Peer information and risk-taking under competitive and non-competitive pay schemes

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Abstract

Incentive schemes that reward participants based on their relative performance are often thought to be particularly risk-inducing. Using a novel, real-effort task experiment in the laboratory, we find that the relationship between incentives and risk-taking is more nuanced and depends critically on the availability of information about peers' strategies and outcomes. Indeed, we find that when no peer information is available, relative rewards schemes are associated with significantly *less* risk-taking than non-competitive rewards. In contrast, when decision-makers receive information about their peers' actions and/or outcomes, relative incentive schemes are associated with more risk-taking than non-competitive schemes. The nature of the feedback—whether subjects receive information about peers' strategies, outcomes, or both—also affects risk-taking. We find no evidence that competitors imitate their peers when they face only feedback about other subjects' risk-taking strategies. However, decision-makers take more risk when they see the gaps between their performance score and their peers' scores grow. Combined feedback about peers' strategies and performance—from which subjects may assess the overall relationship between risk-taking and success—is associated with more risk-taking when rewards are based on relative performance; we find no similar effect for non-competitive rewards.

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1 Introduction

Compensation systems may affect not just the effort exerted by workers, but also the riskiness of their actions. For example, pay schedules that reward salespeople for closing important transactions may also induce workers to over-extend the firms' promises to buyers. Particularly salient examples of workers' excessive risk-taking come from the recent banking and credit crisis. In a *Wall Street Journal* op-ed in 2009, Alan Blinder cited "...the perverse incentives built into the compensation plans of many financial firms" as the fundamental cause of the extreme risk-taking observed prior to the crisis. Decision-makers within the industry seem to agree. In a survey of over 500 senior managers in financial services firms, 52% of respondents indicated that they believed that "incentives and remuneration" were the most significant contributors to the crisis in their industry (KPMG, 2009).

Although commentators hold the incentives primarily responsible, the rewards schemes were not imposed in a vacuum. Indeed, it may be the interplay between incentives and other features of the environment that led to the increased risk-taking. More specifically, individuals' decisions to adopt riskier strategies may be influenced by social and informational factors, such as their relative and absolute performances to date, the norms around risk-taking within their organizations and industry, and the information available to them before and during the competition. Recently, there has been an increasing focus on the impact of social influences on economic decisions.[1] While the extant literature on risk-taking has explored the role of incentives and, separately, the role of feedback about own and peer performance histories, the interaction of the two has been previously largely ignored.

In this paper, we consider the interaction between incentives and information about peers and ask: First, how does the presence and nature of feedback about peers affect risk-taking? Or, more precisely, how is an individual's risk-taking influenced by the availability of information about the performance and/or risk-related strategies of his or her peers? Second, how does the relationship between this information and risk-taking change when individuals are rewarded based on their relative versus absolute performance?

We use an incentivized real-effort task in a controlled laboratory environment to answer these questions. Field data on individuals' incentives, risk-taking strategies, and peer information are largely unavailable and, even if available, they would be difficult to

[1] Although psychologists have a long history of research on social influence, only recently has economic theory modeled social influence as it relates to risk. For example, Maccheroni, Marinacci and Rustichini (2012) present an axiomatic foundation for interdependent preferences that supports the claim that the observation of peers' outcomes can be useful in learning to improve one's own choices.

analyze due to inherent endogeneity issues. The laboratory allows us to use the random assignment of subjects to treatments to infer causal relationships between information, incentives and risk-taking.

The experimental environment is novel. It is is motivated with a hypothetical, framed scenario that asks subjects to imagine themselves as financial analysts making simple predictions about future stock performance. Analysts can gather information prior to announcing their predictions, but that research is costly and limits the resources available for future forecasts. The experimental task asks subjects to decide first how much information to gather before submitting a binary prediction. The amount of information revealed determines the subject's level of risk-taking. The analyst faces a trade-off between the volume of forecasts that he or she can complete and their accuracy. Depending on treatment, the analyst is compensated according to an absolute or relative performance-based pay scheme and receives information about the risk-taking strategies and/or forecasting outcomes of her peers.

Overall, our results suggest that the relationship between incentives and risk-taking depends critically on the features of the environment, including the availability of information about peers' strategies and outcomes.[2] More specifically, when no information is available, relative rewards schemes are associated with significantly less risk-taking than non-competitive rewards. The presence of feedback reverses this relationship: when competitors receive information about their peers' actions and performance, relative incentive schemes are associated with more risk-taking than non-competitive schemes.

The nature of the feedback also matters. In a non-competitive rewards setting, subjects engage in less risk-taking when exposed to simple information about either peers' strategies or outcomes. In a setting with competitive rewards, subjects engage in more risk-taking when they receive information about both the strategies and scores of their peers. We also find that, when the information is available, subjects' risk taking is sensitive to their relative position among their peers when rewards are based on relative performance; we find no similar sensitivity in settings with non-competitive rewards. Although previous studies have documented a preference for conformity in settings with risk (Goeree and Yariv, 2007), we find no evidence that subjects' strategies converge over time within a group or that players' imitate their peers' strategies.

Our paper contributes to two streams of the literature on incentives. The first aims to understand the impact of specific compensation systems on risk-taking, and the second explores the impact of feedback on performance. We find that decision-makers' risk-

[2] We frame the results as decision makers' responses to observing (or not) the strategies and outcomes of other competitors. Anticipation of being observed by others may also influence individuals' risk attitudes (Weigold and Schlenker, 1991).

taking is influenced by both of these features—risk-taking depends critically on both the compensation style and the availability of information about own and peer performances.

Broadly, our paper contributes to managers' understanding of compensation and performance feedback—both important dimensions of organizational design—to align workers' and firms' objectives. The implication of our results varies by context. For example, in settings in which risk-taking stimulates creativity and innovation, firms may wish to pair highly competitive rewards schemes with rich feedback about peers' strategies and outcomes. In settings in which risk-taking undermines the stability of a firm or industry, firms using relative compensation schemes may wish to restrict information about peers' actions and outcomes. If peer information is readily available or not feasibly hidden from workers, then firms may wish to rely on non-competitive rewards to discourage undesirable risk-taking. Although a firm's success likely relies on both the effort and risk-taking of its workers (among other factors), our research suggests a nuanced relationship between incentives and risk-taking that should not be overlooked.

The paper is organized as follows: Section 2 highlights the current paper's position in the literature on risk-taking, information, and incentives; Section 3 describes our novel experimental design; Section 4 provides a theoretical perspective on the experimental task and describes specific empirical predictions; Section 5 summarizes and interprets the results of the experiment; and Section 6 concludes with a discussion of the paper's implications for understanding the relationship between risk-taking and information in competitive and non-competitive settings.

2 Related literature

Although much of the theoretical literature comparing competitive and non-competitive compensation schemes, including the foundational work of Lazear and Rosen (1981), has focused on differences in the incentives for effort, researchers have also modeled the incentives for risk-taking under different types of pay schemes. It is generally believed that tournament-style rewards induce more risk-taking than comparable non-competitive, piece rate rewards. For example, competitors in winner-take-all tournaments are predicted to choose maximal risk and zero effort, regardless of the prize spread (Hvide, 2002). Similarly, in multi-prize settings, more risk-taking is expected when prizes are awarded to a lower proportion of participants (Gaba, Tsetlin and Winkler, 2004).

Ability or interim position in the tournament (if it is revealed) may also affect risk-taking. The common wisdom is that leaders tend to "play it safe" to preserve their position while followers take more risk trying to catch up. Knoeber and Thurman (1994)'s analysis

of chicken producers shows that less able competitors adopt higher variance strategies, and Brown, Harlow and Starks (1996) find that mutual fund managers increase the riskiness of their portfolios when their mid-year performance is below the industry average. The same regularities are observed in a laboratory experiment by Eriksen and Kvaløy (2014). In an asset trading experiment, Schoenberg and Haruvy (2012) observe larger bubbles when subjects receive feedback about the performance of the top trader in their group. Relatedly, in a laboratory experiment on investment portfolio choice Dijk, Holmen and Kirchler (2014) find that when information on subjects' relative positions is available leaders adjust their portfolios in the direction of negatively skewed assets, while followers prefer positively skewed assets. The result holds for both competitive and non-competitive incentives, which suggests that "playing it safe" and "catching up" are driven mainly by social rather than monetary incentives. However, the relationship between ability (or relative position) and risk-taking is not always negative. Taylor (2003) finds, in contrast to the standard theory, that leading mutual fund managers take more risk in their portfolio choices in the presence of interim reviews, whereas trailing managers take less risk. More generally, when players choose sequentially the riskiness of their production technology and their effort, adoption of the risky technology depends critically on the players' relative abilities, the incentives for effort, and their respective likelihoods of success (Kräkel, 2008).

The early experimental literature comparing competitive and non-competitive reward schemes focuses primarily on differences in effort.[3] More recently, a number of experiments test the theoretical predictions about risk-taking in tournaments. Nieken (2010) finds that, as predicted, subjects choose lower efforts when more noise is present in the tournament; however, contrary to the predictions, subjects fail to select the highest level of risk. James and Isaac (2000) and Robin, Strážnická and Villeval (2012) observe a more intense formation of bubbles in an experimental trading market with tournament-style incentives. Vandegrift and Brown (2003) explore the role of ability differences and task difficulty in risk-taking with tournament incentives and find that low-ability subjects are more likely to choose high-risk strategies, but only in a simpler task. Nieken and Sliwka (2010) find that the relationship between ability and risk-taking may be more complex in the presence of correlated shocks.

It has been long understood that information about competitors' own and peer per-

[3]In their groundbreaking paper, Bull, Schotter and Weigelt (1987) note that rank-order tournaments are associated with increased variance in subjects' effort choices, which provides indirect evidence for differences in risk-taking. Subsequent studies replicate these results. For a recent survey of the experimental literature on tournaments, see Dechenaux, Kovenock and Sheremeta (2015).

formance has an impact on people's behavior in games (e.g., Duffy and Feltovich, 1999).[4] Moreover, peer effects on effort have been identified in both strategic and nonstrategic settings. For example, Lount Jr. and Wilk (2014) report that feedback can mitigate the free-riding problem in group production. In their experiment, subjects work better in a group than alone when feedback on performance is provided and worse in a group than alone when it is not provided. Falk and Ichino (2006) demonstrate the presence of peer effects in a real-effort individual production task.

Several studies explore the role of information and peer effects in subjects' risk-taking decisions in nonstrategic environments. Linde and Sonnemans (2012) find that subjects take less risk when they earn at most as much as a peer and more risk when they earn at least as much, which is the opposite to what is predicted by the prospect theory with a social reference point (see also Bault, Coricelli and Rustichini, 2008). Gamba and Manzoni (2014) find that when subjects observe their peers' wages, both wage leaders and wage followers take more risk in a subsequent task. Lahno and Serra-Garcia (2014) separate the effects of imitation of choices from relative payoff considerations and show that peers' choices have a significant impact on risk-taking. Cooper and Rege (2011) suggest that such imitation is driven by "social interaction effect." That is, a person's utility from taking an action increases if others take the same action; a theory including social regret explains data better than preference for conformity.

We are aware of only one study that explicitly compares risk-taking under competitive and non-competitive pay schemes under different information conditions, although it focuses on different features of the environment. Eriksen and Kvaløy (2014) use a simple lottery investment task experiment in which feedback on both strategies and outcomes is provided at various frequencies. Consistent with theory, more frequent feedback leads to less risk-taking under a non-competitive compensation scheme, but more risk-taking when rewards are competitive. In contrast to these authors' interest in the frequency of feedback, we focus on the effect of different types of information contained within the feedback.

3 Experimental design and procedures

We conducted laboratory experiments to study the effect of information about peers' risk-taking and performance on the adoption of risky strategies in competitive and non-competitive settings. We used a real-effort experimental task to study subjects' risk-

[4] In contrast, Eriksson, Poulsen and Villeval (2009) vary the frequency of feedback about subjects' relative positions and find that feedback has no effect on effort in either non-competitive or tournament environments.

taking. A real-effort experiment may be particularly useful in measuring more subtle features of subjects' decision-making (such as risk-taking), whereas a chosen effort environment may be more amenable to studying the direct effects of incentives and peer-related information on effort (Carpenter, Matthews and Schirm, 2010). Before explaining the experimental task, we motivated subjects with a hypothetical, framed scenario by asking them to imagine themselves as financial analysts making projections about the future performance of particular stocks. Specifically, the analyst must assess whether the future price will be higher or lower than the current price, and the analyst's pay reflects both the volume and accuracy of the forecasts. Forecasts are based on information gathered about the stocks being considered, but acquiring information is costly. The scenario highlights the analyst's trade-off: More information improves accuracy but reduces volume (see section "The scenario" of the experimental instructions in Appendix A).[5]

Each experimental session consisted of two parts. First, subjects' risk aversion and ambiguity aversion were assessed using list elicitation methods similar to those described in Sutter et al. (2013). During each assessment, subjects were presented with a list of 20 choices between earning \$2.00 for correctly guessing the color of a ball drawn randomly from an urn and a sure amount of money. The sure amounts of money increased from \$0.10 to \$2.00, and subjects were asked to choose the point at which they were willing to switch from the draw to the sure amount. For the risk-aversion assessment, subjects were informed that the urn contained 10 green balls and 10 red balls. For the ambiguity aversion assessment, subjects were informed that the urn contained balls of the two colors, but the exact number of balls of each color was not disclosed.[6] The results and payoffs from this part of the experiment were not disclosed to subjects until the end of the session.

The second part of the experiment consisted of a forecasting game. Subjects participated in several periods of play, divided into blocks. At the beginning of each period, a subject was presented with an image of 15 blank cards on his or her computer screen. When flipped over, each card was either green or red. The color of the card was determined randomly and either color was equally likely to appear. A subject's task was to predict whether the majority of the 15 cards was green or red. Before making his or her assessment of the majority color, a subject could choose how many cards—between 5 and 15—to flip. Flipping fewer cards is a higher-risk strategy, as the subject has less information on which to base his or her assessment. The highest-risk strategy involves flipping only 5 cards; in contrast, the lowest-risk strategy is one in which a subject reveals

[5] Vandegrift, Yavas and Brown (2007) use a different forecasting task to study performance when subjects can choose between relative (competitive) and absolute (non-competitive) performance-based incentive schemes. Unlike our design, their subjects could not choose explicitly the riskiness of their actions.

[6] Unbeknownst to subjects, the share of red balls was generated randomly from a uniform distribution.

all 15 cards and, therefore, always records a correct assessment. Once the assessment had been submitted, all of the cards were revealed to the subject, and he or she was told if his or her forecast was correct or incorrect.

Periods were divided into blocks in which a subject was allowed to flip a total of 100 cards; a counter on the screen displayed the number of remaining flips. A subject repeated the same assessment task—forecasting the majority color—until he or she had exhausted all 100 flips. Subjects were not constrained to follow the same strategy in each period of a block; as a result, a subject could make between 7 and 20 assessments in a given block.[7]

A subject's score in a block was calculated as the number of correct assessments minus the number of incorrect assessments. At the end of each block, subjects were given a complete history of their individual forecasts, including the number of green and red cards flipped each period, their majority color assessment, and whether the assessment was correct or incorrect. Additionally, subjects received a summary of their own performance (i.e. their score for the block and their average risk-taking strategy, measured by the average number of cards flipped per period). Depending on the experimental treatment, subjects were also presented with information about other participants' strategies and/or scores.

At the beginning of the forecasting game, subjects were randomly assigned to groups of five participants. The identities of group members were not revealed to participants and were described only by identification numbers 1 through 5. Groups and subject identification numbers remained the same throughout the experiment.

The first block of periods was identical across all treatments. After the first block, all subjects received information about their own performance. We also implemented one of four peer information conditions, under either a competitive or a non-competitive compensation scheme: (i) no feedback about peers' risk-taking or scores; (ii) feedback about peers' risk-taking only, shown as the average number of cards flipped for each group member; (iii) feedback about peers' scores only, shown as the score for each group member; and (iv) feedback about peers' risk-taking and scores. The number of subjects and groups in each of the resulting eight treatments are summarized in Table 1.

Subjects played a total of four blocks, and the feedback treatment was repeated after the second and third blocks. To assess the impact of information about peers, the analysis in this paper focuses on subjects' risk-taking in block 2 where subjects are exposed to peer information for the first time.[8]

[7]Subjects were told that they could not flip fewer than five cards in each period and, for that reason, towards the end of the block they would not be allowed to flip a number of cards such that fewer than five cards remained.

[8]Because subjects are exposed to peer information again after blocks 2 and 3, the treatment effects in

Table 1: Summary of experimental treatments.

	Non-competitive Rewards		Competitive Rewards	
Rewards	\$1.50 × Score		\$2.50 × Score if rank=1 \$1.50 × Score if rank=2,3,4 \$0.50 × Score if rank=5	
Peer Information	# of subjects	# of groups	# of subjects	# of groups
None	45	0	45	0
Strategies	35	7	40	8
Scores	40	8	40	8
Both	75	15	80	16

All subjects were rewarded according to a non-competitive scheme for their first block's performance, earning \$1.50 multiplied by their score. In the non-competitive sessions, subjects continued to earn rewards according to this scheme. In the sessions with competitive incentives, subjects were told that their payoffs for subsequent blocks would be calculated according to their rank by score in their group. The player ranked first in the block earned \$2.50 multiplied by his or her score; players in second, third and fourth rank earned \$1.50 multiplied by their individual scores; and the player in fifth place earned \$0.50 multiplied by his or her score.[9] At the end of the session, actual payments were based on subjects' payoffs from one randomly selected block.

At the end of each session, participants were asked the following open-ended questions about their strategies in the forecasting game: (i) What was your strategy? (ii) Did your strategy change over time, and if so, how? (iii) Did your strategy change when you learned what others in your group were doing, and if so, how? (iv) Did you follow/imitate anyone else's strategy? If so, whose strategy? Questions (i) and (ii) were asked in all treatments and questions (iii) and (iv) were asked only in treatments in which subjects received feedback on their peers' strategies and/or outcomes. Answers to the four questions were categorized by two independent reviewers using a common rubric with binary coding.[10] Responses from the two reviewers were aggregated by taking the minimum of their codings (i.e., an answer was coded as belonging to a category only if it was assigned to that

blocks 3 and 4 are confounded by the fact that subjects are now responding to other subjects' responses to their earlier choices. Summary statistics for blocks 3 and 4 are available from the authors by request.

[9]The presence of three distinct piece rates intensifies competition because subjects may not only compete for the top position but they may also compete to avoid the bottom, which has been shown experimentally to lead to higher average effort than comparable two-prize schemes (Dutcher et al., 2015; Gill et al., 2015).

[10]The complete rubric is available from the authors by request.

category by both reviewers).

Four hundred subjects, 49% of whom are female, were recruited using ORSEE (Greiner, 2004) from the pool of more than 3,000 Florida State University students who preregistered for participation in the XS/FS laboratory experiments. Each subject participated in one session. We conducted 20 sessions of the experiment—four sessions for each of the treatments with peer information about both risk-taking and scores, and two sessions otherwise—between July 2013 and October 2014. Sessions lasted approximately 90 minutes, including instructions and payment. On average, subjects earned $22.60, including a $10 participation fee. The experiment was implemented with the software package z-Tree (Fischbacher, 2007) .

4 Theory and conjectures

Before describing the results in Section 5, we provide a brief theoretical description of the experimental task and formulate specific conjectures. Our empirical findings suggest that subjects' choices deviate significantly from the theory predictions; even so, the framework provides helpful structure to understanding risk-taking in the forecasting game.

4.1 Theoretical predictions

Consider first the decision that subjects face in the non-competitive environment. A total of 100 cards are flipped in a block, and 5 to 15 cards must be flipped in each period; thus, the total number of forecasting attempts per block is between 7 and 20. Note that, regardless of subjects' underlying risk preference, the relatively large number of forecasts and accumulation of payoffs within a block effectively induces risk neutrality in the expected utility maximization framework. That is, due to the law of large numbers, for a large enough number of forecasts, the problem of maximization of expected utility can be approximated by the maximization of expected score.

Let M denote the (odd) number of cards considered in each period, and let N denote the total number of cards that can be flipped in one block (e.g. in our experiment, $M = 15$ and $N = 100$). For simplicity, consider a stationary strategy in which a subject flips n cards per period and uses the majority color among the flipped cards to construct his or her forecast. Let p_n denote the probability that a forecast is correct. Recall that a subject's score is calculated as the number of correct forecasts minus the number of incorrect forecasts. The subject's expected score after flipping a total of N cards is[11]

[11] For simplicity, we ignore the fact that $\frac{N}{n}$ may not be an integer.

$$S(n) = \frac{N}{n}(2p_n - 1). \tag{1}$$

Let r denote the number of red cards among the n flipped cards. Suppose n is odd and $r > n - r$ (i.e., red is the predicted majority color). The probability that this forecast is correct is

$$p_{n,r} = \begin{cases} \left(\frac{1}{2}\right)^{M-n} \sum_{m=\frac{M+1}{2}}^{M-n+r} \binom{M-n}{m-r}, & r < \frac{M+1}{2} \\ 1, & \text{otherwise} \end{cases} \tag{2}$$

Indeed, the forecast will be correct with probability one if $r \geq \frac{M+1}{2}$ (i.e., if flipped red cards constitute the majority of M cards). Otherwise, the probability of a correct forecast is given by the sum over all possible realizations of the total number of red cards (both opened and not), m, such that red is the majority color.[12]

The probability of a correct forecast after flipping an odd number of cards n is

$$p_n = 2\left(\frac{1}{2}\right)^n \sum_{r=\frac{n+1}{2}}^{n} \binom{n}{r} p_{n,r}, \quad n \text{ odd}. \tag{3}$$

In equation (3), the factor 2 arises because there are two possible majority colors; $(\frac{1}{2})^n$ is the probability of each realization of colors of n cards; $\binom{n}{r}$ is the number of such realizations for a given r; and the summation includes all cases in which one color is the majority among the flipped n cards,

Suppose now that n is even. For $r > \frac{n}{2}$ (i.e., when r is the majority color), $p_{n,r}$ is given by equation (2). For $r = \frac{n}{2}$ (i.e., with probability $\left(\frac{1}{2}\right)^n \binom{n}{\frac{n}{2}}$), the probability of a correct forecast is $\frac{1}{2}$. Therefore, the probability of a correct forecast after flipping an even number of cards n is

$$p_n = \frac{1}{2}\left(\frac{1}{2}\right)^n \binom{n}{\frac{n}{2}} + 2\left(\frac{1}{2}\right)^n \sum_{r=\frac{n+2}{2}}^{n} \binom{n}{r} p_{n,r}, \quad n \text{ even}. \tag{4}$$

Note that it is never optimal to flip an even number of cards. When an even number of cards n is flipped, there are either an equal number of red and green cards or a difference of at least two cards. When red and green cards are equal in number, the probability of a correct guess is $\frac{1}{2}$ and the expected score is zero; however, a strictly positive expected score could have been obtained by flipping $n - 1$ cards. When the difference between the number of red and green cards is two or more, flipping $n - 1$ cards would lead to the same

[12] The probability of obtaining each configuration of unopened cards is $(\frac{1}{2})^{M-n}$, and the number of possible configurations of unopened cards for a given number of red cards m is $\binom{M-n}{m-r}$.

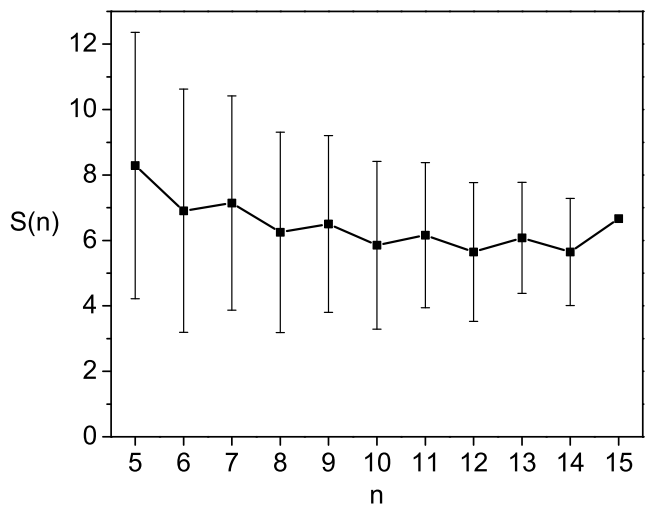

Figure 1: The expected score in a block, $S(n)$, as a function of the number of cards flipped per period, n, calculated for the parameters of the experiment ($M = 15$ and $N = 100$) using equations (1), (2), (3) and (4). The error bars show one standard deviation above and below the expected score for each n. The points are connected by straight lines for better visualization.

forecast. Thus, if n is even, it is always possible to do at least as well by flipping $n - 1$ cards.

Figure 1 shows the expected score for each value of n, calculated using equation (1) and the parameters of the experiment ($M = 15$ and $N = 100$). Recall that subjects had to flip at least 5 cards in each period. From p_n, we calculate the variance in score, $\mathrm{Var}(S) = \frac{4Np_n(1-p_n)}{n}$. The error bars in the figure show one standard deviation above and below the expected score for each n.

As shown in Figure 1, the expected score is highest when $n^* = 5$—the riskiest strategy—but its dependence on n is rather flat, with expected scores between 6 and 8 for all allowed levels of risk-taking. The fluctuations in the dependence of S on n confirm that flipping an even number of cards n is dominated by flipping $n - 1$ cards. The variance in score decreases with n, confirming the trade-off between risk and returns in this environment.

We now turn to analyzing equilibrium behavior in the setting with a competitive rewards scheme. Given that $n^* = 5$ maximizes a subject's expected score, it is a natural candidate for a symmetric Nash equilibrium under competitive rewards. However, since the strategy $n = 5$ is also the riskiest (i.e., it leads to the highest variance in performance), it is not obvious that the choice of $n = 5$ by a player is the best response to all other players choosing $n = 5$. A safer strategy may decrease the player's chances of finishing first, but may simultaneously increase the player's chances of not being last. That is, the

payoff from deviating from maximum risk-taking is not straightforward. Using extensive simulations based on the parameters of the experiment, we found that such a deviation is not profitable—all subjects in the group choosing $n^* = 5$ is a symmetric Nash equilibrium.[13] Indeed, it is the only symmetric equilibrium since a deviation to $n = 5$ is profitable when all other players choose a safer strategy. Thus, for unboundedly rational risk-neutral players, optimal (equilibrium) levels of risk-taking should be the same in all treatments.

4.2 Conjectures

Deciding how many cards to flip each period is a complex problem. Although maximal risk-taking is the optimal strategy for a risk-neutral subject, learning to play this strategy through standard reinforcement mechanisms is extremely difficult, if not impossible, especially with a small number of blocks. As a result, we expect substantial heterogeneity in subjects' behavior. Moreover, in our setting, subjects will likely view information about peers' strategies and outcomes as valuable and will respond to it.

Our experimental task has important features faced by investors and other risk-takers in the field. First, the relationship between strategies and outcomes, although it exists statistically, is weak and noisy. Second, outcomes are determined to a significant extent by luck, and disentangling luck and the effect of strategy is difficult.

The existing literature agrees that competitive incentives encourage more risk-taking than comparable non-competitive incentives, and we expect to find this result, on average, in our setting. However, the literature provides little specific guidance in terms of understanding the interaction between these incentives and the availability of information about peers' decisions and outcomes. Therefore, although we can lean on existing studies to build conjectures, our main research interest is the empirical relationship between incentives and feedback.

In the setting with information about peers' risk-taking only, subjects cannot observe the effectiveness of others' strategies and, hence, we can assess whether subjects engage in "pure" imitation. There are several possible reasons to expect such imitation. First, the environment is complex, and making informed decisions is difficult. Moreover, due to reference group neglect (Moore and Cain, 2007), subjects may believe that the task is difficult for them but not for others; hence, subjects may imitate their peers under the expectation that others know better. Second, it is plausible that subjects derive utility directly from conforming to the group norm or imitate to avoid anticipated social

[13] Details are available upon request.

regret (Cialdini and Goldstein, 2004; Cooper and Rege, 2011). We expect any tendency towards the mean strategy to be especially pronounced in the setting with competitive rewards where relative positions matter and where, by conforming to their group's average behavior, subjects can reduce the riskiness of their overall strategy.[14]

In the setting with information about peers' scores only, there is limited scope for learning and informed strategy updating. Even though subjects do not observe how their peers achieved certain outcomes, they may make broad inferences about how to change their own strategies to improve their scores. For example, a subject pursuing a very safe strategy who learns that his or her score is substantially lower than the leader's score can adopt a riskier strategy in the next round. Conversely, an extreme risk-taker may believe that he or she can mimic the group's leader success only with a safer strategy. Therefore, we expect subjects with scores further away from the group's maximum to change their strategy more dramatically. Subjects' relative positions are salient in the presence of score-only information and, hence, we expect the effects of this information on strategy updating to be stronger in the setting with competitive rewards. It is also of interest to explore the behavior of the leader (i.e., whether the leader will choose to "play it safe" or adopt an even riskier strategy in the following block).

In the presence of information about peers' strategies and scores, subjects may imitate the leading scorer. The rationale is somewhat similar to imitation in the treatments with information about risk-taking only, except that the score leader's strategy (and not the average strategy) may be the attraction point. In the treatments with combined feedback about risk-taking and scores, subjects can observe patterns and, depending on their group, may observe different relationships between strategies and outcomes. Thus, learning will depend critically on what patterns arise (e.g., the strength and direction of correlation between the observed strategies and outcomes). Again, the effect of this feedback on strategy updating is expected to be stronger in the setting with competitive rewards, when relative positions are particularly salient.

Finally, we note that luck plays an important role in this noisy experimental environment and may influence subjects' ability to learn. A subject who was using an (*ex ante*) suboptimal strategy and was lucky (or an *ex ante* optimal strategy and was unlucky) will be less likely to update his or her strategy correctly, relative to a subject whose luck did not distort the signals about the theoretically superior strategies.

[14]Under competitive rewards, it is also possible that subjects will engage in "anti-imitation," whereby they attempt to break away from their peers by choosing a strategy that does not conform to the group mean. Such behavior is similar to choosing a riskier overall strategy and, therefore, it can be rationalized in a tournament setting (Hvide, 2002).

5 Results

In this section, we present and discuss our experimental findings. We first describe *probability matching*, a suboptimal but pervasive guessing heuristic used by many subjects whereby they randomize their predictions to match the underlying probabilities of success. Next, we describe the relationship between the uncertainty attitude measures and subjects' choices. We then describe the main results about the effects of the incentives and peer information on subjects' risk-taking. Finally, we describe some patterns in the individual data that help to explain the observed treatment effects.

5.1 Probability matching

To begin, we examine the basic properties of subjects' decisions. As discussed in the previous section, subjects should never choose to flip an even number of cards because it is dominated by flipping one fewer. It should be noted that at the end of each block, subjects may be forced to flip an even number of cards due to the restriction that the remaining number of cards cannot be less than five. Therefore, we expect to see at most one even flip per subject per block. In fact, we observe that 33.3% of all flips in the experiment are even—on average, subjects chose to make 4.14 even flips per block. The frequency of even flips declines over time, but only moderately, from 38.4% in block 1 to 32.4% in block 2.

The other, and perhaps more important, question is whether subjects always base their forecasts on the majority color of the flipped cards—that is, do subjects make optimal predictions given their signals? Excluding cases in which an equal number of green and red cards are revealed, subjects forecast against the majority color in 20.3% of their predictions. There is a very slight decline in the frequency of non-majority guesses between the first and second block, from 21.2% to 20.6%, but it is not statistically significant. Only 8 of the 400 subjects (2%) never made a non-majority guess, and 34.2% of subjects made 10 or more such guesses.

The presence of suboptimal, non-majority guesses is a manifestation of the pervasive phenomenon of *probability matching* that has been studied extensively in psychology, dating back to Estes (1950). Vulkan (2000) provides a recent survey of this literature from an economist's perspective. A typical experiment on probability matching involves subjects observing a random sequence of two signals (e.g., red and green lights) that they are told are independent draws in which the red signal appears with some probability p. Having observed a sufficiently long sequence, subjects are then asked to predict what the next signal will be. Clearly, red is the optimal prediction if and only if red light

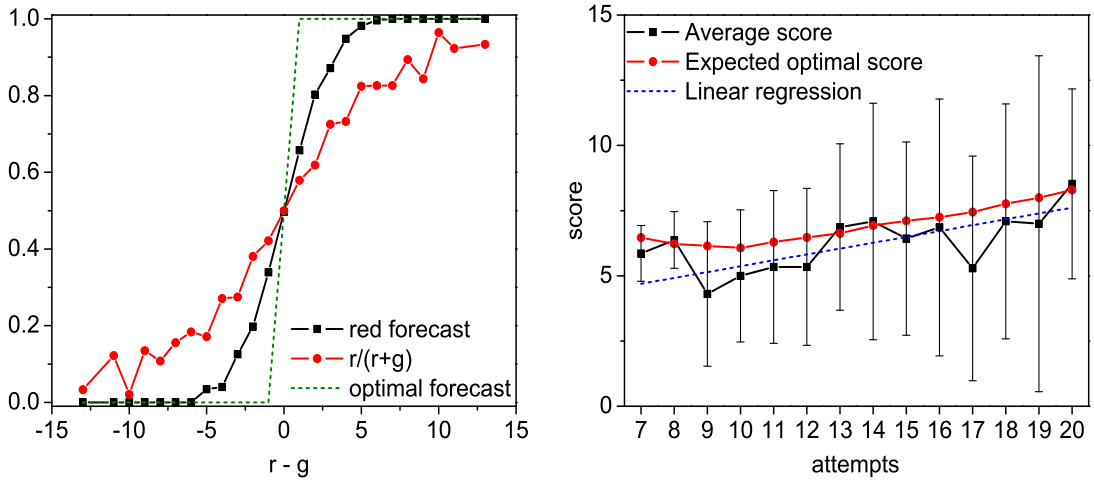

Figure 2: *Left*: the average frequency of forecasting red color as a function of $r - g$ (squares); average ratio $r/(r + g)$ as a function of $r - g$ (circles); the optimal forecasting strategy (dashed line). *Right*: average score in block 1 as a function of the number of attempts (squares), with error bars showing one standard deviation above and below the average score; average expected score in block 1 if all forecasts were optimal (circles); regression line of average score on attempts, including an intercept (dashed).

was observed more than half of the time (or $p > 0.5$ if probability p is known). Instead, many subjects randomize their predictions and predict red with a frequency close to p. This suboptimal randomizing behavior is robust to learning, although it can be partially mitigated through guided deliberation and advice (Koehler and James, 2009). Recently, Gaissmaier and Schooler (2008) proposed that probability matching serves as an evolutionarily "smart" heuristic whereby individuals look for patterns and serial dependence in naturally occurring stimuli.

Our forecasting task differs in two significant ways from the simple settings in which probability matching has been studied previously. First, it includes variation in the intensity of the signal; our subjects see different numbers of red and green cards revealed. Second, there is variation in the amount of noise; our subjects observe the differences in the numbers of red and green cards revealed and the number of hidden cards. Suppose that a subject flips n out of M total cards, r of which turn out to be red and g are green. The larger the difference $|r - g|$ and the smaller the number of hidden cards $M - n$, the more likely it is that the majority color forecast will be correct. Thus, while a payoff maximizer will choose the majority color all of the time, a probability matcher will choose the majority color with a probability that is increasing in $|r - g|$ and n. Testing this formally in a probit regression, we find negative and statistically significant effects of $|r - g|$ and n on the probability of a non-majority guess. In our experiment, probability matching is

present across all of the compensation and peer information conditions.

In the left panel in Figure 2, the squares plot the observed average frequency of red forecasts against the difference between the number of red and green cards, $r - g$. The optimal forecasting strategy is shown by a dashed line. The circles plot the average ratio of red cards to the total number of cards, $\frac{r}{r+g}$, against each value of $r - g$ observed in the experiment. The ratio $\frac{r}{r+g}$ represents the behavior of a "pure" probability matcher. The observed average behavior lies between pure probability matching and the optimal behavior, suggesting that probability matching varies across subjects and with the level of noise, as observations for each $r - g$ are averaged over different values of n. As expected, the frequency of forecasting red increases monotonically in $r - g$, starting at zero for $r - g \leq -6$ and reaching one at $r - g \geq 7$.

The pattern of choices observed in the experiment is consistent with random choice models, such as the Quantal Response Equilibrium (QRE) model introduced by McKelvey and Palfrey (1995). In the QRE framework, it is assumed that instead of choosing a utility-maximizing strategy, a subject chooses strategy s with probability $p(s) = \frac{\exp[\lambda u(s)]}{\sum_{s' \in S} \exp[\lambda u(s')]}$, where S is the set of possible strategies and $u(s)$ is the expected utility of strategy s. Parameter λ represents the (inverse) level of noise (or intensity of errors in decision-making), where $\lambda \to 0$ corresponds to completely random behavior and $\lambda \to \infty$ corresponds to fully rational behavior. In our setting, there are two strategies: choose red (R) or choose green (G). Let $p_{n,r}$ denote the probability that red is the majority color given that n cards have been flipped and r of them are red (see equation (2)). The expected utility of choosing R is $u(R) = 2p_{n,r} - 1$, and the expected utility of choosing G is $u(G) = 2(1 - p_{n,r}) - 1$. Therefore, the logistic probability of choosing red is $p(R) = \frac{1}{1+\exp[2\lambda(1-2p_{n,r})]}$. Maximum likelihood estimation using choice data from the experiment yields $\lambda = 1.4$ (standard error of 0.02). There is little variation in λ across blocks and treatments, suggesting that the amount of noise in the random choice model does not depend on the compensation or feedback conditions.

Given the presence of suboptimal probability matching behavior, we consider the extent to which such decisions distort the risk-taking incentives in the experiment. In particular, we explore how probability matching affects the trade-off between risk and expected returns predicted by the theory in Section 4, which assumes that subjects always forecast the majority color. The squares in the right panel of Figure 2 plot subjects' average score in the first block against the number of forecasting attempts. The error bars around the squares show one standard deviation above and below the mean. The number of forecasts ranges from 7 (the safest strategy, flipping 15 cards in each period except the last one) to 20 (the riskiest strategy, flipping 5 cards in each period). The dashed line

is a linear regression line for the average score as a function of the number of forecasts, including an intercept. The slope is positive and statistically significant at conventional levels. The circles show the expected score that a subject would have received if he or she always followed the majority guessing strategy. Due to suboptimal decision-making, the average score in the experiment is approximately 0.7 lower than the expected optimal score, and the difference is statistically significant. However, the observed dependence of score on the number of forecasting attempts is essentially a parallel shift down from what fully rational theory predicts, and the trade-off between risk and returns is preserved despite the presence of probability matching.

5.2 Summary statistics

Table 2 presents summary statistics by treatment, for the first and second blocks. Throughout our analysis, we use the number of forecasts in a block as a measure of subjects' risk-taking. More forecasts means that the subject assumed more risk by turning over fewer cards per period, whereas fewer forecasts means that the subject pursued the safer strategy of turning over more cards per period. Overall, an average subject turns over approximately 7 cards per period, leading to roughly 13 forecasts per block. The number of forecasts is not statistically different across treatments in block 1, a reassuring finding that confirms the experimental randomization.[15] Table 2 also includes a measure of subjects' "luck" in block 1, measured as the difference between subjects' actual and expected scores. Expected score is calculated using the theoretical probability of a correct assessment, shown above in equation (1), given the actual number of cards flipped by subject. Subjects' luck in the first block did not vary statistically across treatments.[16]

Table 2 also presents the summary statistics for the measures of risk and ambiguity aversion elicited at the start of the sessions. Risk aversion (RA) is measured as the number of safe choices in the risk aversion elicitation list. Ambiguity aversion (AA) is measured as the difference between the number of safe choices in the ambiguity aversion elicitation list and RA, where a positive difference suggests an aversion to ambiguity. Neither measure is statistically different across treatments, suggesting that subjects' attitudes towards uncertainty did not vary systematically by treatment.[17]

Ideally, the risk and ambiguity aversion measures would capture the underlying preferences of individual subjects and, as a result, explain subjects' turnover decisions in the

[15] A Kruskal-Wallis rank test yields a chi-squared statistic of 3.2 ($p = 0.87$).

[16] A Kruskal-Wallis rank test yields chi-squared statistics of 8.4 ($p = 0.29$).

[17] Comparing the risk and ambiguity aversion measures across treatments, Kruskal-Wallis tests yield chi-squared statistics of 4.4 ($p = 0.73$) and 6.0 ($p = 0.54$), respectively.

Table 2: Summary statistics

	Non-competitive Rewards				Competitive Rewards			
Peer Information:	None	Strategies	Scores	Both	None	Strategies	Scores	Both
				Block1				
# of forecasts	13.11	13.31	12.58	12.79	13.40	13.20	13.30	13.09
	(3.39)	(3.13)	(3.42)	(3.14)	(3.05)	(3.00)	(2.95)	(3.38)
Score	6.22	5.14	5.18	6.09	6.56	5.70	7.25	6.09
	(3.17)	(3.60)	(3.49)	(3.45)	(3.64)	(3.64)	(3.74)	(3.94)
Luck in block 1	-0.54	-1.67	-1.53	-0.065	-.022	-1.02	0.46	-0.70
	(3.08)	(3.85)	(3.52)	(3.41)	(3.64)	(3.71)	(3.53)	(3.77)
				Block2				
# of forecasts	13.11	11.94	11.48	12.48	12.36	12.70	13.40	13.46
	(3.85)	(3.42)	(3.73)	(3.32)	(3.32)	(3.55)	(3.48)	(4.08)
Score	6.00	6.29	5.88	6.05	6.84	6.00	6.40	6.36
	(4.00)	(3.14)	(2.65)	(3.72)	(3.03)	(3.53)	(2.86)	(3.80)
				Subject characteristics				
RA	8.71	7.66	7.75	8.83	8.56	8.73	8.95	8.80
	(4.14)	(3.80)	(5.00)	(4.12)	(4.48)	(3.84)	(4.90)	(3.95)
AA	0.00	1.54	1.48	.76	1.13	1.85	0.15	0.56
	(4.49)	(3.63)	(5.30)	(4.80)	(5.75)	(5.00)	(5.78)	(5.74)
Female	0.42	0.34	0.43	0.56	0.56	0.55	0.53	0.51
	(0.50)	(0.48)	(0.50)	(0.50)	(0.50)	(0.50)	(0.51)	(0.50)

Note: The first block of periods was identical across treatments. After the first block, all subjects received information about their own performance. We also implemented one of four peer information conditions: "None" indicates that subjects received no feedback about peers' risk-taking or scores; "Strategies" indicates that subjects received feedback about peers' risk-taking only; "Scores" indicates that subjects received feedback about peers' scores only; and "Both" indicates that subjects received feedback about peers' risk-taking and scores. Luck in block 1 is a subjects' actual score minus the expected score predicted by theory given the actual number of flipped cards. Standard deviations are reported in parentheses.

first block of the experiment. To test this hypothesis, we regressed subjects' risk-taking in the first block (the number of forecasts in block 1) on the risk and ambiguity aversion measures. As expected, the coefficient estimates on both measures are negative, although only the coefficient for risk aversion is statistically significant ($p = 0.06$),[18] and the R^2 of the regression is 0.01. Although subjects' risk aversion measure is correlated with their risk-taking in the first block, very little of the variation in subjects' strategies is explained by individuals' observable characteristics. Therefore, in the analysis that follows, we use the subjects' risk-taking in the first block (the number of forecasts in block 1) as a subject-specific control.

By focusing on risk-taking in block 2 after subjects' first exposure to information about their peers, we can assess cleanly the impact of information treatments.[19] Across all of the treatments, we find that there is a statistically significant decline in the average level of risk-taking between the first and second block; this decline can be primarily attributed to subjects who took more than average risk in the first block.[20]

5.3 Main results

With eight experimental conditions across two blocks, it is difficult to glean a simple conclusion about the effect of information about peers' strategies and outcomes on risk-taking from only the summary statistics in Table 2. Examining the average number of forecasting attempts in block 2—the block following the information treatment—competitive rewards appear to be associated with more risk-taking (i.e. more forecasts) when subjects receive information about their peers, although the difference is statistically significant only in treatments in which subjects receive information about other subjects' risk-taking strategies. Of course, it is critical to recognize that Table 2 summarizes only the *average* risk-taking strategies and scores of all subjects within a treatment. Regression analysis allows us to identify treatment effects in the data while accounting for subject-level heterogeneity.

Table 3 presents the baseline results comparing subjects' risk-taking under competitive

[18] Numerous studies have documented differences in the risk attitudes of men and women (for a review, see, e.g., Croson and Gneezy, 2009); however, the inclusion of an indicator for gender ($female = 1$ if the subject is female, zero otherwise) does not change the sign, magnitude or statistical significance of the coefficient estimates for the risk and ambiguity aversion measures in the regression. The coefficient on the gender indicator itself is negative and not statistically significant.

[19] As noted above, the treatment effects in blocks 3 and 4 are confounded by the fact that subjects are now responding to other subjects' responses to their earlier choices.

[20] In a regression of the change in the number of forecasts between blocks 1 and 2 on the number of forecasts in block 1 and a constant, with standard errors clustered by group, we estimate a positive constant and a negative coefficient on the number of forecasts in block 1 ($p < 0.01$).

Table 3: Risk-taking, incentives, and peer information

Dependent variable: *# of forecasts in block 2*	3.A	3.B	3.C	3.D	3.E
1(Competitive)	0.89*	0.65*	0.51	-1.15*	-1.14*
	(0.49)	(0.37)	(0.34)	(0.68)	(0.68)
1(Peer information)				-0.83	
				(0.58)	
1(Competitive)×1(Peer information)				2.13***	
				(0.78)	
1(Peer information: strategies only)					-1.28**
					(0.63)
1(Peer information: scores only)					-1.20*
					(0.63)
1(Peer information: strategies & scores)					-0.43
					(0.66)
1(Competitive)×1(Peer information: strategies only)					1.94**
					(0.81)
1(Competitive)×1(Peer information: scores only)					2.29**
					(0.96)
1(Competitive)×1(Peer information: strategies & scores)					2.16**
					(0.91)
# of forecasts in block 1		0.80***	0.79***	0.79***	0.80***
		(0.06)	(0.06)	(0.06)	(0.06)
Luck in block 1			0.28***	0.28***	0.27***
			(0.05)	(0.05)	(0.05)
Constant	12.28***	1.94**	2.33***	2.95***	2.90***
	(0.35)	(0.84)	(0.77)	(0.90)	(0.90)
N	400	400	400	400	400
Pseudo R^2	0.01	0.09	0.11	0.11	0.12

Note: The table summarizes results of Tobit regressions of the number of forecasts in block 2 on on indicators for types of incentives and feedback, their interactions, and controls for subject-level risk-taking and luck in the block 1. Luck in block 1 is a subjects' actual score minus the expected score, where expected score is predicted by theory given the actual number of flipped cards. Group-level clustered standard errors are reported in parentheses; there are 152 clusters in each regression. Group size is five in all treatments except those treatments without feedback, where the group size is one because subjects were not exposed to information about their peers. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

and non-competitive rewards with and without information about peers' risk-taking and scores. The regressions build up from a simple specification to one that captures the full heterogeneity of the experimental design. In all regressions, the dependent variable is the number of forecasting attempts by individual subjects in the second block. Each column reports results of a Tobit specification, accounting for the fact that forecasts are bounded between 7 and 20. Robust standard errors are clustered at the group level.[21]

We begin by examining the common notion that, in general, competitive reward schemes lead to more risk-taking. Indeed, the results reported in column 3.A are consistent with the simple conclusion drawn from a comparison of means in Table 2. The estimated coefficient on the indicator for competitive incentives is positive and statistically significant ($p < 0.1$), suggesting that relative rewards schemes are associated with more risk-taking.

Drawing from our earlier discussion of subjects' strategies and the extant literature on risk-taking, we expect subjects' to vary in terms of their underlying attitude towards risk-taking and their experiences in the first block. In column 3.B, we include a control for each subjects' risk-taking in the first block (the number of forecasts in block 1). Again, the estimated coefficient on the indicator for competitive incentives is positive and statistically significant ($p < 0.1$). The coefficient estimate on the control itself is positive and statistically significant ($p < 0.01$), indicating that the risk-taking measure from the first block serves as an individual "fixed effect."

One might also ask whether subjects' own experiences in the first block influence their choices in the second block. To that end, in column 3.C, we add a measure of the subject's "luck" in the first block, defined as the difference between the subject's actual score and the expected score predicted by theory, given the number of cards flipped. The coefficient estimate for the competitive incentives indicator remains positive, but it is no longer statistically significant at conventional levels. The luck measure itself has explanatory power—the coefficient is positive and statistically significant ($p < 0.01$), suggesting that subjects increase their risk-taking in response to previous good luck.

While columns 3.A, 3.B and 3.C address the question of the average impact of competitive rewards scheme, our main research question focuses on the interaction of incentives and peer information. We first analyze the effect of peer information in general, without separating different types of feedback. In column 3.D, we report results from a regression that includes an indicator for the presence of any peer information (scores, strategies or

[21] In treatments with feedback, groups are defined as the five subjects who were presented with information about each others' scores, strategies or both; in treatments without feedback about peers, groups include only a single subject, since these individuals are not exposed to information about other participants.

both) and its interaction with the indicator for competitive incentives. When no peer information is available to subjects, competitive rewards are associated with less risk-taking than non-competitive rewards; the coefficient on 1(Competitive) is negative ($p < 0.10$). In contrast, when peer information is available, competitive rewards are associated with more risk-taking; the sum of the coefficients on 1(Competitive) and 1(Competitive)×1(Peer Information) is positive ($p < 0.05$).

We can also hold the incentives fixed and isolate the effect of feedback. Peer information appears to have no significant impact on risk-taking in the non-competitive setting; the coefficient on 1(Peer information) is not statistically significant. At the same time, peer information leads to more risk-taking when subjects face competitive rewards; the sum of the coefficients on 1(Peer information) and 1(Competitive)×1(Peer Information) is positive ($p < 0.05$).

Result 1 *(a) There is no evidence of a robust effect of competitive incentives on the average level of risk-taking.*

(b) In the absence of information about peers, there is less risk-taking under competitive incentives than under non-competitive incentives.

(c) In the presence of information about peers, there is more risk-taking under competitive incentives than under non-competitive incentives.

Results 1 describes a surprising finding. In contrast to the conventional view that tournament-style incentives schemes are always associated with more risk-taking relative to non-competitive incentives, we find that competitive rewards may lead to less risk-taking when subjects receive no information about other competitors. This result is overturned in the presence of peer information, when competitive rewards are associated with more risk-taking. In short, the availability of information about peers appears to matter critically. Of course, the coarse indicator for peer information in column 3.D may obscure the heterogeneous impact of different types of feedback.

To explore the impact of different types of peer information, we report the results a regression with indicators for feedback about peers' strategies, scores or both under each incentive scheme in column 3.E. To begin, we compare the effect of competitive and non-competitive incentives while holding fixed the information available to subjects. In the absence of peer information, competitive compensation is associated with less risk-taking than a non-competitive pay scheme ($p < 0.1$). When information about peers' risk-taking, scores or both is available, subjects engage in more risk-taking when they face competitive rewards; for each type of information, the sum of the coefficients on the indicator for competitive rewards and its interaction with the indicator for specific

information type is positive and statistically significant ($p < 0.1$). Information appears to matter similarly; there is no statistically significant difference between the effects of information about strategies, scores or both on risk-taking.

We can also estimate the impact of each type of peer information while holding fixed the incentive scheme. Under non-competitive rewards, subjects make less risky choices when they receive feedback about their peers' strategies only ($p < 0.05$) or scores only ($p < 0.1$), but not about both strategies and scores. In contrast, under competitive rewards the combined information on peers' strategies and scores is associated with significantly more risk-taking ($p < 0.01$), whereas the effects of feedback on peers' strategies only or scores only are not statistically significant.

Result 2 *(a) Comparing settings with competitive and non-competitive compensation, competitive rewards are associated with more risk-taking for each type of peer information.*

(b) In a non-competitive setting, information about either peers' risk-taking or peers' scores is associated with less risk-taking; however, the availability of information about both risk-taking and scores has no effect.

(c) In a setting with competitive rewards, information about either peers' risk-taking or peers' scores does not affect risk-taking; however, information about both risk-taking and scores is associated with more risk-taking.

Result 2(a) decomposes Result 1(b)—competitive rewards lead to more risk-taking than non-competitive schemes for each type of peer information, despite the fact that the three types of feedback convey different information about the competitive environment.

Our results suggest that tournament-style, competitive compensation does not inherently induce more risk-taking. In the presence of information about peers' strategies, scores or both, subjects rewarded according to their relative performance may adopt riskier strategies than they would with non-competitive rewards. However, in settings without peer information, competitive rewards may be associated with *less* risk-taking. Overall, the presence or absence of information matters critically in terms of how competitive rewards schemes affect risk-taking. That is, to achieve a particular risk-related objective, one needs to consider both the incentives and the availability of information to competitors. Moreover, the nature of the feedback also matters—holding incentives fixed, the type of peer information may affect the riskiness of competitors' actions.

Our main results suggest that the interaction of peer information and incentives schemes is more subtle than previously discussed in the literature. Moreover, the results raise questions about *how* feedback reverses the unexpected difference between subjects' risk-related choices in competitive and non-competitive settings. For example, does information about peers' scores motivate more aggressive decision-making by giving average

competitors a sense of how far they lag behind the leaders? Does information on risk-taking give subjects a view into possible strategies to imitate? Does information about strategies and scores allow competitors to identify a path to success? For each type of peer feedback, there may be different mechanisms driving the higher risk-taking that we observe under competitive compensation schemes. In the following sections, we shed light on possible mechanisms.

5.4 Information about peers' scores

We start with an analysis of an environment in which subjects learn about peers' outcomes, but not the strategies that underlie those successes or failures. Outside of the laboratory, this setting aligns with situations in which, for example, colleagues share stories about their portfolios' returns, the volume of completed deals, or their year-end totals, without describing *how* they achieved these successes. Alternatively, workers may describe their losses or shortfalls without explaining what led to these failings.

Table 4 reports Tobit regression results using the number of forecasts in block 2, our risk-taking measure, as the dependent variable and examines the two treatments in which subjects received only score-related feedback about their peers. As in Table 3, a Tobit specification accounts for the fact that forecasts are bounded between 7 and 20. To understand how feedback about a subject's relative position in the group affects risk-taking, we include a measure of the distance between a subject's score and the highest or lowest score in the group and their respective interactions with the indicator for competitive incentives. To ease interpretation, for each distance measure, the sample mean is subtracted from the variable before it is interacted. These coefficient estimates are presented in columns 4.A and 4.B; the regression reported in column 4.C includes both measures and their respective interactions. All specifications include subject-specific controls for the number of forecasts and luck in block 1.

In settings with non-competitive rewards, the distance between group members' scores appears to have little influence on risk-taking; across the three columns in Table 4, the coefficient estimates on the (uninteracted) distance measures are not statistically significant. In contrast, subjects facing competitive rewards may adopt riskier strategies as they fall farther behind the leader and as they pull farther away from the worst-ranked position. In column 4.C, the sum of the distance measures and their respective interactions are positive and statistically significant ($p < 0.01$ for the distance to the highest score and $p < 0.05$ for the distance to the lowest score).[22]

[22] As a falsification exercise, we estimated the same specification reported in column 4.C examining only treatments in which subjects received *no* information about their peers. Using these data, none of

Table 4: Distance to the best- and worst-scoring peers

Dependent variable: *# of forecasts in block 2*			
	4.A	4.B	4.C
1(Competitive)	-0.34	0.82	0.45
	(0.53)	(0.77)	(0.55)
Distance to the group's highest	0.02		-0.08
score in block 1	(0.16)		(0.20)
1(Competitive)×Distance to the	0.26***		0.58***
group's highest score in block 1	(0.09)		(0.22)
Distance to the group's lowest		0.10	0.02
score in block 1		(0.13)	(0.12)
1(Competitive)×Distance to the		-0.01	0.42*
group's lowest score in block 1		(0.16)	(0.22)
# of forecasts in block 1	0.88***	0.82***	0.86***
	(0.09)	(0.11)	(0.11)
Luck in block 1	0.56***	0.38**	0.44**
	(0.19)	(0.14)	(0.18)
Constant	1.18	1.58	1.21
	(1.24)	(1.42)	(1.42)
N	80	80	80
Pseudo R^2	0.24	0.23	0.26

Note: Examining only data from treatments in which subjects received information about peers' scores only, the table summarizes results of Tobit regressions of the number of forecasts in block 2 on indicators for types of incentives and feedback, their interactions, and the distance to best- and worst-scoring peer, as well as controls for subject-level risk-taking and luck in the block 1. For both distance measures, the sample mean is subtracted from the variable before it is interacted with the indicator for competitive rewards. Luck in block 1 is a subjects' actual score minus the expected score, where expected score is predicted by theory given the actual number of flipped cards. Group-level clustered standard errors are reported in parentheses; there are 16 clusters in each regression. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

We also examine the text responses to the open-ended questions described in Section 3. Subjects in the treatment with competitive rewards and information about peers' scores are more likely to claim that they followed a strategy, relative to subjects in the non-competitive treatment with similar information (question (i)). In response to question (ii), 73% of the subjects claim that their strategy changed over the rounds of experiment. In response to question (iii), 23% of the subjects claim that they changed strategies after observing peers' performance, with 4% (11%) stating that they switched to a safer (riskier) strategy.[23] As expected for treatments involving only performance information, no subject states that they were imitating their peers (question (iv)).

Result 3 *Distances between own score and the highest and lowest scores in the group matter in the setting with competitive rewards, where greater distance is associated with more risk-taking, but not in the non-competitive setting.*

Subjects' position in the distribution—in this case, distance from peers' scores—affect their risk-taking in environments where payoffs are determined according to competitors' relative performance. Specifically, in the setting with competitive rewards, subjects follow riskier strategies when they are farther away from the highest scorer and the lowest scorer. This suggests that subjects adopt riskier strategies when they need to overcome a larger gap to catch up with the leader and when they face a smaller chance of falling into last place. In contrast, in the non-competitive setting, relative position appears to have little impact on risk-taking.

We also separately examined how the behavior of the highest and lowest-scoring subjects changes between blocks 1 and 2. We regress the difference between a subject's risk-taking in the first and second block on the indicators for peer information and competitive rewards, and their interactions, along with the controls for first block risk-taking and luck.[24] By focusing the analysis on the treatments with no peer information and information about peers' scores, we identify how a change in a subject's risk-taking between blocks 1 and 2 is affected by *learning* that he or she has either the highest or lowest score in the group. Whereas subjects who learn that they are leading do not adjust their risk-taking between the first and second blocks, subjects who learn that they are trailing behind their group do change their strategies. In the setting with non-competitive rewards, the lowest-scoring subject decreases his or her risk-taking ($p < 0.1$); facing a com-

the distance measures or interactions is statistically significant.

[23]Note that 4% and 11% do not add up to 23% because the remaining subjects did not unambiguously state how their strategy changed.

[24]For brevity, we do not report the full results here; however, they are available from the authors by request.

petitive compensation scheme, the lowest-scoring subject increases his or her risk-taking ($p < 0.05$).

5.5 Information about peers' strategies

Information about peers' actions might lead to the convergence of subjects' strategies within the groups. To consider the possibility that feedback facilitates convergences in risk-taking strategies, we calculate the difference between the standard deviations of submitted forecasts in the first and second block for each group. Overall, we find no evidence that the presence of feedback about risk-taking led subjects towards a common strategy.

More specifically, we first compare the change in the dispersion of forecasting strategies under the two incentive structures, holding fixed the type of information. In the treatments without peer information, the group-level standard deviation declines in the non-competitive treatment and is unchanged in the competitive setting; however, the difference between these changes is not significantly different from zero ($p = 0.27$). When subjects receive information about peers' risk-taking, the difference is even smaller in magnitude (both changes are negative) with an even larger standard error.

The changes are similarly small when we consider the impact of peer information, holding fixed the incentive structure. Under both competitive and non-competitive schemes, comparing the treatments without peer information and with only information about peers' strategies, the differences in standard deviations of the forecasts in the first and second blocks are small and not statistically different from zero. A comparison of treatments without peer information and with only information on risk-taking yields $p = 0.73$ when subjects face non-competitive rewards and $p = 0.17$ when subjects face competitive rewards.

One might ask whether subjects who learn about their peers' risk-taking then attempt to imitate some of those strategies. To consider this question, we examine the impact of the mean, median, minimum and maximum risk-taking by peers and of the difference between those measures and a subject's risk-taking in block 1 (similar to column 4.A for scores); however, we find no statistically significant relationships between subjects' own risk-taking strategies and those of their peers.

Overall, we find little evidence that the presence of information about peers' risk-taking influences subjects' choices. In the text responses to the follow-up questions, 68% of the subjects claim that their strategy changed over the rounds of the experiment (question (ii)). Only 16% of the subjects write that these changes occurred after observing peers' risk-taking, with 11% (4%) of subjects stating that they switched to a safer (riskier) strategy (question (iii)). Moreover, when asked directly in question (iv), only 1% of the

subjects indicate that they imitated other players' strategies. This pattern of responses did not vary between the competitive and non-competitive treatments.

Result 4 *In both the competitive and non-competitive settings, information about peers' risk-taking alone does not lead to convergence of subjects' strategies, and we find no evidence that players imitate their peers' strategies.*

5.6 Information about peers' scores and strategies

Subjects who are presented with information about both the risk-taking and scores of their peers in block 1 receive the richest feedback in our experimental design. Given this information, subjects can evaluate their success and risk-taking relative to other subjects in their group. Moreover, these subjects can assess the overall relationship between risk-taking and success.

Table 5 presents Tobit regression results with the number of forecasts in block 2, our risk-taking measure, as the dependent variable and examines the treatments in which subjects received feedback about both the risk-taking and outcomes of their peers. The first two columns of Table 5 repeat specifications from earlier tables, using only data from the treatments with feedback about risk-taking and scores. Similar to the specification in column 3.C, column 5.A includes an indicator for competitive rewards, along with the controls for subjects' forecasts and luck in the first block. After controlling for individuals' decisions and outcomes in block 1, the coefficient on 1(Competitive) is not statistically significant. Column 5.B includes a measure of the distance between a subject's score and the score of the best- and worst-ranked peers in the group and their interactions with the indicator for competitive rewards, similar to the specification in column 4.C. In column 5.B, the coefficient estimated on the distance to the highest scorer is positive and statistically significant ($p < 0.1$); holding all else fixed in the non-competitive treatment, subjects adopt riskier strategies as the distance between their score and the leader's score increases. A similar effect is observed under the competitive compensation scheme; the total effect of changes in the distance to the highest scoring peer is positive and statistically significant ($p < 0.05$). The estimates for the effect of changes in the distance to the lowest scorer are not statistically significant.[25]

Subjects in treatments with peer information about both risk-taking and scores can learn about not just their relative positions, but also about the overall relationship between risk-taking and outcomes in this environment. We capture the empirical relationship

[25] In contrast, in Table 4, the distances to both the highest and lowest scorer were statistically significant for groups in settings with competitive rewards, but not in the non-competitive treatments.

Table 5: Strategies and scores

Dependent variable: *# of forecasts in block 2*	5.A	5.B	5.C	5.D	5.E
1(Competitive)	1.04	0.39	1.33**	-0.09	1.13**
	(0.63)	(1.04)	(0.57)	(1.13)	(0.51)
Distance to the group's highest		0.26*		0.08	
score in block 1		(0.14)		(0.19)	
1(Competitive)×Distance to the		0.10		0.18	
group's highest score in block 1		(0.18)		(0.19)	
Distance to the group's lowest		-0.15		-0.14	
score in block 1		(0.15)		(0.14)	
1(Competitive)×Distance to the		0.079		0.153	
group's lowest score in block 1		(0.12)		(0.13)	
Correlation of forecasts and			2.36***	1.87**	2.11***
scores in block 1			(0.74)	(0.89)	(0.76)
1(Competitive)×Correlation of forecasts			-2.02	-1.62	-2.94**
and scores in block 1			(1.22)	(1.39)	(1.28)
# of forecasts by subject with highest					0.264*
score in block 1					(0.14)
# of forecasts by subject with lowest					0.13
score in block 1					(0.10)
# of forecasts in block 1	0.77***	0.79***	0.739***	0.761***	0.68***
	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)
Luck in block 1	0.24***	0.59***	0.18**	0.38*	0.17**
	(0.08)	(0.17)	(0.08)	(0.21)	(0.08)
Constant	2.826**	2.28*	2.745**	2.84**	-1.80
	(1.35)	(1.25)	(1.18)	(1.36)	(1.65)
N	155	155	155	155	155
Pseudo R^2	0.098	0.11	0.11	0.116	0.119

Note: Examining only data from treatments in which subjects received information about peers' strategies and scores, the table summarizes results of Tobit regressions of the number of forecasts in block 2 on indicators for incentives and peer information, and controls for subject-level attitudes towards risk-taking and luck in the block 1. Luck in block 1 is a subjects' actual score minus the expected score, where expected score is predicted by theory given the actual number of flipped cards. Group-level clustered standard errors are reported in parentheses; there are 31 clusters in each regression. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

between risk-taking and score by calculating, for each group, the Spearman rank-order correlation coefficient of the number of forecasts and subjects' scores in the first block. The correlation coefficients ranged from -0.89 to 0.82 across the 31 groups that were presented with the combined information.

Column 5.C includes the correlation coefficient of the risk-taking and score data presented in the feedback after block 1 and its interaction with the indicator for competitive incentives. The coefficient estimate on the correlation variable is positive and statistically significant ($p < 0.01$). We interpret the results by considering three cases: correlation coefficients of -1, 0, and 1. A correlation coefficient of -1 implies that scores decrease with risk-taking and conveys a noiseless and theoretically incorrect assessment of the relationship. Interpreting the estimates in column 5.C suggests that a subject in the presence of this precise but incorrect information would take similar risk under competitive and non-competitive rewards. In contrast, a correlation coefficient of 1 implies that scores increase with risk-taking and conveys a noiseless and theoretically correct assessment of the relationship. Presented with this information, our estimates suggest that subjects would take more risk when they face competitive compensation, relative to their risk-taking under non-competitive rewards ($p < 0.05$). A correlation coefficient of 0 implies no observable, linear relationship between risk-taking and scores. With noisy information, our subjects again would take more risk when they face competitive rewards, rather than non-competitive compensation ($p < 0.05$).

Keeping incentives fixed, the results in column 5.C imply that under non-competitive incentives subjects exhibit a correct and statistically significant reaction to the correlation. The stronger the correlation between risk and rewards they observe in their group, the more risk they take. Under competitive incentives, however, the effect of the correlation on risk-taking disappears.

Result 5 *Under non-competitive incentives, subjects take more risk the stronger the observed correlation between risk and rewards in their group. However, no similar effect is found for the setting with competitive incentives.*

Column 5.D includes the distance and correlation variables and their respective interactions with the indicator for competitive rewards. The coefficient estimates for the correlation variable and its interaction with the indicator for competitive incentives are similar in sign, magnitude and statistical significance to the results in column 5.C. The coefficient estimates for the distance to the highest scorer are not statistically significant for subjects' facing non-competitive rewards, and the effects of changes in the distance to the low scorer is not statistically significant under either compensation scheme. However,

the effect of changes in the distance to the highest scorer is statistically significant with competitive rewards ($p < 0.10$).

Column 5.E includes the measure of the correlation between risk-taking and scores and the number of forecasts made by the best- and worst-scoring members of each group in block 1. In this specification, a higher highest score in the previous block is associated with more risk-taking ($p < 0.10$). Coefficient estimates on the correlation measure and its interaction with the indicator for competitive rewards are both statistically significant ($p < 0.01$ and $p < 0.05$, respectively). We can interpret the coefficients to compare competitive and non-competitive incentives treatments. When the correlation coefficient is -1 (an incorrect characterization of the relationship between risk and score) or 0 (no obvious relationship), there is more risk-taking in the competitive compensation treatments relative to the non-competitive treatments; however, when the correlation coefficient is 1 (a correct characterization of the relationship), competitive incentives are associated with less risk-taking.

Similar to the within-subject analysis discussed briefly in Section 5.4, we examine the difference between a subject's risk-taking in the first and second block in treatments with no peer information and information on peers' strategies and scores. Regressing the change in risk-taking on the indicators for peer information and competitive rewards, and their interactions, along with the controls for first block risk-taking and luck, we identify how a subject's risk-taking is affected by learning not just that he or she has either the highest or lowest score but also information about *why* they lead or lag their group. In contrast to the treatments with information about peers' scores only, the risk-taking of subjects who learn that they are the highest- or lowest-scorers in their group does not change in a statistically significant way. This is consistent with the results in columns 5.B and 5.D, where the risk-taking in treatments with feedback about peers' strategies and scores appears unaffected by subjects' relative position in the group.

In the text responses to the follow-up questions, 70% of the subjects claimed that their strategy changed over the rounds of the experiment (question (ii)). Approximately 35% of the subjects wrote that these changes occurred after observing peers' risk-taking and scores, with 8% (15%) of the subjects stating that they switched to a safer (riskier) strategy (question (iii)). However, when asked directly in question (iv), nearly no subject indicated that he or she imitated other players' strategies. This pattern of responses did not vary between the competitive and non-competitive treatments.

6 Discussion and conclusion

In this paper, we explore the effect of incentives and peer information on risk-taking in a complex forecasting task. In the field, excessive risk-taking is often attributed to competitive incentives *per se*. Our results suggest that the relationship between incentives and risk-taking is more nuanced and depends critically on both the availability and the nature of peer information to which decision-makers are exposed. Specifically, we observe that, in the absence of peer information, subjects take less risk in a setting with competitive incentives than in a setting with non-competitive incentives. At the same time, in the presence of peer information, subjects take more risk under competitive incentives.

Our baseline finding that competitive incentives lead to less risk-taking without peer information is somewhat surprising and reinforces the notion that the basic prediction of tournament theory may be sensitive to many features of the environment, including the type of task and available information. In our experimental setting, the more cautious behavior of subjects under competition without feedback may be attributed to the complexity of the environment, underconfidence, and the fear of being last in the three-level prize structure: Without knowing what their peers are doing, subjects may be underconfident when completing difficult tasks due to "reference group neglect" (Moore and Cain, 2007) and, combined with the fear of being last (Dutcher et al., 2015), subjects may be more inclined to make low-risk choices. This baseline result makes the positive effect of competitive incentives on risk taking in the presence of peer information even more striking as it reverses the baseline predisposition of subjects to respond to competition cautiously in our setting.

In the presence of peer information, regardless of its type, most subjects observe that their strategies and/or outcomes are not that far off from their peers'. Peer information, therefore, may reduce subjects' underconfidence and their concerns about a last-place finish. Overall, feedback about others may serve as a simple mechanism that restores "normal" attitudes to competition and, as a result, leads to more risk-taking under competitive incentives.

While the effect of incentives on risk-taking does not seem to depend systematically on the type of peer information (as long as it is present), different types of information affect differently the levels of risk-taking keeping incentives fixed. Under individual incentives, subjects take less risk, as compared to the no-feedback baseline, when provided with information about peers' strategies or outcomes separately, but not when provided with both. In the cases of information on strategies or outcomes only, subjects do not seem to be reacting to the content of the feedback in any imitative manner. In the case of feedback on strategies, they do not imitate the highest, lowest or median levels of risk-taking, nor

do they converge to the mean. In the case of feedback on scores, subjects' behavior is not affected by the distance to their group's highest or lowest score. Both types of partial information are not particularly useful and may reaffirm subjects' impression that the game is complex and noisy; in the case of non-competitive incentives, partial information reduces risk-taking. At the same time, when the combined feedback on peers' strategies and scores is provided, subjects react correctly to the correlation between the observed risk-taking and scores and, as a result, do not reduce their risk-taking relative to the no-feedback case.

Under competitive incentives, there is no effect of peer information on risk-taking when only peers' strategies are provided. However, in the case of feedback on peers' outcomes subjects react to the payoff-relevant distances between their score and the scores of the top and bottom performers in their group. Risk-taking increases in either of the two distances keeping all else fixed. At the same time, when combined information is provided, unlike in the case of individual incentives, subjects do not react to the correlation between the strategies and outcomes of their peers.

In all treatments, subjects react positively to luck, defined as the difference between a subject's score and the theoretically expected score given his or her strategy in the first block. The effect of luck is asymmetric: If a subject takes a lot of risk and gets lucky, there is little room to increase risk-taking further; if that same subject is unlucky, he or she can take substantially less risk. Similarly, if a subject takes very little risk and is unlucky, there is no room to reduce risk-taking; if the same subject is lucky, there is room to take much more risk. Of course, the difference is that the variance of score is much higher for high levels of risk. That is, subjects are much more likely to be lucky or unlucky (and the amount of good or bad "luck," as defined above, is likely to be larger) if they take more risk. Therefore, the effect of prior luck on risk-taking is driven primarily by the reduction in risk taking by the unlucky high-risk subjects.

Some insights into the effects of peer information can be gained by analyzing subjects' responses to the open-ended questions at the end of the experiment. Interestingly, a substantial number of subjects state that they changed behavior after observing their peers. As one would expect, the lowest number of such subjects is observed in the case of feedback on strategies only, whereas the highest number is observed when the combined information is provided. At the same time, almost no subjects claim that they imitate anyone in particular. Taken along with the empirical results, subjects' written responses suggest that peer information is interpreted in an aggregate, inferential manner, as opposed to a tool for simple imitation.

We conclude that although incentives can be a powerful driver of risk-taking behavior,

peer information is also important—it is the interaction of the two that leads to the highest levels of risk-taking in our environment. More broadly, our results suggest that excessive risk-taking in, for example, the financial sector may be the combined result of incentives, culture, norms, and the feedback received by the decision-makers. The nature of the information clearly matters, as it shapes decision-makers' understanding of the sources of success in a noisy environment. Of course, selection may distort the availability of information in the field and spur increased risk-taking. In many settings, success stories are more likely to be propagated; in high-variance environments in which success has a large random component, this selection may lead to excessive risk-taking.

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A Experimental instructions

Instructions for Part 1a

In this task, your decision will generate a set of 20 choices between a lottery that will be referred to as "Urn A" and sure amounts of money. After you have made your decision, one of the 20 choices will be selected randomly and played.

Urn A contains 20 balls, 10 of which are green and 10 are red.

If your preference in the choice that turns out to be actually played is Urn A, you earnings will depend on your guess about the color of a ball randomly drawn from Urn A. If you guess the color correctly, you will earn $2.00. If you guess the color incorrectly, you will earn zero.

If your preference in the choice that turns out to be actually played is a sure amount of money, you will earn that amount of money.

On the screen, you can see all the 20 choices. This is practice screen, and all buttons are now inactive. Urn A is on the left, and the sure amounts of money ranging from $0.10 to $2.00 are on the right. Notice that the sure amounts increase from top to bottom. Thus, you should only decide on a line where you would like to SWITCH from preferring Urn A to preferring a sure amount.

When you click on the corresponding SWITCH HERE button, Urn A will be your choice everywhere above that line, and a sure amount of money will be your choice everywhere below that line. All the 20 choices that you generate will be highlighted. If you want to change your decision, simply click on another SWITCH HERE button. When you are ready to finalize your decision, click SUBMIT.

You will be informed about your earnings from this part of the experiment at the very end of the session today, after you have completed all parts of the experiment.

Are there any questions before you begin making your decisions?

Instructions for Part 1b

In this task, your decision will generate a set of 20 choices between a lottery that will be referred to as "Urn B" and sure amounts of money. After you have made your decision, one of the 20 choices will be selected randomly and played.

Urn B contains 20 balls that are either green or red. The exact numbers of green and red balls are unknown to you.

If your preference in the choice that turns out to be actually played is Urn B, earnings will depend on your guess about the color of a ball randomly drawn from Urn B. If you guess the color correctly, you will earn $2.00. If you guess the color incorrectly, you will earn zero.

If your preference in the choice that turns out to be actually played is a sure amount of money, you will earn that amount of money.

On the screen, you can see all the 20 choices. This is practice screen, and all buttons are now inactive. Urn B is on the left, and the sure amounts of money ranging from $0.10 to $2.00 are on the right. Notice that the sure amounts increase from top to bottom. Thus, you should only decide on a line where you would like to SWITCH from preferring Urn B to preferring a sure amount.

When you click on the corresponding SWITCH HERE button, Urn B will be your choice everywhere above that line, and a sure amount of money will be your choice everywhere below that line. All the 20 choices that you generate will be highlighted. If you want to change your decision, simply click on another SWITCH HERE button. When you are ready to finalize your decision, click SUBMIT.

You will be informed about your earnings from this part of the experiment at the very end of the session today, after you have completed all parts of the experiment.

Are there any questions before you begin making your decisions?

Instructions for Part 2

<u>The scenario</u>

Imagine that you are a financial analyst hired by an investment company to make projections about the future performance of particular stocks. Your job is to assess whether a company's stock price next year will be HIGHER or LOWER than the current price. You are assigned one project at a time and are paid based on the volume and accuracy of your forecasts – your employer rewards you for correct forecasts and punishes you for incorrect forecasts.

You make your forecasts based on information that you can gather about the companies in question. Each piece of information provides a signal about the true direction of the stock price, suggesting that it is either going to be higher or lower next year. No single signal tells the full story; however, the more signals you observe the more confident you may be about whether the stock price will be higher or lower.

Recall that you are paid based on the *volume* and the *accuracy* of your forecasts. The challenge that you face is that gathering lots of information can improve the accuracy of your forecasts, but means that you cannot do many assessments. Making forecasts with a small amount of information means that you can complete many projects, but these assessments may not be very accurate.

Decision sequences

This part of the experiment will consist of several decision sequences. At the end of the experiment, one of the sequences will be randomly chosen and your actual earnings will be based on that sequence.

Sequence 1

Task

On the screen, you will be presented with 15 blank cards. Each card, when flipped over, is either GREEN or RED. The color of the card was determined randomly, and each of the two colors is equally likely.

Your task is to predict the *majority color* of the 15 cards (hidden and revealed). At least 8 of the 15 cards are going to be of one color, GREEN or RED. If 8 or more cards are GREEN, then the majority color is GREEN; if 8 or more cards are RED, then the majority color is RED.

At the bottom of the screen, you can submit your forecast of whether the majority of the 15 cards (hidden and revealed) are GREEN or RED.

Before you make a forecast about the majority color, you should choose how many cards, **between 5 and 15**, you want to flip to reveal their color. After you make a forecast, all cards will be revealed and you will be informed whether your forecast was correct or not. You will then be given the next task.

In this sequence, you will be allowed to flip a **total of 100 cards**. How many cards you flip before each forecast is up to you. The counter in the upper part of the screen will tell

you how many cards you have left to flip in this sequence. It starts with 100 cards and counts down. New tasks will be generated randomly until the counter of 100 cards runs out.

Note that you should reveal 5 or more cards for each forecast. Towards the end of the sequence when you nearly exhaust all of your 100 cards, you will not be allowed to reveal a number of cards such that the remaining number of cards is less than 5.

At the end of the sequence, you will be provided with a summary of your decisions and forecasts.

Score and payoff
Your performance score in this sequence will be based on the net number of correct majority color forecasts calculated as

Score = (# of correct forecasts) - (# of incorrect forecasts).

For example, if you make 3 correct forecasts and 1 incorrect forecast, your score would be $3 - 1 = 2$.

Your payoff from this sequence is **your score times $1.50**. Recall that there will be several sequences, and only one of them will be chosen at the end of the experiment for your actual earnings.

Are there any questions before you begin?

You will now start the actual decision rounds. Please do not communicate with other participants or look at their monitors. If you have a question or problem, from this point on please raise your hand and one of us will assist you in private.

The following instructions are shown on the screen in PIECE-RATE treatments after the first block is completed.[26]

This is the end of Sequence 1.

The next sequence is about to begin.

In this sequence, you will belong to the same group of 5 participants as in the previous sequence.

[26]The same instructions (with a different sequence number) are shown on the screen after blocks 2 and 3.

The following instructions are shown on the screen in TOURNAMENT treatments after the first block is completed.[27]

This is the end of Sequence 1.

The next sequence is about to begin.

In this sequence, you will belong to the same group of 5 participants as in the previous sequence.

Note the change in how your payoff will be calculated.

You will be ranked in your group based on your score, with rank 1 corresponding to the highest score, and rank 5 to the lowest score. Ties will be broken randomly.

Your payoff will be calculated as follows:
Payoff = \$2.50 $\times$ score, if your rank is 1
Payoff = \$1.50 $\times$ score, if your rank is 2, 3 or 4
Payoff = \$0.50 $\times$ score, if your rank is 5

[27] The same instructions (with a different sequence number), with the exception of the sentence in bold, are shown on the screen after blocks 2 and 3.