individuals, is that our findings do not depend on a specific sequence of random numbers. This approach, using different numbers for each participant, increases the inherent variability of our data, making it more difficult to find effects if they exist. In this sense, our tests are conservative.

For the remaining treatments the parameters were kept the same as the BASE treatment except for the following manipulations: a) in HROV we nearly tripled $\frac{v_r}{v_c + v_r} = 21.5\%$, b) in NREV we set $w_0 = 0$ and adjusted other parameters accordingly so the expected profit was the same, c) in HSUNK we adjusted $c_1$ such that the average amount of sunk costs was 55%. Finally, the transformation between the parameters in the penalty frame and the reward frame followed Proposition 4.

In constructing the random variables related to R&D cost ($\xi$ and $\zeta$) we were guided by three objectives. First, use the same support for both variables to make the cost transitions between phases easy to understand. Second, interpret the realization of the signal as the mode of the updated cost distribution which follows a unimodal beta distribution to make it easier for subjects to understand.
Finally, keep the conditional variance of $\zeta|\xi$ independent of $\xi$, which means for any two values of $\xi$, $\xi$ has the same quality in terms of prediction error.

The following, technical, derivation was performed upfront to support these objectives. This mathematical information was not shared with subjects. Rather, subjects simply saw the resulting histograms of possible cost/profit outcomes in the first and second phase. The appendix of the instruction sheet (cf. Appendix B) provides some examples of the format of information that subjects saw.

Let $l$ denote a lower bound and $u$ denote an upper bound on the support of $\xi$ and $\zeta|\xi$. Let $\xi \sim \mathcal{U}[l,h]$, where $\mathcal{U}$ is the uniform distribution over interval $[l,h]$. $\zeta|\xi$ shall follow the beta distribution, hence $\zeta|\xi \sim B_{\alpha,\beta}[l,h]$ where $B_{\alpha,\beta}$ is the beta distribution with shape parameters $\alpha > 0$ and $\beta > 0$ over the interval $[l,h]$. In order to meet our second and third objectives we need to express mode ($\zeta|\xi$) and variance $V(\zeta|\xi)$ in terms of the realization of $\xi$. For any beta distribution, mode and variance can be calculated as follows (Gupta and Nadarajah 2004):

$$\text{mode}(\zeta|\xi) = \frac{(\alpha - 1)u + (\beta - 1)l}{\alpha + \beta - 2}$$

$$V(\zeta|\xi) = \frac{\alpha \beta}{(\alpha + \beta)^2(\alpha + \beta + 1)}(u - l)^2$$

Allowing $\alpha$ and $\beta$ to be functions of $\xi$ and a constant parameter $v$, our objective is to solve

$$\text{mode}(\zeta|\xi) = \frac{(\alpha(\xi,v) - 1)u + (\beta(\xi,v) - 1)l}{\alpha(\xi,v) + \beta(\xi,v) - 2}$$

$$V(\zeta|\xi) = \frac{\alpha(\xi,v)\beta(\xi,v)}{(\alpha(\xi,v) + \beta(\xi,v))^2(\alpha(\xi,v) + \beta(\xi,v) + 1)}(u - l)^2 = v$$

This requires solving the non-linear system of equations,

$$\frac{\xi - l}{u - l}\beta(\xi,v) + \frac{u + l - 2\xi}{u - \xi} - \alpha(\xi,v) = 0$$

$$\alpha(\xi,v)\beta(\xi,v) - \frac{v}{(u - l)^2}(\alpha(\xi,v) + \beta(\xi,v))^2(\alpha(\xi,v) + \beta(\xi,v) + 1) = 0$$

This is a third-order polynomial and thus has at least one real root. Further analysis was carried out numerically and offline based on the random numbers streams.
Appendix D: Coding of qualitative strategy descriptions

After performing the two main tasks of the experiment, subjects were asked to describe the strategies they used in making acceptance and continuation decisions. We used their responses to this question as a control for whether or not the subjects understood the task and reacted to the given data. Specifically, the responses were coded and placed into one of three categories: (1) reacted to data, (2) ignored data, or (3) unclear response. A typical quote for category (1) is “I accepted a contract if the rewards were sufficiently high.”, since this shows that the subject is taking data from the problem context into account. This is opposed to the following rationale for acceptance which would be coded as category (2), “Innovation [...] is exciting and keeps the workers interest piqued. People like variety and excitement (to an extent) - boredom kills companies”. If the response was not understandable or left blank, if was coded as category (3).

In order to categorize each subject objectively, we asked three Ph.D. students (who are not part of our research team) to independently code each statement. We tested the results for interrater agreement, which was supported with a combined $\kappa = 0.37$ ($p < 0.0001, z = 156.7$). For statements where the codes of at least two of the three raters were in agreement, we categorized the item by this majority code. For the 1.2% of statements where there was no agreement among raters, we created a new code (4) to separate these out. Table 7 summarizes the percentage of subject responses within each category. These “strategy codes” were used in the statistical models as an additional control, capturing individual differences in how well subjects understood the tasks.

<table>
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<th>strategy code</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<td>15%</td>
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Table 7 Percent of subjects coded as (1) reacted to data, (2) ignored data, (3) unclear response, (4) no agreement among raters
### Appendix E: Data analyses results summary

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<th>Type-I-error rates</th>
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**Table 8** Random effects probit models on the acceptance decision. Further controls omitted. ***p < 0.001; **p < 0.01; *p < 0.05; +p < 0.1
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Marginal effects
| Effect (HROV)               | -0.11 | 0.07 | 0.18 | 0.22 |
| Effect (NREV)               | 0.05 | 0.07 | 0.07 | 0.2 |
| Effect (HSUNK)              | -0.1 | 0.1 | -0.05 | 0.3 |
| Frame (Reward)              | -0.06 | 0.05 | -0.13 | 0.14 |

Table 9  Random effects probit models on the continuation decision. Further controls omitted. *** p < 0.001; ** p < 0.01; * p < 0.05; p < 0.1
References


Visnjic, I., T. Taija, A. Neely. 2013. When innovation follows promise.


