Procuring New Ideas: On the Value of Performance Information in Innovation Tournaments*

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Abstract

We use a stylized model of a dynamic innovation tournament to show that the effectiveness of monetary incentives depends on whether contestants receive cardinal, ordinal, or no information about their rival's performance. The model's main implication is that performance information acts as a substitute for prize money in creating incentives to invest in new ideas: The investment-maximizing information policy switches from no to ordinal to cardinal information as the tournament's prize is reduced. A laboratory experiment provides support for our theory but also unveils an unpredicted pattern of behavior capable of overturning the model's conclusions concerning optimal policy.

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1 Introduction

In recent years, innovation tournaments have become a vital source of research and development (R&D).[1] These tournaments are structured procurement mechanisms aimed at obtaining the best idea, product, or solution for a well-defined objective in a prespecified amount of time. They come in various forms such as innovation contests inside organizations, competitive procurement of governmental agencies, and crowd-sourcing tournaments on online platforms.

While celebrated for iconic achievements, such as Facebook's "Like" button and the rebuilt face of Notre-Dame Cathedral, the true value of innovation tournaments lies in their ability to "procure innovation from the masses", by tapping the creative ideas generated by small businesses and individual innovators. This potential has become magnified by the emergence of crowd-sourcing platforms (e.g., Kaggle or Wazoku Crowd), which provide an institutionalized framework and the necessary tools to match innovators and clients. However, while a few acclaimed tournaments have awarded prizes in the millions (e.g., Netflix Prize), most frequently prize purses are small, making it especially important to understand how a tournament should be designed to provide contestants with maximal incentives to innovate.

In this article, we investigate—both theoretically and experimentally—whether and to what extent information about a rival's performance can substitute for prize money in providing contestants with incentives to innovate. Innovation tournaments differ markedly in their information policy. Competitive procurement tournaments are typically "blind" in that contestants are uninformed about their rivals' performance until the final results of the tournament are revealed. In contrast, public leaderboards constitute the default mode on crowd-sourcing platforms. These leaderboards inform contestants about the client's evaluation of individual submissions by providing either ordinal rankings or even cardinal information about rival performances.

To shed light on this issue, in Section 2 we analyze a stylized model of a two-player, two-stage innovation tournament. In each stage, each player decides whether to invest in an "idea" whose value is an independent and identically distributed draw from a commonly known distribution. Players face the same cost of investing in an idea but this cost may vary across stages. The tournament awards a prize to the player who provides the idea with the highest value at the end of the second stage. Players always observe the value of their own ideas, immediately upon investment, but with respect to players' information about

[1]Bhattacharya (2021) documents that the U.S. Department of Defense spends over one billion U.S. dollars per year on innovation tournaments organized under its Small Business Innovation Research Program.

the value of their rival's ideas we distinguish between three settings. Under *No Performance Information (NPI)*, players learn nothing about their rival's performance until the end of the tournament. Under *Rank Performance Information (RPI)*, players learn about the ranking of performances, i.e., each player learns whether he is the *follower* or the *leader*—the player with the most-valued idea at the end of the first stage. Finally, under *Full Performance Information (FPI)* players also learn the value of their rival's first-stage idea before deciding whether to invest in the second stage.

Our starting point is the observation that information about a rival's performance can have ambiguous effects on players' incentives to invest in new ideas. To understand these effects it turns out to be useful to decompose performance information into its ordinal and cardinal components. The provision of ordinal information, i.e., the switch from NPI to RPI, boosts the follower's incentive to improve upon his idea whereas it reduces incentives for the leader. The provision of cardinal information, i.e., the switch from RPI to FPI, motivates the follower to invest when he learns that the leader's idea leaves ample *room for improvement* whereas otherwise it demotivates the follower's investment.

The main contribution of our theory is to show that whether the positive or the negative effects of performance information dominate depends on the effectiveness of monetary incentives, that is, on the size of the tournament's prize relative to the players' costs of investment. Our model reveals that prize money and performance information act as substitutes in the creation of investment incentives: A reduction in the tournaments prize, makes a switch from less to more information more desirable in terms of aggregate investment.

Our results have important implications for a tournament's information policy. They imply that in the extremes, i.e., for low-prize and high-prize tournaments, aggregate investment is maximized when contestants have full or no information, respectively, about rival performance. This finding is in line with the observation that public leaderboards are ubiquitous in crowd-sourcing tournaments where, arguably, prize money is rather restricted. Yet, we also prove that there exists an intermediate prize range for which rank information maximizes incentives. This insight might be particularly valuable in practice, because in many settings, rank information is the only information available.[2] It is consistent with the deliberate restriction of feedback to a comparison of *individual* and *average* performance which is frequently observed in related settings such as education (e.g., Azmat et al., 2019) and labor (e.g., Blanes i Vidal & Nossol, 2011).

While our model delivers clear predictions about how investment incentives respond to performance information, their empirical relevance ultimately depends on how contestants

[2]For instance, in architectural and design contests, organizers can rank the submitted proposals but there exists no absolute scale for quantifying the performance differences.

process and act upon such feedback. In Section 3, we therefore complement our theoretical analysis with a laboratory experiment whose design mirrors our theoretical model. We chose a laboratory experiment rather than a field experiment to isolate the incentive effects predicted by our theory from possible participation effects arising from the variation in monetary incentives necessary for our test.

The experiment provides evidence showing that prize money and performance information constitute substitutes in the creation of investments. In particular, we find that the provision of cardinal information, in form of a switch from RPI to FPI, reduces the slope with which investments increase with the tournament's prize by about one third. In contrast, our experiment fails to provide evidence for the optimality of RPI and reveals that investment under FPI is higher than predicted.

To understand why investments exceed the predicted levels under FPI, we first consider whether our experimental subjects indeed follow the threshold strategies that arise in our model. Under NPI and RPI, subjects should invest in a new idea when the value of their own idea falls below a threshold. Under FPI subjects should invest when the leading idea leaves sufficient room for improvement. Indeed, we find that the majority of subjects employ threshold strategies, and a comparison of the role-specific thresholds under RPI shows that followers are more motivated to invest than leaders, as predicted by theory.

Yet, a comparison of investments under RPI and FPI also reveals that cardinal information induces followers to condition their investment on the difference between their own idea and the leading idea, resulting in larger-than-predicted investments when this difference is small. Furthermore, our data indicate that leaders react strategically by increasing their investments. In other settings, such as innovation races and labor contests, such head-to-head competition is well documented and consistent with theory because current performance builds on past performance so that small performance gaps encourage investments. However, in our setting, the sampling of new ideas is independent of the value of existing ideas, and the finding of head-to-head competition is thus surprising. By explaining why investments under FPI exceed predicted levels, our experimental results complement the theory and provide an additional argument for full transparency in innovation tournaments.

Related Literature

We contribute to the literature on innovation tournaments, initiated by the seminal article of Taylor (1995). While Taylor's model abstracts from performance information by assuming that contestants observe only their own ideas (NPI), a first indication that performance information affects incentives has been obtained by Rieck (2010). He shows that, under the assumption that investment costs are homogeneous across periods, FPI has an unambiguously deteriorating effect on aggregate incentives. Our model reveals a more nuanced picture by showing that, when this assumption is relaxed, FPI can dominate NPI in low-prize tournaments.

This finding resonates well with more recent empirical research which has revived the debate about the desirability of performance information. Lemus and Marshall (2021) use a structural approach calibrated to the characteristics of prediction contests hosted on the online platform Kaggle.com to explore the effects of a public leaderboard. They estimate that without its leaderboard Kaggle would receive 21 percent less submissions. They also provide empirical support for the dominance of FPI in form of a field experiment.

The results of Lemus and Marshall (2021) contrast with Hudja et al. (2025) who use a laboratory experiment to show that a leaderboard can have a negative effect on investment incentives. Hudja et al. (2025) explain the dominance of NPI by showing numerically that, in Taylor's (1995) model, aggregate investment under FPI can be lower than under NPI when the distribution of ideas is exponential and the tournament's number of stages is sufficiently small.

We reconcile these polar views by showing that whether a leaderboard has a positive or negative effect on aggregate investment depends on the size of a tournament's prize relative to the costs of investment. On the one hand, our model proves and our data indicates that aggregate investment is higher under FPI than under NPI in low-prize tournaments which is consistent with Lemus and Marshall's (2021) result that the difference in the average number of submissions with and without a leaderboard increases with a higher cost-to-prize ratio. On the other hand, our result that investment under NPI exceeds investment under FPI in high-prize tournaments is in line with Hudja et al.'s (2025) finding that a reduction in a tournament's number of stages can make a leaderboard harmful for incentives, because, everything else equal, such a change amounts to a decrease of the tournament's prize relative to the per-period costs of investment.

Our theoretical findings motivate a comparison of the extreme cases of NPI and FPI to the more moderate policy of RPI. While the incentive effects of rank information have been studied in related settings (e.g., Gill et al., 2019; Heursen, 2023; Kajitani et al., 2020; Tran & Zeckhauser, 2012), to the best of our knowledge, an analysis of RPI in innovation tournaments is still missing. We close this gap by adding the analysis of RPI to a two-stage version of the models by Taylor (1995) and Rieck (2010). Our theory offers a more complete understanding of the incentive effects of performance information by allowing for a decomposition of these effects into their ordinal and cardinal components.

Our finding that aggregate incentives can become maximized by providing players with an *intermediate* degree of information in the form of RPI is noteworthy in the light of the literature on information design in contests. This literature typically finds that either no information or full information is optimal (e.g., Antsygina & Teteryatnikova, 2023; Aoyagi, 2010). Our theory implies that, even in settings where performance can be quantified, withholding cardinal information while informing players only about their ordinal ranking can be optimal.

Our focus on the incentive effects of performance information is shared by an emerging literature on innovation races (e.g., Gross, 2017; Halac et al., 2017; Mihm & Schlapp, 2019) and labor tournaments (e.g., Aoyagi, 2010; Ederer, 2010; Gershkov & Perry, 2009; Goltsman & Mukherjee, 2011). These settings differ from ours in that performance is *cumulative*: the tournament's prize (e.g., patent or promotion) is awarded to the contestant who obtained the highest performance, *aggregated over all stages.* This implies that incentives depend not only on the absolute value of the leader's performance but also on the distance relative to the follower's achievement. More specifically, it is commonly understood and well documented that aggregate investments are highest when the "race is close" or the "tournament is balanced". It is surprising that our experiment reveals a similar pattern, although our sampling competition leaves no room for the aggregation of performance across stages.

The effect of performance information on incentives has also received attention in education economics (e.g., Azmat & Iriberri, 2010, 2016; Azmat et al., 2019) and human resource management (e.g., Blanes i Vidal & Nossol, 2011; Clark et al., 2010; Song et al., 2018). While in those settings past performances have no direct payoff-relevant effect on future outcomes, knowing one's position relative to others or in comparison to the average is generally found to affect the provision of efforts.

Finally, a more general lesson for policy emerges from our findings if the definition of a tournament's "prize" is broadened to incorporate the market value of the contested innovation. This links us to a literature investigating the (causal) relationship between competition or patent policy and R&D (e.g., Aghion et al., 2018; Galasso & Schankerman, 2015). Our findings suggest that fine-tuning the institutional details of an innovation tournament should be performed against the background of any policy shaping the overall value of an innovation.

2 Theory

In this section, we provide a stylized model of an innovation tournament to study the effects of performance information on incentives. By decomposing performance information into its ordinal and cardinal components, our theory offers a complete understanding of its motivating and demotivating effects. The main insight of our theory is that performance information has a systematic influence on the effectiveness of monetary incentives. An important implication is that the information policy that maximizes aggregate incentives depends on the size of a tournament's prize relative to the costs of investments.

2.1 Model

We consider two identical, risk-neutral players $i, j \in \{A, B\}$ engaged in an innovation tournament consisting of two stages $t = 1, 2$. At each stage, each player decides whether to invest in a potential innovation, an idea. If a player i invests at stage t he incurs a cost of investment $C_t \geq 0$. Note that we divert from Taylor (1995) by allowing costs to differ across periods, which we feel is a necessary consequence of restricting his model to only two stages.[3] A player that invests obtains an idea whose value is drawn from an interval $[0, b]$ with a strictly positive probability density function h. The cumulative distribution function is denoted by H. Ideas are thus independent and identically distributed across stages and players. We denote by x_t^i the value of the idea player i obtains in stage t and set $x_t^i = 0$ when player i chooses not to invest in stage t. Moreover, we let $X_t = \max(x_t^A, x_t^B)$ denote the players' best idea in stage t. The player with the best idea across all stages wins the tournament and receives a prize of size $V > 0$, with ties broken randomly.

We follow Taylor (1995) by assuming throughout that at the beginning of the second stage, players become informed about the value of their own first-stage idea. However, we distinguish between three policies that differ with respect to the information players receive at the beginning of the second stage about the value of their rival's first-stage idea. Under *Full Performance Information (FPI)*, players become fully informed about the value of their rival's first-stage idea. Under *Rank Performance Information (RPI)*, players observe only the ranking of their rival's first-stage idea relative to their own idea, i.e., they learn whether they are the *leader* or the *follower*. Finally, under *No Performance Information (NPI)*, players receive no information at all about their rival's first-stage idea.

Note that if players fail to invest in the first stage, all three policies trivially generate the same information and hence identical second-stage investments. Given our focus on the players' aggregate incentives to invest, we therefore focus on the non-trivial case where C_1 is sufficiently small for both players to invest in the first stage. In the subsequent section, we thus characterize the (unique) second-stage equilibrium for each information policy and derive the corresponding expected aggregate investment, defined as the sum of players' second-stage investments, with the expectation taken over all possible first-stage realizations of ideas (x_1^A, x_1^B).

[3]The assumption that the costs of R&D may vary across different phases of the innovation process is common in the literature on R&D races. See, e.g., Fudenberg et al. (1983).

Finally, note that the characterization of equilibrium depends on the tournament's prize V and the players' cost of investment C_2 only through their ratio $\rho = \frac{C_2}{V}$. Our analysis restricts attention to the case where $\rho < \frac{1}{2}$. For $\rho \geq \frac{1}{2}$, it is straightforward to see that information can have only a positive effect on the players' aggregate investment (see our discussion in Section 2.3.)

2.2 Equilibrium Characterization

This section characterizes the players' equilibrium investment separately for the three distinct information policies. For each policy, players' investment choice in the second stage takes the form of a cut-off rule. If observable, each player i conditions his investment on X_1, that is, on the best performance in the first stage. If player i does not observe X_1, player i makes his investment conditional on his own past performance x_1^i. The following subsections derive the corresponding equilibrium cut-offs, below which players choose to invest. The main lesson that emerges is that players invest in new ideas when there exists sufficient "room for improvement", either of their own existing idea or, if observable, of the tournament's leading idea. This simple intuition is sufficient to understand the arguments for and against performance information that we develop in Section 2.3. The following Subsections 2.2.1–2.2.3 may therefore be skipped.

2.2.1 Full Performance Information (FPI)

When players observe not only their own performance but also their rival's performance, we can rename players by denoting the player with the higher-valued first-stage idea as the leader (L) and the player with the lower-valued first-stage idea as the follower (F). The leading performance $X_1 = \max\{x_1^L, x_1^F\} = x_1^L$ is then known to both players. The leader has a weaker incentive to invest than the follower, because he may win the tournament already with his existing idea. Hence, in addition to the trivial case of an equilibrium in which no player invests, there exist only two potential candidates for an equilibrium: either both players invest or only the follower invests.

We first analyze the conditions under which a unilateral investment by the follower constitutes an equilibrium. If the leader refrains from investing, it is optimal for the follower to invest if and only if

$$\mathbb{P}(x_2^F > X_1)V - C_2 = [1 - H(X_1)]V - C_2 \geq 0. \qquad (1)$$

Investing is optimal for the follower if and only if the leader's existing idea leaves enough room for improvement, i.e., as long as

$$X_1 \leq \bar{X}^F \equiv H^{-1}(1-\rho). \tag{2}$$

Conversely, if the follower invests, it will be optimal for the leader to refrain from investing if and only if the value of his existing idea is high enough. In particular, not investing is optimal for the leader if and only if

$$\mathbb{P}(x_2^F < \max(X_1, x_2^L))V - C_2 \leq \mathbb{P}(x_2^F < X_1)V. \tag{3}$$

Because ideas are independent and identically distributed it holds that

$$\mathbb{P}(x_2^F < \max(X_1, x_2^L)) = \mathbb{P}(x_2^F < X_1) + \frac{1}{2}\mathbb{P}(x_2^F > X_1)\mathbb{P}(x_2^L > X_1) \tag{4}$$

and the above inequality can thus be rewritten as

$$[1 - H(X_1)]^2 \leq 2\frac{C_2}{V} \Leftrightarrow X_1 \geq \bar{X}^L \equiv H^{-1}(1 - \sqrt{2\rho}). \tag{5}$$

Note that it follows from $\rho < \frac{1}{2}$ that the leader's cutoff $\bar{X}^L$ is positive and strictly smaller than the follower's cutoff $\bar{X}^F$. Thus, we have shown that a unilateral investment of the follower constitutes an equilibrium if and only if $X_1 \in (\bar{X}^L, \bar{X}^F)$. Combining this result with the fact that the follower's incentive to invest is always stronger than the leader's gives us the following:

Lemma 1 (Equilibrium Characterization: FPI)**.** *Under Full Performance Information, players condition their investments on the value of the leading idea X_1, and there exist thresholds $0 < \bar{X}^L < \bar{X}^F < b$, given by (2) and (5), such that the following holds: The follower invests in a new idea if and only if $X_1 < \bar{X}^F$, and the leader invests if and only if $X_1 < \bar{X}^L$.*

Lemma 1 can be used to calculate expected aggregate investment of the two players in the second stage, which we denote as I^{FPI}. For this purpose, note that, when both players have invested in the first stage, the value of the best idea, X_1, is determined by the first-order statistic with cumulative distribution H^2. Because both players invest when $X_1 < \bar{X}^L$ and only the follower invests when $\bar{X}^L \leq X_1 < \bar{X}^F$, we can use (2) and (5) to obtain expected aggregate investment under FPI as

$$I^{FPI} = 2H^2(\bar{X}^L) + H^2(\bar{X}^F) - H^2(\bar{X}^L) = 2 - \sqrt{8\rho} + \rho^2. \tag{6}$$

2.2.2 No Performance Information (NPI)

When players observe only their own performance but have no information about their rival's performance, our analysis follows Taylor (1995) and is included for completeness. In equilibrium, player i will invest if and only if the value of his own idea, x_1^i, falls below a certain threshold $\bar{x}$. The threshold $\bar{x}$ can be determined from the condition that for $x_1^i = \bar{x}$ player i must be indifferent between investing and not investing. If $x_1^i = \bar{x}$ and player i refrains from investing, then player i wins the tournament if and only if two conditions are satisfied: (i) player j's existing idea must be of lower value than $\bar{x}$, and (ii) given that when the first condition is satisfied, player j would invest in a new idea, player j's new idea must also fall short of $\bar{x}$. Player i's expected payoff from not investing is thus given by the expression

$$\mathbb{P}(x_1^j \leq \bar{x})\mathbb{P}(x_2^j \leq \bar{x})V = H^2(\bar{x})V. \tag{7}$$

If, instead, player i invests in a new idea, his expected payoff is

$$H^2(\bar{x})V + [1 - H^2(\bar{x})] \int_{\bar{x}}^{b} \frac{H(x_2^i) - H(\bar{x})}{1 - H(\bar{x})} h(x_2^i) dx_2^i \, V - C_2. \tag{8}$$

The benefit that player i derives from his investment is due to the added possibility that he wins the tournament even when his rival obtains a better idea than player i's existing idea $\bar{x}$. Player i is indifferent between investing and not investing when the following equation is satisfied

$$[1 + H(\bar{x})] \, [1 - H(\bar{x})]^2 = 2\rho. \tag{9}$$

In the proof of Lemma 2 contained in Appendix A.1, we show that this implicit equation defines a unique threshold $\bar{x} \in (0, b)$. We summarize these findings in the following:

Lemma 2 (Equilibrium Characterization: NPI)**.** *Under No Performance Information, players condition their investments on the value of their own idea, and there exists a threshold* $\bar{x} \in (0, b)$*, given by the unique solution of (9), such that the following holds: Player i invests in a new idea if and only if* $x_1^i < \bar{x}$*.*

Because the players' investment rules are identical and independent, Lemma 2 implies that under NPI, expected aggregate investment is given by

$$I^{NPI} = 2\mathbb{P}(x_1^i \leq \bar{x}) = 2H(\bar{x}). \tag{10}$$

Note that since $\bar{x}$ is defined only implicitly through equation (9), a closed form solution for I^{NPI} cannot be obtained without further assumptions on the idea-distribution H. However, as we will see below, the absence of such an explicit solution does not prevent us from obtaining a comparison of investments across the three information policies. In fact, because our theory could be rewritten in rank-space where the distribution of idea-ranks is uniform due to our assumption that ideas are iid, this comparison turns out to be independent of the distribution H.

2.2.3 Rank Performance Information (RPI)

When players observe only the relative ranking of performances, the leading performance is known to the leader but not to the follower. As in the case of FPI, a leader with $x_1^L = \bar{X}^L$ correctly anticipates the follower to invest. This is because a leader with $x_1^L = \bar{X}^L$ does not need to observe x_1^F to know that the follower will invest. All he needs for this conclusion is to know what he observes, namely that $x_1^F < \bar{X}^L$ and to anticipate (correctly in equilibrium) that the follower's incentive to invest is stronger than his own. This means that the leader's behavior under RPI will be identical to the leader's behavior under FPI, that is, in equilibrium, the leader invests if and only if $x_1^L \leq \bar{X}^L$ with the threshold $\bar{X}^L$ given by (5).

Similarly to the case of no information, the follower can condition his investment decision only on his own performance, i.e., he invests if and only if $x_1^F \leq \bar{x}^F$ with the threshold $\bar{x}^F$ yet to be determined. Furthermore, we conjecture (and confirm below) that, as in the case of FPI, the follower has a stronger incentive to invest than the leader, i.e., $\bar{X}^L < \bar{x}^F$. Requiring a follower with $x_1^F = \bar{x}^F$ to be indifferent between investing and not investing then gives the following equation:

$$V \int_{\bar{x}^F}^{b} \mathbb{P}(x_2^F > x_1^L) \frac{h(x_1^L)}{1 - H(\bar{x}^F)} dx_1^L - C_2 = 0. \tag{11}$$

To understand this equation, note that a follower with $x_1^F = \bar{x}^F$ knows that the leader's idea x_1^L is better than $\bar{x}^F$ and that his rival will therefore refrain from investing in a second idea (given our equilibrium conjecture). Hence, from the viewpoint of the follower, the idea that has to be overcome is $x_1^L \in [\bar{x}^F, b]$ distributed with density $\frac{h(.)}{1-H(\bar{x}^F)}$. Substituting $\mathbb{P}(x_2^F > x_1^L) = 1 - H(x_1^L)$ and integrating by parts, equation (11) simplifies to

$$1 - H(\bar{x}^F) = 2\frac{C_2}{V} \Leftrightarrow \bar{x}^F = H^{-1}(1 - 2\rho). \tag{12}$$

Note that $\rho < \frac{1}{2}$ implies that the follower's threshold $\bar{x}^F$ is indeed larger than the leader's threshold $\bar{X}^L = H^{-1}(1 - \sqrt{2\rho})$ as conjectured. We have thus shown the following:

Lemma 3 (Equilibrium Characterization: RPI)**.** *Under Rank Performance Information, players condition their investments on the value of their own ideas, and there exist thresholds*

$0 < \bar{X}^L < \bar{x}^F < b$, given by (5) and (12), such that the following holds: The follower invests if and only if $x_1^F < \bar{x}^F$, and the leader invests if and only if $x_1^L < \bar{X}^L$.

To calculate expected aggregate investment under RPI, note that, in the equilibrium characterized by Lemma 3, at least one player invests unless both players' past performances exceed $\bar{x}^F$. Moreover, both players invest when both players' performance falls short of $\bar{X}^L$. Therefore, it follows from Lemma 3 and equations (5) and (12) that

$$I^{RPI} = 1 - [1 - H(\bar{x}^F)]^2 + H^2(\bar{X}^L) = 2 - \sqrt{8\rho} - 4\rho^2 + 2\rho. \tag{13}$$

2.3 The Incentive Effects of Performance Information

After characterizing the players' equilibrium investment rules for the three distinct information policies, we now compare the corresponding expected aggregate investments. This allows us to derive our main results about the incentive effect of performance information.

Ultimately, the designer of an innovation tournament might want to select the information policy that maximizes the tournament's expected winning idea. However, this policy depends on the distribution H of performances, whereas the policy maximizing investments turns out to be independent of H. In the absence of knowledge about the distribution of ideas, a tournament designer might thus choose to maximize players' aggregate incentives even when this objective is not always aligned with the maximization of the best idea.

To shed light on the pros and cons of performance information, it turns out to be helpful to decompose performance information into its ordinal and cardinal components. Therefore, our subsequent analysis follows a two-step approach. Step 1 considers how investment incentives are affected when players learn the ordinal ranking of their performance, i.e., we consider the switch from NPI to RPI. Step 2 explores the switch from RPI to FPI which informs us about the incentive-effects that arise when players that already know their relative positions become informed about the cardinal value of the leading performance.

2.3.1 Ordinal Information

In this section, we consider the changes in investments resulting from the provision of ordinal information in the form of a switch from NPI to RPI. This comparison is complicated by the fact that under NPI investments cannot be expressed in closed form. More specifically, while under RPI, the thresholds $\bar{X}^L$ and $\bar{x}^F$ determining investments are given by (5) and (12), no explicit formula for the corresponding threshold $\bar{x}$ under NPI is available.

An important step in our subsequent argument is the insight that incentives under no information are given by an "average" of the incentives under rank information, or, more precisely, $\bar{X}^L < \bar{x} < \bar{x}^F$. To see this formally, note from (9) that the benefit from investing under no information, $\frac{V}{2}[1 + H(\bar{x})][1 - H(\bar{x})]^2$ can be written as a weighted sum of the leader's and the follower's benefits from investing under rank information, $\frac{V}{2}[1 - H(\bar{x})]^2$ and $\frac{V}{2}[1 - H(\bar{x})]$, with the weights equal to the likelihoods $H(\bar{x})$ and $1 - H(\bar{x})$ that a player with performance $\bar{x}$ turns out to be the tournament's leader or follower, respectively.

Given that $\bar{X}^L < \bar{x} < \bar{x}^F$, the *changes* in investment choices that arise from players observing their rank, are therefore as depicted in Figure 1.

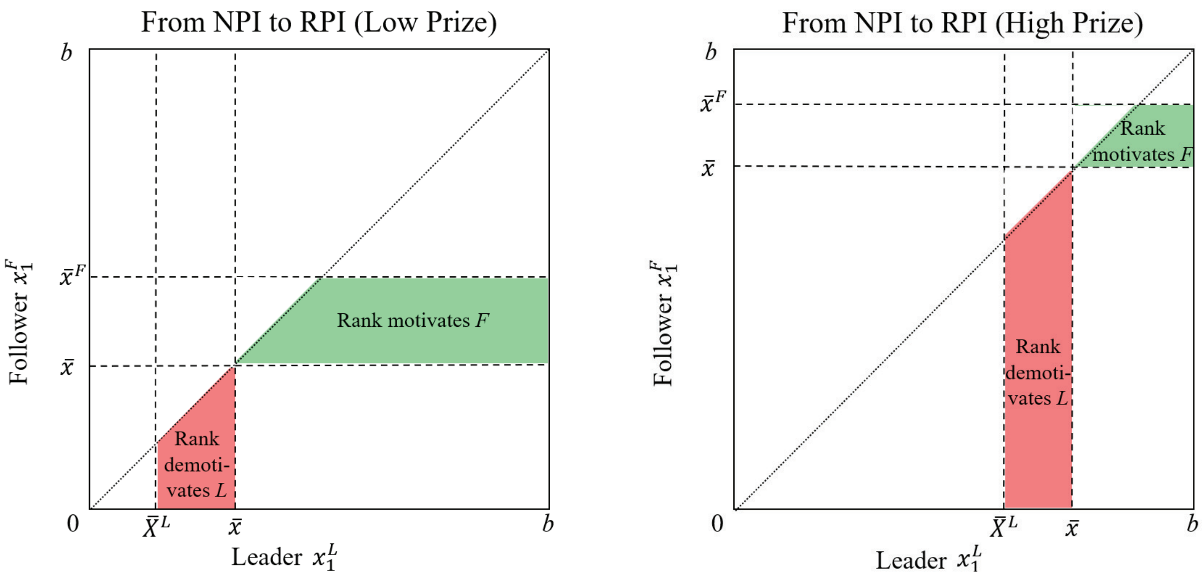

Figure 1: Incentive Gains and Incentive Losses from Ordinal Information. The green (red) area depicts realizations of first-stage performances of leader and follower (x_1^L, x_1^F) for which RPI induces a gain (loss) in investment relative to NPI. Left and right panel depict low-prize and high-prize tournaments, respectively.

Rank information affects investments in two ways. On one hand, learning to be the follower motivates a player to switch from not investing (under NPI) to investing (under RPI) when the value of his own idea lies between $\bar{x}$ and $\bar{x}^F$. In the figure, the set of ideas whose minimum (cf. follower) lies between those values is depicted by the green area. On the other hand, learning to be the leader demotivates a player to switch from investing (under NPI) to not investing (under RPI) when the value of his own idea lies between $\bar{X}^L$ and $\bar{x}$. In the figure, the set of ideas whose maximum (cf. leader) lies between $\bar{X}^L$ and $\bar{x}$ is depicted as the red area. From an ex ante perspective, investment under RPI is thus larger than investment under NPI if and only if

$$I^{RPI} - I^{NPI} = [1 - H(\bar{x})]^2 - [1 - H(\bar{x}^F)]^2 - [H(\bar{x})^2 - H(\bar{X}^L)^2] \tag{14}$$

is positive. In Appendix A.1 we prove the following:

Proposition 1 (Incentive Effects of Ordinal Information)**.** *RPI induces higher aggregate investment than NPI, i.e.,* $I^{RPI} - I^{NPI} > 0$*, if and only if* $\rho > \tilde{\rho}$. $\tilde{\rho} \in (0, \frac{2}{5})$ *is independent of* H*.*

To derive this result, note that, although a closed form solution for $\bar{x}$ is not available, we can determine the probability $y(\rho) = H(\bar{x})$ with which players have to invest under NPI to make aggregate investment the same as under RPI. In particular, setting $I^{RPI} = I^{NPI}$ in (14) and substituting (5) and (12) gives

$$y(\rho) = H(\bar{x}) = 1 - \sqrt{2\rho} + \rho - 2\rho^2. \tag{15}$$

Because $I^{RPI} - I^{NPI}$ is decreasing in y, the curve $y(\rho)$ divides the (ρ, y) space into two areas, as shown in Figure 2: $I^{RPI} > I^{NPI}$ for $y < y(\rho)$, whereas $I^{NPI} > I^{RPI}$ for $y > y(\rho)$.

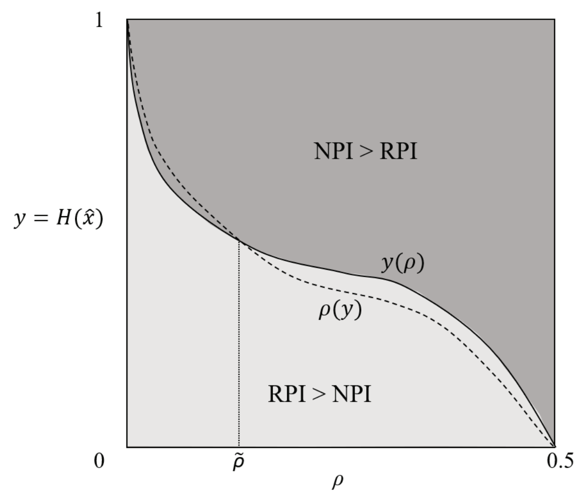

Figure 2: Determination of Critical Cost-Prize Ratio $\tilde{\rho}$**.** The curve $y(\rho)$ depicts the players' probability of investment under NPI necessary to make aggregate investment the same as under RPI. The curve $\rho(y)$ depicts the cost-prize ratio that induces players to invest under NPI with probability y. Note that any $\rho > \tilde{\rho}$ induces a y in the light-shaded area where RPI dominates NPI whereas any $\rho < \tilde{\rho}$ induces a y in the dark-shaded area where NPI dominates RPI.

Figure 2 also depicts the cost-prize ratio $\rho(y)$ that induces players to invest with probability y under NPI. $\rho(y)$ follows immediately from (9) defining the threshold $\bar{x}$ implicitly and is given by

$$\rho(y) = \frac{1}{2}(1 + y)(1 - y)^2. \tag{16}$$

In the proof of Proposition 1, we show that $y(\rho)$ and $\rho(y)$ intersect exactly once as depicted and thus define a unique critical cost-prize ratio $\tilde{\rho}$. For $\rho < \tilde{\rho}$, investments are easy to incentivize and, as can be seen from the figure, players are induced to invest under NPI with a likelihood higher than necessary to equate aggregate investments across the two information policies. The opposite holds for $\rho > \tilde{\rho}$, where investments are difficult to incentivize and players are induced to invest under NPI with a likelihood smaller than necessary to equate investments.

2.3.2 Cardinal information

In this section, we consider the changes in investments resulting from the provision of cardinal information in the form of a switch from RPI to FPI. This comparison is simplified by the fact that in both cases aggregate investment is available in closed form. From (6) and (13), we get

$$I^{FPI} - I^{RPI} = 2 - \sqrt{8\rho} + \rho^2 - (2 - \sqrt{8\rho} - 4\rho^2 + 2\rho) = \rho(5\rho - 2). \tag{17}$$

This immediately establishes the following:

Proposition 2 (Incentive Effects of Cardinal Information)**.** *FPI induces higher aggregate investment than RPI, i.e.,* $I^{FPI} > I^{RPI}$*, if and only if* $\rho > \frac{2}{5}$.

To understand this result, first recall that the switch from RPI to FPI affects only the follower's behavior but not the leader's. Hence, any effect of cardinal information on aggregate investment has to originate from changes in the follower's behavior. Figure 3 shows that informing the follower about the cardinal value of the leader's performance has two countervailing effects.

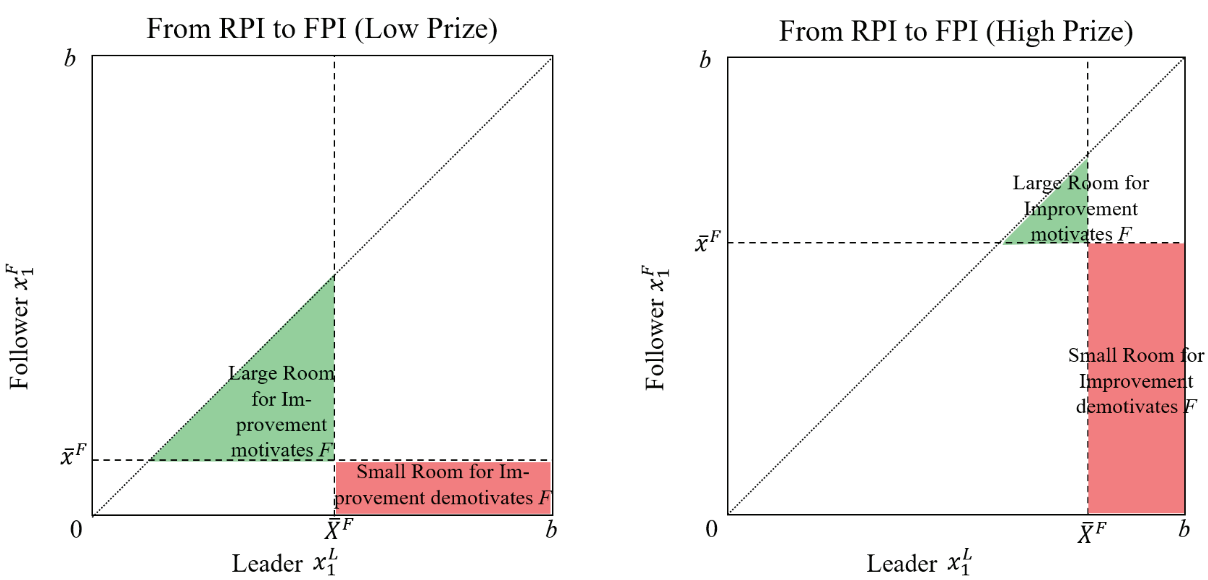

Figure 3: Incentive Gains and Incentive Losses from Cardinal Information. The green (red) area depicts realizations of first-stage performances of leader and follower (x_1^L, x_1^F) for which FPI induces a gain (loss) in follower investment relative to RPI.

First, the news that the leader's performance is "bad" motivates a follower who is willing to invest only when he learns that the leader's performance leaves ample room for improvement. This happens when $x_1^F > \bar{x}^F$ and $x_1^L < \bar{X}^F$, that is, when first-stage ideas fall into the green area. Second, the news that the leader's performance is "good" demotivates a follower who would be willing to invest in the absence of information about the leader's performance. This happens when $x_1^F < \bar{x}^F$ and $x_1^L > \bar{X}^F$, that is, when first-stage ideas fall into the red area.

From an ex ante perspective, investment under FPI is thus larger than investment under RPI if and only if

$$I^{FPI} - I^{RPI} = [H(\bar{X}^F) - H(\bar{x}^F)]^2 - 2H(\bar{x}^F)[1 - H(\bar{X}^F)] \tag{18}$$

is positive. Note next that, for a follower with performance $\bar{x}^F$ to be indifferent between investing and not investing under RPI, the likelihood that the leader's performance is "good" has to equal the likelihood that the leader's performance is "bad". It thus follows from the definition of $\bar{x}^F$ that $H(\bar{X}^F) - H(\bar{x}^F) = 1 - H(\bar{X}^F)$. To weigh the gains against the losses in investment it is therefore sufficient to compare the mass of follower-types that can be motivated by the news that the leader's performance is "bad", $H(\bar{X}^F) - H(\bar{x}^F) = \rho$, with the mass of follower-types that can be demotivated by the news that the leader's performance is "good", $2H(\bar{x}^F) = 2-4\rho$. Intuitively, an increase in ρ raises the mass of followers that cardinal information can motivate, while reducing the mass of followers that cardinal information can demotivate. This explains why FPI becomes more beneficial relative to RPI when the cost-prize ratio ρ increases.

2.4 Optimal Information Policy

Propositions 1 and 2 establish that performance information constitutes a substitute for monetary incentives in the creation of investments. They show that a reduction in monetary incentives in form of an increase in the cost-prize ratio ρ makes more performance information desirable.

Note from Propositions 1 and 2 that the critical cost-prize ratio determining the dominance of RPI over NPI ($\rho = \tilde{\rho}$) is smaller than the corresponding ratio governing the dominance of FPI over RPI ($\rho = \frac{2}{5}$). While we establish this result formally in the proof of Lemma 1, the underlying intuition can be explained as follows. As we have argued before, cardinal information affects only the follower's incentives, whereas ordinal information affects the incentives of the follower *and* the leader. Because the leader has weaker incentives to invest than the follower, the critical cost-prize ratio balancing gains and losses in investment is therefore smaller for ordinal than for cardinal information. As a consequence, Lemmas 1 and 2 have as a direct implication the following:

Proposition 3 (Optimal Information Policy)**.** *To maximize aggregate investment, a reduction in monetary incentives should be accompanied by an increase in performance information. NPI is optimal when* $\rho \leq \tilde{\rho}$ *whereas FPI is optimal when* $\rho \geq \frac{2}{5}$*. For intermediate cost-prize ratios* $\rho \in (\tilde{\rho}, \frac{2}{5})$*, RPI is optimal.*

Proposition 3 is illustrated in Figure 4, depicting expected aggregate investments as a function of the cost-prize ratio for the three information policies. A noteworthy feature of our model is that expected aggregate investments and hence the thresholds characterizing the designer's optimal information policy are *independent* of the distribution H of ideas. In particular, to plot Figure 4 we do not need to pick a particular distribution H.[4]

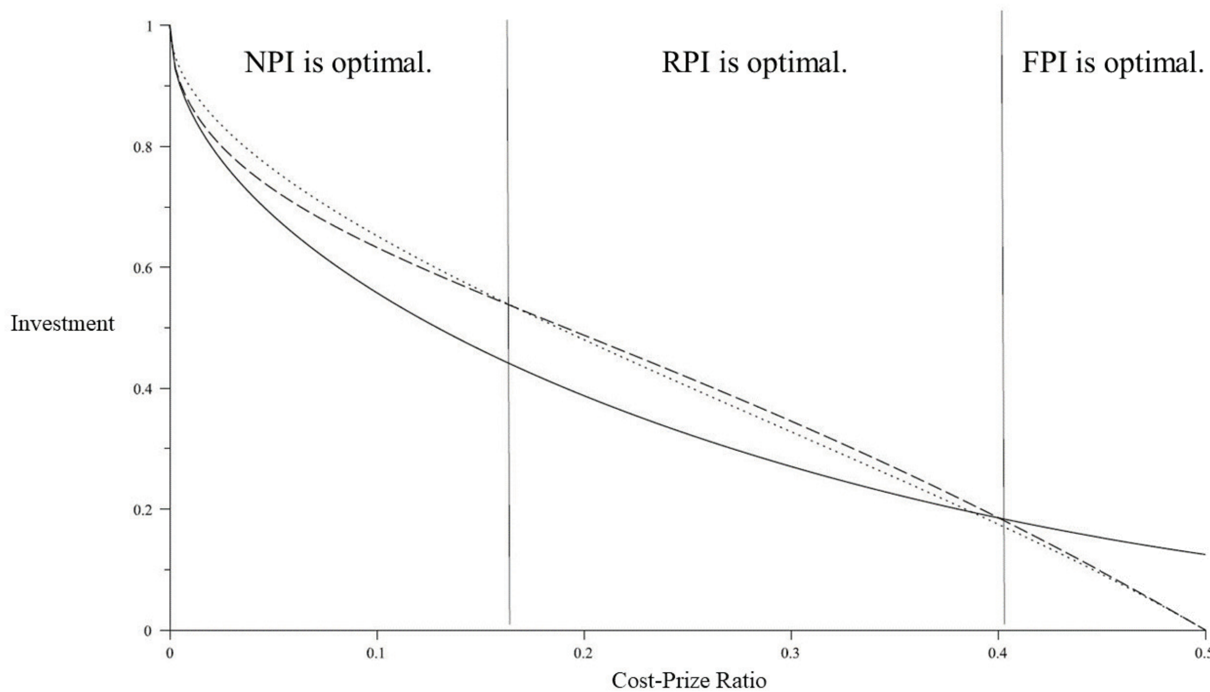

Figure 4: Optimal Information Policy. The figure shows the (ex ante) probability with which each player invests in a new idea, $\frac{1}{2}I$, as a function of the tournament's cost-prize ratio, ρ. Depicted are the three distinct information policies: NPI (dotted), RPI (dashed), and FPI (solid).

Finally, as our analysis has restricted attention to the (more interesting) case where $\rho < \frac{1}{2}$, it remains to comment on the remaining case where $\rho \geq \frac{1}{2}$. For $\rho \geq 1$, no player will ever invest because the tournament's prize falls short of the costs of innovation. Similarly, for $\rho \in (\frac{1}{2}, 1)$, the cost-prize ratio is so high that a player is motivated to invest only

[4]To plot investment under NPI we can substitute $I^{NPI} = 2H(\bar{x})$ into (9) which gives us the $\rho(I^{NPI})$ necessary to induce a given level of investment I^{NPI}.

when he learns that he is the follower and that the leader's performance is "bad". To see this, note that for $\rho \to \frac{1}{2}$, the threshold $\bar{x}$ determining investments under no information converges to zero. A player with a zero first-stage performance knows that he can win only when his second-stage performance exceeds the rival's first-stage performance, which happens with a probability equal to the cost-prize ratio of one half. The same is true under rank information, because learning to be the follower contains no news for a player with a zero first-stage performance. For this reason, the threshold $\bar{x}^F$, determining the follower's investment under rank information, also converges to zero for $\rho \to \frac{1}{2}$. For $\rho \in (\frac{1}{2}, 1)$, a player can thus be motivated to invest in the second stage only when he learns that he is the follower and that the leader's first-stage performance was below $\bar{X}^F = H^{-1}(1-\rho) > 0$. Hence, full information is necessary to induce *any* investment in the second stage, and we can conclude that for cost-prize ratios $\rho \geq \frac{1}{2}$, FPI maximizes incentives.

3 Laboratory Experiment

In this section, we report the results of a laboratory experiment that we conducted to test the predictions of our theory. The experiment supports our theoretical finding that in innovation tournaments, the effectiveness of monetary incentives varies with performance information. In particular, the experiment provides evidence that a reduction in monetary incentives reduces investments in new ideas less strongly when players are fully informed about their rivals' performance.

While offering support for the threshold behavior predicted by our theory, the experiment also indicates that behavioral responses, not captured by our model, can change the model's conclusions with respect to optimal policy. More specifically, in spite of innovation taking the form of a pure sampling competition, where the benefits from investing in new ideas are independent of the "distance" to the leading idea, our experiment provides evidence that players increase their investment when they learn this distance to be small. Providing cardinal (as opposed to only ordinal) information thus induces investments that are larger than predicted by our theory which may explain why our experiment fails to provide support for the optimality of RPI.

A laboratory experiment allows us to overcome important challenges that are present in the field. Identifying exogenous variation in a tournament's performance information to establish a causal effect on investment is difficult. In cases where this has been successfully achieved (e.g., Lemus & Marshall, 2021), the tournament's prize has remained fixed. However, because our theory hinges on the *interaction* of performance information with monetary incentives in shaping investment, we also require variation in the tournament's prize.

It is well established that the design of tournament prize structures can produce non-trivial participation and selection effects (Azmat & Möller, 2009, 2018). A laboratory experiment allows us to focus on the incentive effects of prize money and performance information, by fixing the set of participants.

A second issue that a laboratory experiment can effectively address is that real innovation never takes the form of a pure sampling competition. Innovation tournaments in the field allow participants to "add and improve" upon their ideas and hence contain an element of an innovation *race* not captured by our theory. A laboratory experiment thus allows for a "cleaner" test of our theory by focusing on the players' incentives to invest in new ideas as opposed to the improvement of existing ideas.

3.1 Design and Procedures

Our experimental setting follows our theoretical model by focusing on two-player, two-stage innovation tournaments. In each stage, subjects choose simultaneously between investing and not investing. In each tournament, subjects start with an initial monetary endowment of $E = 15$ and face homogeneous investment costs of $C_1 = 1$ in the first stage and $C_2 = 10$ in the second stage. Similar to our theory, first-stage costs are chosen so low as to ensure initial investment, enabling information about first-stage performance to become meaningful.

If a subject decides to invest, he obtains a random draw from the set of values $X = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$, where each value is equally likely. If a subject chooses not to invest, he incurs no cost and receives a draw of value 0. At the end of the second stage, the winner, i.e., the subject with the highest draw over the two stages, receives the tournament's prize, V. In the event of a tie, both subjects are equally likely to be declared the winner.

Our main treatment dimension is the information about rival performance that each subject receives at the end of the first stage, before deciding whether to invest in the second stage. We employ a between-subjects design, where each subject is assigned to one of three experimental treatments: *NPI*, *RPI*, and *FPI*. In the *NPI* treatment, each subject learns only the value of his own draw. In the *RPI* treatment, each subject additionally learns the ordinal ranking of his draw. Finally, in the *FPI* treatment, subjects learn the value not only of their own draw but also their rival's draw. Figure 5 shows the investment decision screen for each information treatment. At the end of the second stage, each subject sees a summary table of the tournament, displaying the values of the player's own draws and the rival's draws across both stages, the winning draw, and the subject's realized payoff for that tournament (see Figure 6).

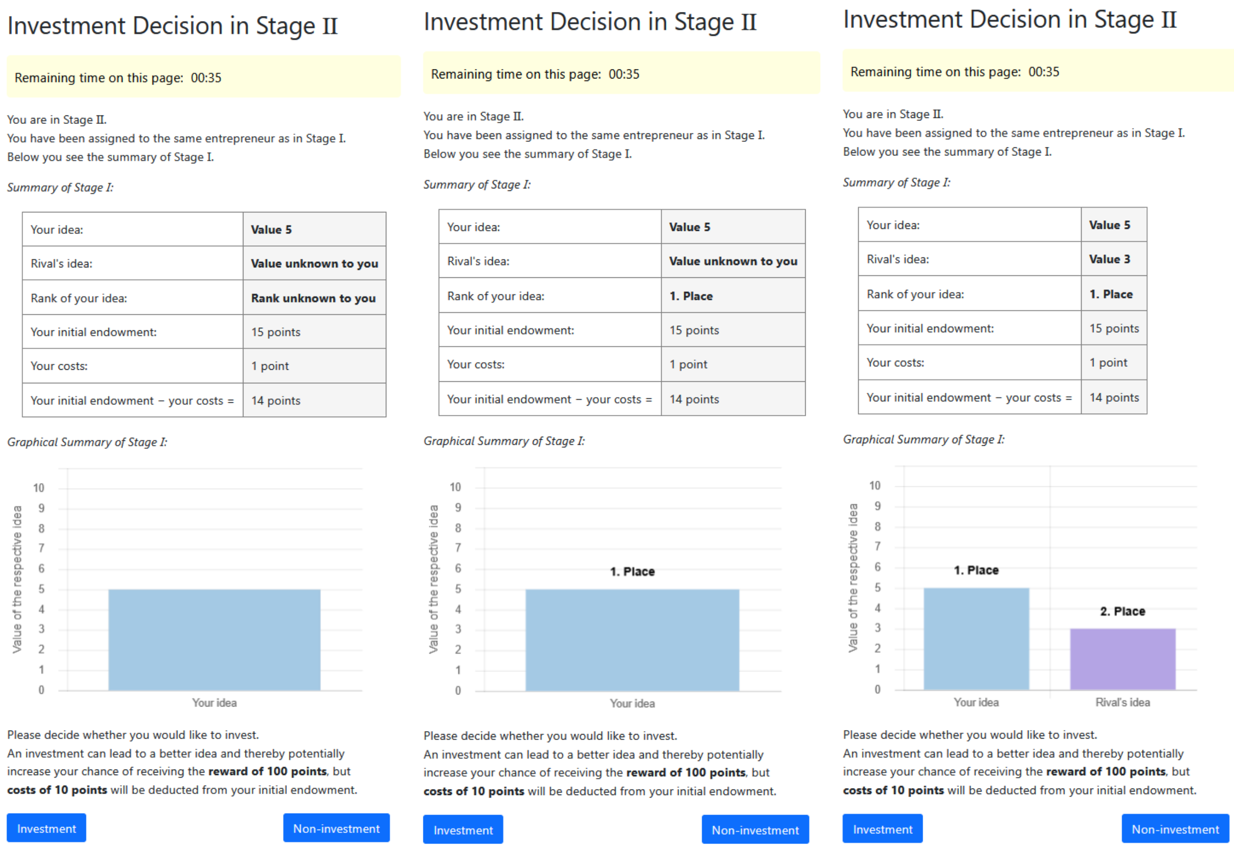

Figure 5: Investment Decision. At the beginning of the second stage, each subject sees one of the depicted screens, conditional on the subject's treatment: *NPI* (left), *RPI* (middle), or *FPI* (right). Numbers depend on the outcome of the first stage and are for illustrative purposes.

Each treatment consists of 60 rounds of the two-stage tournament described above. At the beginning of each round, pairs of subjects are randomly drawn from a matching group consisting of subjects who all receive the same treatment. When a new round begins and subjects are re-matched (stranger matching), they have no knowledge of their rival's previous decisions. We introduce prize variation as a second treatment dimension using a within-subjects design. Specifically, we implement three different prize levels: *High* ($V = 100$), *Intermediate* ($V = 40$), and *Low* ($V = 20$), with each subject playing 20 rounds at each prize. The corresponding second-stage cost-prize ratios are $\rho = 0.1$, $\rho = 0.25$, and $\rho = 0.5$. To control for potential order effects, we use a partial counterbalancing strategy with three distinct prize sequences, such that each prize appears at least once in first position. We then include prize order as a control variable in our analysis.

The experiment was conducted at the WiSo Experimental Research Laboratory of the University of Hamburg between January and June 2025. Recruitment was carried out via hroot (Bock et al., 2014), and the experiment was implemented using oTree (Chen et al.,

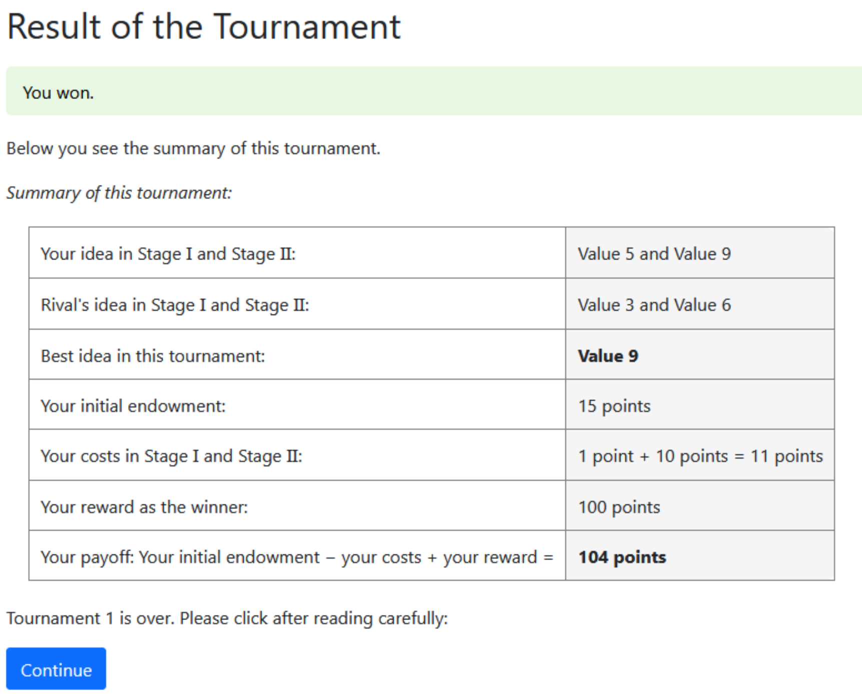

Figure 6: Summary Screen. Each player sees this screen at the end of each tournament, independently of the information treatment. Numbers are for illustrative purposes.

2016). The subjects were undergraduate students at the University of Hamburg. We conducted 24 sessions with a total of 324 subjects, 108 in each information treatment.

Subjects received written instructions on-screen, detailing the features of the tournaments (for the English translation of the instructions, see Appendix A.3). Following Hudja et al. (2025), we used an economic framing, presenting the strategic situation as competition between entrepreneurs investing in ideas for a new product. After reading the instructions and before moving to the 60 payoff relevant tournament rounds, subjects first engaged in five practice rounds and answered a set of control questions. At the end of the experiment, all subjects completed a questionnaire covering risk aversion, socio-demographics, and questions concerning the investment strategies they used during the experiment.

Payments were determined as the sum of the subjects' payoffs over the 60 tournament rounds. In the experiment, payoffs were denominated in points. Each point was converted to Euros at the end of the experiment at the rate of 100 points to 1 Euro. Each session lasted approximately 75 minutes, with average earnings of 21.71 Euro. Table A1 in Appendix A.2 provides a detailed summary of the experimental sessions. The experimental design was preregistered in OSF registries prior to data collection.[5]

[5] https://osf.io/tuh5a

3.2 Testable Predictions

To test our theory it is useful to organize its results into three testable predictions. These predictions are presented here in their natural order, with lower-ranked predictions representing necessary conditions for higher-order predictions.

Our first prediction is concerned with the effectiveness of monetary incentives. In particular, the following prediction is an immediate implication of the fact that the investment thresholds in Lemmas 1-3 are decreasing functions of the tournament's cost-prize ratio ρ:

Prediction 1. *Monetary incentives are effective: In each information treatment, investment rates are larger in tournaments with higher prizes.*

Support for Prediction 1 should be easy to find, given that the role of prizes for incentives to innovate is well documented in the empirical literature (Love & Hubbard, 2007; Murray et al., 2012). Our second prediction is more ambitious as it is concerned with the way in which the effectiveness of monetary incentives varies with information. From Figure 4 we see that, over the range that is relevant for our experiment ($\rho \in [0.1, 0.5]$) investment under FPI is less sensitive with respect to changes in the tournament's cost-prize ratio ρ than investment under RPI and NPI. We thus have as a second testable prediction:

Prediction 2. *Prize money and information are substitutes in creating investment incentives: Under FPI, investment rates decrease less strongly in response to reductions in the tournament's prize than under RPI or NPI.*

Finding evidence for Prediction 2 would lend support to the main result of our theory (Proposition 3) which arises as a consequence of the differences in the slopes of the investment-curves in Figure 4. More specifically, our main insight that the investment maximizing information policy varies with the strength of monetary incentives hinges upon the fact that the drop in investment in response to a decrease in monetary incentives is less pronounced when players are better informed about the performance of their rivals. It is in this sense that our last prediction is also the most ambitious:

Prediction 3. *A tournament's investment-maximizing information policy varies with the strength of monetary incentives: NPI maximizes investment in high-prize tournaments, RPI maximizes investment in intermediate-prize tournaments, and FPI maximizes investment in low-prize tournaments.*

3.3 Results

In this section, we present the results of our experiment. Figure 7 shows the mean investment rates for each treatment. From the figure it is clear that a reduction in monetary incentives—

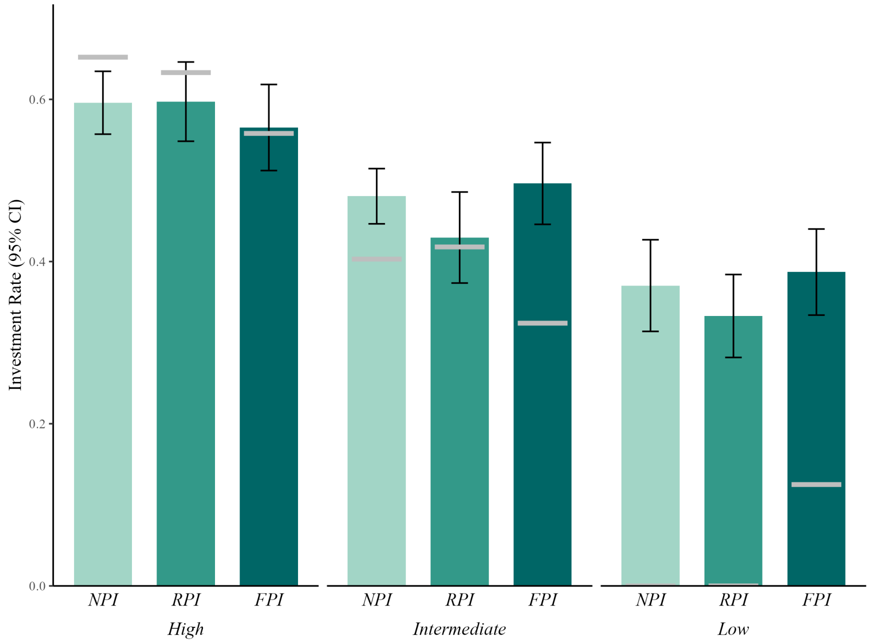

Figure 7: Investment Rates. The investment rate is the frequency with which a subject decides to invest in a new idea in the second stage. The figure depicts the mean investment rate with 95 percent confidence intervals for each prize and information treatment. Confidence intervals are based on standard errors clustered at the matching-group level. Grey solid lines mark the values predicted by theory.

from *High* to *Intermediate* to *Low*—leads to a decrease in aggregate investment for all information treatments (Prediction 1). Less clear but somewhat apparent is that investments in the *FPI* treatment decrease less strongly in response to a reduction of monetary incentives than investments in the *RPI* or *NPI* treatments (Prediction 2). Finally, with respect to the investment maximizing information treatment (Prediction 3), no clear picture emerges from the figure.

Motivated by these observations, our subsequent analysis is divided into two steps. In the first step, we focus on Predictions 1 and 2 of our theory, relating to the effectiveness of monetary incentives to invest in new ideas and its dependence on performance information. We show that our experimental results lend support to these predictions. In the second step, we consider Prediction 3, concerned with the implications of Predictions 1 and 2 for the investment-maximizing information policy. Our experiment offers some support for the optimality of *FPI* in low-prize tournaments, but provides no evidence for the optimality of *RPI* or *NPI* at higher prizes.

Finally, to explain why our experiment provides only little support for Prediction 3, we discuss evidence for behavior not predicted by our theory. This evidence complements our theory by indicating that the cardinal component of performance information can trigger behavioral responses—akin to head-to-head competition in innovation races—which increase investment even when innovation takes the simple form of a pure sampling competition.

3.3.1 Monetary Incentives and Performance Information (Predictions 1 and 2)

To test how prize money and performance information combine in creating incentives to invest in new ideas, we run the logistic regression reported in Table 1. We regress the decision to invest on the tournament's prize, the information treatment, and their interaction. Our estimation uses *RPI* as the reference category and controls for prize-order fixed effects while clustering standard errors at the matching-group level.

Table 1: Monetary Incentives and Information

Dep. Variable: Investment		
	(1) Prize	(2) Prize × Info
Prize	0.210***	0.261***
	(0.015)	(0.029)
Prize × *NPI*		−0.049
		(0.037)
Prize × *FPI*		−0.101***
		(0.036)
NPI		0.203
		(0.128)
FPI		0.292**
		(0.128)
Constant	−0.459***	−0.625***
	(0.096)	(0.137)
Prize-order FE	✓	✓
LR χ^2 (df)	608.37 (3)	646.71 (7)
LR p-value	0.000	0.000
McFadden R^2	0.023	0.024
Num. obs.	19440	19440

Notes: Logit regression of investments. Prize is measured in units of 20 points (experiment's currency) and starts at *Low* (20 points = intercept). *RPI* is the reference category in column (2). Controls for prize order are included. Robust standard errors clustered at the matching-group level are reported in parentheses. *** if $p < 0.01$, ** if $p < 0.05$, * if $p < 0.10$.

Prize has a positive effect on investment which is significant at the 1 percent level. From the odd ratios we calculate that a prize increase from *Low* to *Intermediate* (20 points) raises the rate of investment by 5.1 percentage points when we average over all information treatments. Similarly, a prize increase from *Intermediate* to *High* (60 points) leads to a 15.3 percentage point increase in the rate of investment.

Importantly, the interaction between Prize and *FPI* is significant at the 1 percent level. From the coefficients we calculate that the provision of cardinal information reduces the slope with which investment increases with prize by more than one third. In particular, while in the *RPI* treatment a decrease in monetary incentives from *Intermediate* to *Low* reduces the rate of investment by 6.2 percentage points, the corresponding reduction in the *FPI* treatment is only 4 percentage points. No significant difference is found between *RPI* and *NPI*, which is not surprising given that our theory predicts this difference to be small (see Figure 4). In summary, these results offer strong support for Predictions 1 and 2 of our theory.

3.3.2 Optimal Information Policy (Prediction 3)

We use the results of our logistic regression reported in Table 1 to estimate the probabilities of investment at a given prize. We then conduct pairwise comparisons between information treatments using two-sided Wald tests with cluster-robust standard errors. These tests report contrast estimates, corresponding to differences in predicted mean probabilities.[6]

We find no statistically significant differences between *RPI* and *NPI* at any prize-level. Again, given that our theory predicts relatively small differences between these two information treatments, this result might not be surprising. For the comparison between *RPI* and *FPI*, we find that *FPI* increases the probability of investment in the *Low* prize tournaments at the 5 percent significance level (contrast estimate = 0.06895, SE = 0.0299, $p = 0.021$). No differences at the 5 percent level are observed neither in *Intermediate* prize tournaments ($p = 0.098$) nor in *High* prize tournaments ($p = 0.435$) .

There are two potential explanations for why our experiment offers only little support for Prediction 3. First, note that because our theory predicts opposing effects of information on investment, depending on an individual's role (follower versus leader), aggregate investment rates may provide a rather noisy measure of individual treatment effects. In particular, switching from *NPI* to *RPI* is predicted to increase investment for followers while decreasing investment for leaders. When roles are collapsed through aggregation, these opposing effects may largely cancel out.

Second, because our theory identifies Prediction 3 as an implication of Predictions 1 and 2 and because these predictions are supported by our data, our experimental results suggest

[6] Assuming linearity and using standard t-tests to compare average treatment effects leads to similar results. We also ran nonparametric Wilcoxon rank-sum tests comparing the distribution of investment rates across treatments. Again, results are similar.

the existence of behavior beyond the patterns predicted by our theory. Do subjects employ the simple threshold strategies predicted by theory? Do other considerations related to performance information also play a role? To answer these questions, we now complement our analysis of aggregate investment by examining behavior separately for leaders and followers.

3.3.3 Thresholds and Role-Specific Effects

To what extent do subjects employ the threshold strategies that arise in our theory, and if so, do thresholds vary with information as predicted? Our post-experimental survey provides qualitative evidence for the importance of thresholds in determining investments. When we group the subjects' open-ended responses about the factors determining their choices by recurring keywords, three dominant categories emerge: idea values, prize size or costs, and comparisons between own performance and rival's performance. These qualitative patterns are consistent with subjects relying on threshold-type decision rules. Indeed, some subjects explicitly articulate such rules.

To evaluate quantitatively whether a subject employs a threshold strategy, we adapt the procedure of Avoyan and Onuchic (2025), originally developed for determining disclosure thresholds in group communication. In the following, we first explain this procedure for the *NPI* case, before commenting on the potential adjustments necessary for the alternative information treatments.

Given a prize-level V, we construct for each subject s an investment set $I^s(V)$ and a non-investment set $N^s(V)$. $I^s(V)$ and $N^s(V)$ contain all first stage realizations x_1^s of the subject's ideas during his 20 tournaments at prize level V which induced s to invest or not to invest, respectively, in the second stage. Using subscripts to denote the minimum, maximum, and average of these sets, we classify subject s as following a threshold strategy if $I^s(V)$ contains smaller values than $N^s(V)$ and the "overlap" of the two sets is small. Formally, subject s follows a threshold strategy if

$$I^s_{\text{avg}}(V) < N^s_{\text{avg}}(V) \quad \text{and} \quad I^s_{\max}(V) - N^s_{\min}(V) \leq 1.$$

If this procedure classifies s as following a threshold strategy, the subject's threshold value is determined as $I^s_{\max}$. Subjects who always choose to invest or not to invest, independently of their first-stage idea, are assigned a threshold of $I^s_{\max} = 10$ or $I^s_{\max} = 0$, respectively.

For the *RPI* treatment, we apply the same procedure, but condition on whether the subject finds himself in the role of follower or leader. Finally, for the *FPI* treatment, the procedure is analogous but, in accordance with the theory, the construction of the sets $I^s(V)$ and $N^s(V)$ conditions not on a subject's own idea x_1^s but on the leading first-stage idea X_1.

Table 2 reports mean investment thresholds by information and prize treatment, with the proportion of subjects following a threshold strategy shown in parentheses. Within each information treatment, average thresholds increase systematically with the tournament's prize. Moreover, in the *RPI* and *FPI* treatments, thresholds of followers are consistently higher than thresholds of leaders, showing that followers are indeed more motivated to invest. Both of these results are consistent with the equilibrium characterizations of our theory contained in Lemmas 1-3.

Table 2: Threshold Strategies

	Prize		
Information	*High*	*Intermediate*	*Low*
NPI	6.68	5.17	3.33
	(53%)	(43%)	(43%)
RPI Leader	6.41	4.04	1.84
	(71%)	(73%)	(68%)
RPI Follower	7.59	4.69	2.71
	(53%)	(49%)	(44%)
FPI Leader	6.77	5.60	3.25
	(68%)	(72%)	(69%)
FPI Follower	8.32	7.00	6.18
	(57%)	(42%)	(50%)

Notes: Mean investment thresholds by information and prize treatment. Note that in *NPI* and *RPI*, thresholds refer to a subject's own first-stage idea x_1^s whereas in *FPI*, thresholds refer to the leading first-stage idea X_1. Proportion of subjects classified as using a threshold strategy shown in parentheses.

Comparing the mean thresholds in the *NPI* treatment with the role-specific mean thresholds in the *RPI* treatments for subjects that employ threshold strategies in both roles reveals that leader thresholds are significantly lower, both for tournaments with *Low* and *Intermediate* prizes, at the 1 and 10 percent level, respectively (Wilcoxon rank-sum test). In contrast, follower thresholds in the *RPI* treatment are significantly higher than mean thresholds in the *NPI* treatment at the 5 percent level in *High* prize tournaments. Taken together, these findings suggest that ordinal information affects investment behavior in line with the theoretical predictions, but its role-specific effects are largely masked when examined at the aggregate level.

Finally, for leaders (but not for followers) we can compare the mean thresholds in the *FPI* and *RPI* treatments, because under both treatments thresholds refer to the same (leading) idea realizations $X_1 = x_1^L$. Theory predicts that leaders should behave identically under both information treatments. In contrast, our experiment reveals that in the *FPI* treatment, leader thresholds are significantly higher than leader thresholds in the *RPI* treatment at the 5 percent level, both in *Low* and *Intermediate* prize tournaments. This finding is a first indication for the existence of behavioral responses to the cardinal component of performance information that increase investments beyond the levels predicted by theory. We investigate this issue next.

3.3.4 Behavioral Responses to Cardinal Information

To understand why investments in the *FPI* treatment are larger than predicted by our theory, consider the heat plots in Figure 8. These plots visualize the change in the rate of investment when switching from *RPI* to *FPI*, separately for leaders and followers. Each panel maps, across the set of possible first-stage outcomes (x_1^L, x_1^F), whether investment increases (green), decreases (red) or remains unchanged (yellow), when performance information is switched from *RPI* to *FPI*. Recall that our theory predicts no changes for leaders. For followers, investment is predicted to increase for first-stage outcomes such that $x_1^F > \bar{x}_1^F$ and $x_1^L < \bar{X}_1^F$ whereas investment is predicted to decrease for outcomes such that $x_1^F < \bar{x}_1^F$ and $x_1^L > \bar{X}_1^F$ (cf. Figure 3). Although Figure 8 offers some support for these patterns, what stands out is that a switch from *RPI* to *FPI* increases investments more than predicted by theory, in particular for leaders. Subjects increase their investments in response to cardinal information and this is particularly true when the difference between the leader's and the follower's first-stage performances is small (along the diagonal).

Figure 8 suggests a pattern of behavior that is well known from innovation races. In an innovation race, competitors improve or refine their ideas in a stepwise manner and thereby build upon their past performance. The theory of innovation races, pioneered by Harris and Vickers (1987) predicts that incentives to invest are maximized when the race is close, that is, when the *distance* between the leader's and the follower's performance is small. There is ample evidence documenting this head-to-head nature of competition, both in experiments (Mago et al., 2013) and in the field (Iqbal & Krumer, 2019; Malueg & Yates, 2010).

It is surprising to see that in our setting a similar pattern emerges. We have followed the literature on innovation tournaments by assuming that innovation takes the form of a pure sampling competition, both in our model and in our experiment. In particular, in our *FPI* treatment, the distance between a follower's and a leader's first-stage performance should have no effect on investment.

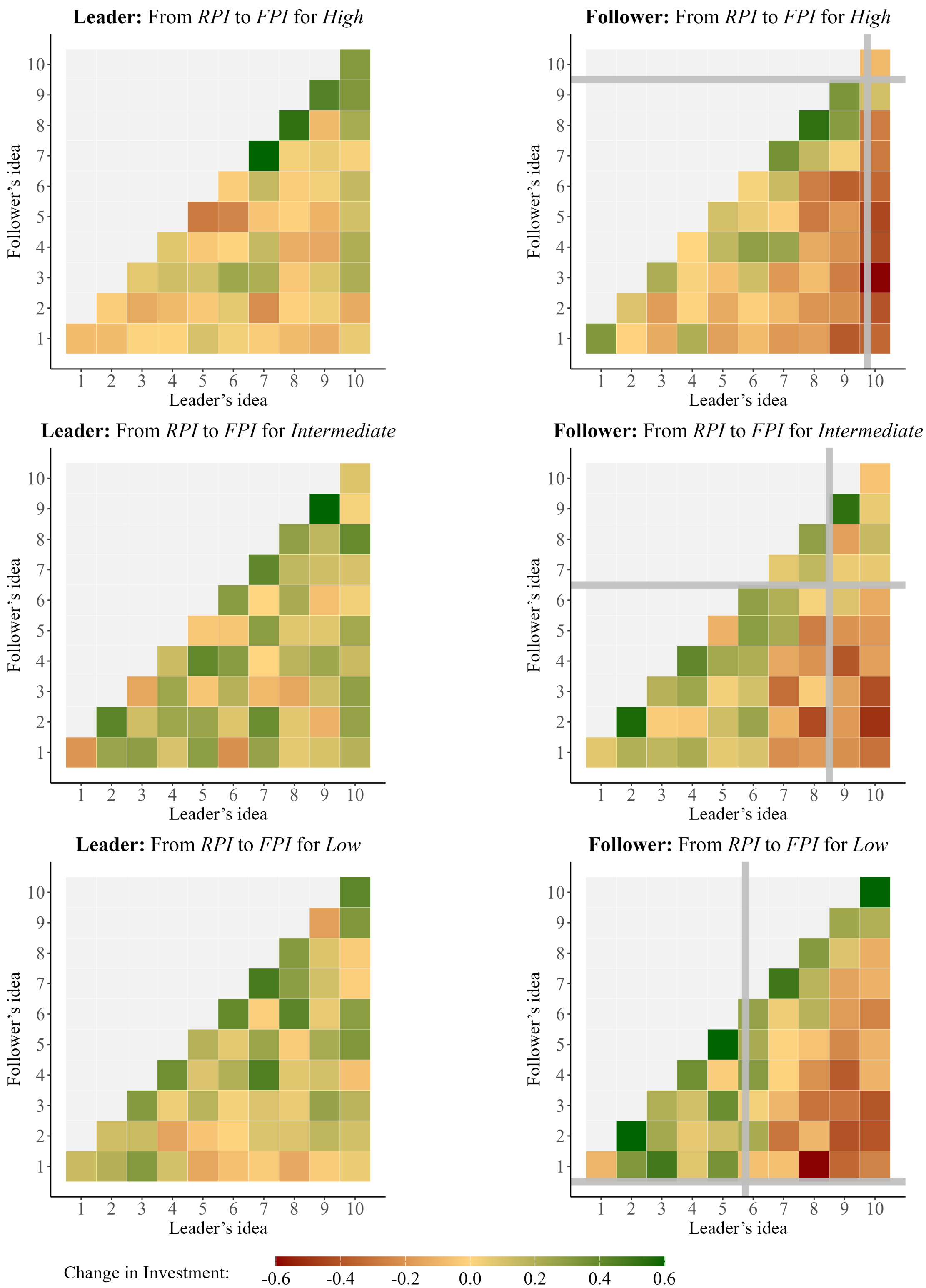

Figure 8: Response to Cardinal Information. Changes in investment rates of leaders (left panel) and followers (right panel) in response to a switch from *RPI* to *FPI*. Colors indicate the size of changes (see scale), conditional on first-stage realizations (x_1^L, x_1^F). Grey solid lines show predicted follower thresholds under RPI ($\bar{x}^F$) and FPI ($\bar{X}^F$).

To improve our understanding of the determinants of role-specific investments, Table 3 presents logistic regressions explaining second-stage investment in the *FPI* treatment, estimated separately for leaders and followers. For both roles, investment decreases significantly with the leaders' first-stage idea. This confirms that, as predicted by our theory, a larger room for improvement encourages further investment. However, Table 3 also shows that investments decrease significantly with the distance between the leader's and the follower's first-stage performance. Leaders and followers alike invest more when their ideas are closer to one another, suggesting that the proximity to the rival's performance motivates additional investment, even though theory predicts no such effect.

Table 3: Determinants of Investment under *FPI*

Dep. Variable: Investment	(1) Leaders only	(2) Followers only
Leader idea	−0.247***	−0.264***
	(0.038)	(0.050)
Distance	−0.082***	−0.113**
	(0.020)	(0.045)
Prize	0.154***	0.218***
	(0.031)	(0.042)
Constant	1.610***	1.956***
	(0.268)	(0.349)
Prize-order FE	✓	✓
LR χ^2 (df)	404.32 (5)	521.21 (5)
LR p-value	0.000	0.000
McFadden R^2	0.090	0.116
Num. obs.	3240	3240

Notes: Logit regression of investments in *FPI*, separated by subject's role. Distance measures the absolute difference between the leader's and follower's first-stage ideas. Prize is measured in units of 20 points (experiment's currency) and starts at *Low* (20 points = intercept). Controls for prize order are included. Robust standard errors clustered at the matching-group level are reported in parentheses. *** if $p < 0.01$, ** if $p < 0.05$, * if $p < 0.10$.

These experimental findings complement our theory by revealing a behavioral response to cardinal performance information that is unpredicted by our model: Even when innovation takes the form of a pure sampling competition, providing contestants with cardinal performance information allows contest organizers to capitalize on the head-to-head nature of competition. In the context of our experiment, the emergence of head-to-head competition may explain why investment in *FPI* is considerably larger than predicted (cf. Figure 7).

4 Conclusion

How do the incentives to invest in an innovation tournament depend on the contestants' information about their competitors' performance? In this article, we have shed light on this issue by offering a stylized theory and an experimental test.

Our theory's main insight is that performance information can act as a substitute for monetary incentives in the creation of investments. A direct implication, particularly relevant in light of the recent proliferation of crowd-sourcing tournaments for innovations of smaller and smaller value, is that a reduction in monetary incentives should be accompanied by an increase in performance information. Noteworthy from a practitioner's viewpoint is our theoretical result that rank information can be optimal for incentives, because in many settings only ordinal but no cardinal information can be provided.

Our experiment lends support to our theory by confirming that the provision of cardinal information makes a reduction in monetary incentives less harmful for investment. However, our experiment also reveals that cardinal information induces a form of head-to-head competition that is familiar from related settings but unpredicted by our theory. In particular, by informing contestants about the performance *difference* between the leader and the follower, cardinal information induces additional investments when this difference is small. Our experimental results thus complement our theory by providing yet another argument in favor of transparency in innovation tournaments.

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A Appendix

A.1 Omitted proofs

Proof of Lemma 2

In this proof, we first derive equation (9) formally before showing the existence of a unique solution. Player i is indifferent between not investing and investing if the following holds

$$V\int_{\bar{x}}^{b} H^2(\bar{x})h(x)dx = V\int_{\bar{x}}^{b}\{H^2(\bar{x}) + [1-H^2(\bar{x})]\frac{H(x)-H(\bar{x})}{1-H(\bar{x})}\}h(x)dx - C_2.$$

Factoring out $[1+H(\bar{x})]$ and rearranging yields

$$0 = V[1+H(\bar{x})]\{\int_{\bar{x}}^{b} H(x)h(x)dx - H(\bar{x})\int_{\bar{x}}^{b} h(x)dx\} - C_2.$$

Integration by parts yields $\int_{\bar{x}}^{b} H(x)h(x)dx = \frac{1}{2}[1-H^2(\bar{x})]$ which can be substituted in the equation above

$$0 = V[1+H(\bar{x})]\{\frac{1}{2}[1-H^2(\bar{x})] - H(\bar{x})[1-H(\bar{x})]\} - C_2.$$

Rearranging yields

$$0 = V[1+H(\bar{x})]\{\frac{1}{2} + \frac{1}{2}H^2(\bar{x}) - H(\bar{x})\} - C_2.$$

Substituting ρ for the cost-prize ratio yields equation (9).

To see that (9) has a unique solution $\bar{x} \in [0,b]$ define

$$k(x) = [1+H(x)][1-H(x)]^2 - 2\rho,$$

and note that $k(0) = 1-2\rho > 0$, $k(b) = -2\rho < 0$, and

$$k'(x) = -h(x)[1-H(x)]\{1+3H(x)\} < 0.$$

Proof of Proposition 1

Investment under RPI is larger than investment under NPI if and only if

$$I^{RPI} - I^{NPI} = [1 - H(\bar{x})]^2 - [1 - H(\bar{x}^F)]^2 - [H(\bar{x})^2 - H(\bar{X}^L)^2] > 0.$$

Note that $I^{RPI} - I^{NPI}$ is strictly decreasing in the value of $y = H(\bar{x})$ and let $y(\rho) \in (0,1)$ denote the value that makes $I^{RPI} - I^{NPI} = 0$. Substituting for $\bar{X}^L$ and $\bar{x}^F$, $y(\rho)$ is readily calculated as

$$y(\rho) = 1 - \sqrt{2\rho} + \rho - 2\rho^2,$$

and $I^{RPI} - I^{NPI} > 0$ if and only if $y = H(\bar{x}) < y(\rho)$. Now use the implicit equation defining the threshold $\bar{x}$ to determine the inverse prize $\rho(y)$ necessary to induce a particular value $y = H(\bar{x}) = y$ as

$$\rho(y) = \frac{1}{2}(1 + y)(1 - y)^2.$$

A fixed point of the mapping $\rho(y(.))$ corresponds to an inverse prize ρ that induces $y = H(\bar{x})$ to take a value that equates investments across the two informational policies. In the following, we argue that there exists a unique such fixed-point $\tilde{\rho} \in (0, \frac{1}{2})$ solving $\tilde{\rho} = \rho(y(\tilde{\rho}))$. Any $\rho > \tilde{\rho}$ induces a value $y = H(\bar{x}) < y(\rho)$ that leads $I^{RPI} - I^{NIP} > 0$ whereas any $\rho < \tilde{\rho}$ induces a value $y = H(\bar{x}) > y(\rho)$ that leads $I^{RPI} - I^{NPI} < 0$.

To prove the existence of a unique fixed point let $r(y)$ denote the inverse of $y(\rho)$ and consider the functions $\rho(y)$ and $r(y)$ for $y \in (0,1)$. From $\lim_{y\to 0} \rho(y) = \frac{1}{2} = \lim_{y\to 0} r(y)$, $\lim_{y\to 0} \rho'(y) = -\frac{1}{2} = \lim_{y\to 0} r'(y)$, and $\lim_{y\to 0} \rho''(y) = -1 < -\frac{3}{8} = \lim_{y\to 0} r''(y)$ it follows that in $y = 0$, $r(.)$ crosses $\rho(.)$ from below, i.e., $r(.)$ lies above $\rho(.)$ for y close to zero. Moreover, from $\lim_{y\to 1} \rho(y) = 0 = \lim_{y\to 1} r(y)$, $\lim_{y\to 1} \rho'(y) = 0 = \lim_{y\to 1} r'(y)$, and $\lim_{y\to 1} \rho''(y) = 2 < 1 = \lim_{y\to 0} r(y)$ it follows that in $y = 1$, $r(.)$ crosses $\rho(.)$ from below, i.e., $r(.)$ lies below $\rho(.)$ for y close to one. Finally, because both $r''(.)$ and $\rho''(.)$ change their sign only once (from negative to positive) in the interval $(0,1)$ there has to exist exactly one point where $r(.)$ crosses $\rho(.)$ from above. Hence, we have shown that there exists a unique $\tilde{\rho} \in (0, \frac{1}{2})$ solving $\tilde{\rho} = \rho(y(\tilde{\rho}))$. Finally, to understand how $\tilde{\rho}$ compares with the threshold $\rho = \frac{2}{5}$ from the previous lemma note that $\rho(y(\rho)) < \rho$ if and only if $\rho > \tilde{\rho}$ and that $\rho(y(\frac{2}{5})) < \frac{2}{5}$.

A.2 Additional Table of Experiment

Table A1: Summary of the Sessions

		# Sessions	# Matching Groups	# Subjects	# Decisions
Total		24	54	324	19440
NPI		7	18	108	6480
	Low Intermediate High	3	6	36	2160
	Intermediate Low High	3	6	36	2160
	High Low Intermediate	2	6	36	2160
RPI		8	18	108	6480
	Low Intermediate High	3	6	36	2160
	Intermediate Low High	3	6	36	2160
	High Low Intermediate	2	6	36	2160
FPI		9	18	108	6480
	Low Intermediate High	4	6	36	2160
	Intermediate Low High	4	6	36	2160
	High Low Intermediate	3	6	36	2160

Notes: This table shows a detailed summary of the sessions. Within a session we ran only one information treatment. That said, for some of the sessions in *NPI* and *FPI* different prize orders were run in parallel which is why the sum of the sessions for each prize order can be higher than the total number of sessions.

A.3 Instructions of Experiment

The instructions in our experiment are originally written in German. In the following, we provide an English translation. The instructions are identical for all between-subjects treatments unless otherwise indicated by [*NPI*], [*RPI*], [*FPI*], in which case the bracketed text applies only to the respective treatment. We also have a within-subjects treatment where we vary the prize. Note that in the instructions shown here, we start with a high prize (100). In the actual experiment, we varied the order of the three prizes. The 100 was changed in the instructions to 20 when the experiment started with a low prize and to 40 when the experiment started with an intermediate prize.

General Instructions

We are pleased to welcome you to this scientific study. This study will take approximately 60 minutes. It is important that you read these instructions carefully, as you can earn a considerable amount of money. The exact amount depends on your decisions and the decisions of the other participants[1]. Your anonymity is guaranteed.

During the study, your payoff will initially be calculated in points. Where:

$$100 \text{ points} = 1 \text{ Euro.}$$

The points you score during the study will be added up and paid out in Euros at the end of today's session.

We will describe the exact procedure of the study on the following pages. Please do not talk to other participants during the study. If you have any questions, please contact the supervisor.

Please click after reading carefully:

Continue

[1] For simplicity, only the masculine form is used.

Procedure of the Study

The study is divided into 60 standalone tournaments. In each tournament you compete with another participant for the best idea for a product, which is rewarded with a payoff. At the beginning of each tournament, you will be assigned to a randomly selected rival.

Each tournament consists of two stages. In each stage, you and your rival act as entrepreneurs by both making an investment decision independently of each other. Investment generates a product idea. The best product idea is rewarded. This means that at the end of the tournament, either you or your rival will win the reward.

On the following pages we explain the procedure of a tournament. Please click after reading carefully:

Continue

Description of a Tournament

At the start of each tournament you receive 15 points as an initial endowment. A tournament consists of two stages. In each stage, you decide between two options: Investment or Non-investment.

- **Investment** generates a product idea with a randomly determined value between 1 and 10. The higher the value, the better the idea. Each value is equally likely. Investment comes with costs. In Stage I, the investment costs are 1 point. In Stage II, the investment costs are 10 points.
- **Non-investment** is free, but generates an idea with a value of 0.

[*NPI*] [At the end of Stage I, you will be informed of the value of your own idea. You will neither be told the value of your rival's idea nor the ranking of your idea. Therefore, you do not know whether you are ranked first (your idea is better than your rival's idea) or ranked second (your rival's idea is better than your own). If both ideas are of equal value, a preliminary ranking is determined at random (you will not be informed about it). Your rival receives the same information in relation to his idea.]

[*RPI*] [At the end of Stage I, you will be informed of the value of your own idea. You will not be told the value of your rival's idea, but you will be told the ranking of your idea. Therefore, you know whether you are ranked first (your idea is better than your rival's idea) or ranked second (your rival's idea is better than your own). If both ideas are of equal value, a preliminary ranking is determined at random. Your rival receives the same information in relation to his idea.]

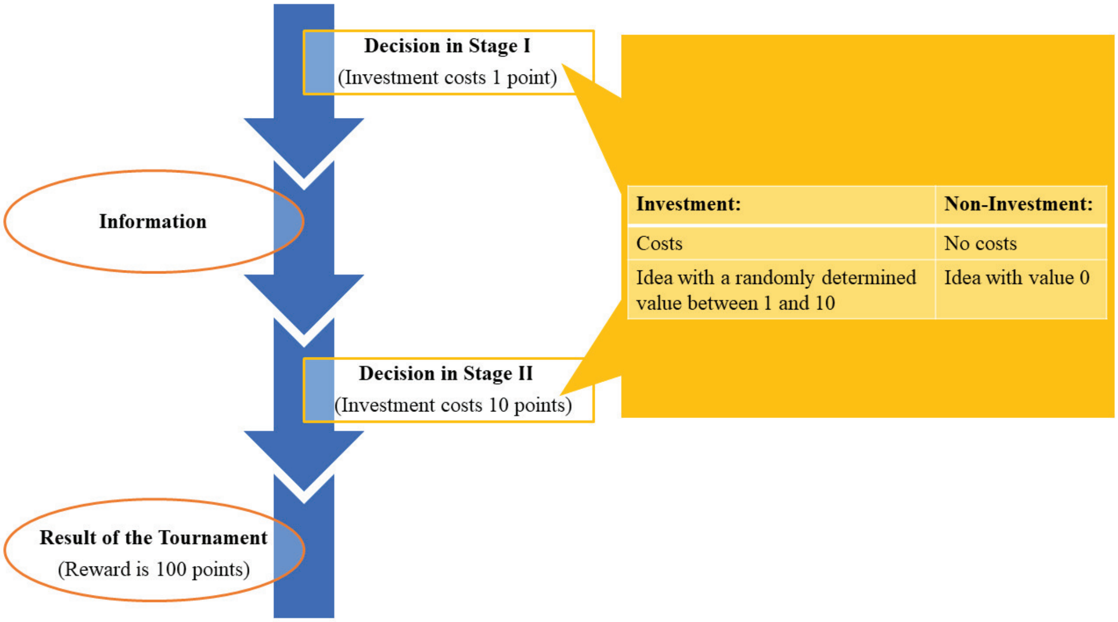
[*FPI*] [At the end of Stage I, you will be informed of the value of your own idea. You will also be told the value of your rival's idea and the ranking of your idea. Therefore, you know whether you are ranked first (your idea is better than your rival's idea) or ranked second (your rival's idea is better than your own). If both ideas are of equal value, a preliminary ranking is determined at random. Your rival receives the same information in relation to his idea.]

At the end of Stage II, the winner is determined, who then receives the reward of 100 points. For this, the four values of the ideas of both entrepreneurs in both stages are compared. The entrepreneur with the idea with the highest value wins. If the highest value is achieved by both entrepreneurs, the winner is chosen at random. If Stage II does not lead to an improvement of the best idea so far, the winner will be determined on the basis of the preliminary ranking from Stage I.

On the next page you will see the exact procedure of a tournament schematically displayed. Please click after reading carefully:

Continue

Schematic Procedure



Please click after reading carefully:

Continue

Result of the Tournament

At the end of each tournament, you will learn its result.

Afterwards, a new tournament begins with a new rival randomly assigned to you. None of your rivals will be told about your decisions in other tournaments.

Now you can practice. During the practice, your decisions are not payoff-relevant. Please click after reading carefully:

Continue
