

# Informational Difference and Performance: Experimental Evidence

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## Abstract

This paper provides experimental evidence on how informational differences may translate into performance differences in competitive environments. In a laboratory tournament setting, we manipulate beliefs about the effort-reward relationship by varying how much information people receive on the potential impact of luck on outcomes. We find that an informational disadvantage worsens the understanding of the effort-reward relationship, and significantly lowers performance. Our study is inspired by informational differences in the labor market where some individuals have less data on the determinants of economic success than others—due to social networks or the availability of similar others to learn from. (JEL C91, D81, M50)

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# 1 Introduction

People differ in the degree to which they attribute economic outcomes to effort and luck. For example, Europeans are more likely than Americans to believe that luck, rather than effort or education, determines income (Mesina et al. 2001), and similarly women are more likely than men to attribute success to luck (Fisman and O’Neill 2009). In addition, differences in information may affect how people perceive the effort-reward relationship. Specifically, some individuals might have more precise information on the determinants of economic success at their disposal than others, depending on how many people they have available to learn from.

The number of similar others seems crucial for such information transmission. For example, in organizations, the demographic mix determines the set of comparable others. Role models and mentors tend to have the same demographic characteristics as their mentees (e.g., Holmes and O’Connell 2007; Ibarra 1992, 1993; Ragins 1999 for a review). Country-of-origin or same-language social networks facilitate job seeking (Edin et al. 2003, Munshi 2003), business relationships (Jackson and Schneider 2010), as well as the participation in welfare and social programs (Bertrand et al. 2000, Figlio et al. 2011). Information derived from a smaller sample will likely be less precise, i.e., have a higher variance, than when derived from a larger sample, potentially creating an informational disadvantage for members of smaller groups.

We conduct a laboratory experiment inspired by such labor market realities where some individuals have less information on the determinants of economic success than others. We assign information conditions randomly, and form two groups that differ in the amount of information they receive on the effort-reward relationship. The effect of such informational differences on performance is measured in a competitive setting. Similar to Orrison et al. (2004), we view (promotion) tournaments as an essential incentive device in modern hierarchical organizations. In tournaments, the impact of informational differences on performance also depends on whom people compete with and what they know about their competitors. To this end, we theoretically and experimentally examine competition between equally informed as well as between differentially informed agents.

In the experiment, performance was measured in a real-effort task, namely by the number of words found in a word-find task, where subjects were assigned to pairs and competed against their anonymous counterpart for a tournament prize. Tournament outcomes were determined by both individual effort and a random bonus component. We created two information conditions regarding the bonus component and, thus, the effort-reward relationship: one group received information from

a large sample of data, and another group received information from a small sample. Depending on the information condition, a person was either well or poorly informed on the potential impact of the random component on tournament outcomes, and competed either with an equally or with a differentially informed counterpart. We conjecture that individuals that are better informed on the role of the luck component for economic success will exert more effort.

Experimental participants receiving less information on the effort-reward relationship indeed perceived the variance of their bonus component to be larger, and subsequently performed worse than better informed participants. Furthermore, the performance of an informationally disadvantaged agent was particularly depressed when competing with a better rather than an equally informed counterpart. This suggests that information potentially affects performance through two channels: by affecting how well agents understand the effort-reward relationship and by creating “informational injustice” that additionally discourages the disadvantaged from exerting effort.

Our work contributes to earlier experimental studies examining the role of uncertainty and information on individual performance in competitive environments, which is not conclusive. Bull et al. (1987) and Freeman and Gelber (2010) varied the amount of information on the past performance of competitors that their experimental subjects had available. For a hypothetical effort task, Bull et al. (1987) reported that subjects who were informed of their counterparts’ decisions after each round exerted less effort than those who did not receive any information. In contrast, Freeman and Gelber (2010) who used a real-effort task (mazes) found that providing more information on the historical performance of competitors led to higher effort on average. In both cases, the uncertainty about the effort-reward relationship was influenced by the amount of information subjects had available on their competitors’ past performance, making best-responding a difficult problem, as past performance may not necessarily map directly into future performance and responses are interdependent. We vary information exogenously – unlike, for instance, Celen and Hendman *forth.*, who allowed their subjects to costlessly acquire information about the decisions of predecessors – and independently of subject performance, enabling us to determine the impact of the perceived importance of luck on effort. In our setup, informational differences result from differences in sample sizes, which – in addition to mimicking labor market reality – is an intuitive way to communicate differential degrees of uncertainty to subjects.

The remainder of the paper is organized as follows. In Section 2, we discuss the theoretical framework, and derive hypotheses for our experiment. The experimental design is presented in Section 3. Section 4 reports the experimental results, and Section 5 concludes.

## 2 Theoretic Framework

We model effort choices among competing agents using a tournament-theoretical framework (Lazear and Rosen 1981). We propose a setting in which two agents compete against each other. They belong either to the better informed group receiving a **large** data sample or the worse informed group with a **small** data sample. Each agent can control the mean of the output distribution through means of effort exertion, which is costly ( $C(\cdot) > 0$ ). Furthermore, a stochastic luck component  $\epsilon$  is realized. This leads to the following observable output:

$$q_i = \mu_i + \epsilon_i; i = L, S \quad (1)$$

here **L** and **S** stand for two different agents with a large and a small data sample, respectively.

In this rank-order tournament, agent **L** differs from agent **S** in the perceived distribution of the luck component, so that **L** is better informed about the effort-reward relationship. As in the experiment, we distinguish between two cases: we compare the performance of **L**- and **S**-players when each type of player either assumes to compete with an equally informed counterpart, or assumes to compete with a differentially informed counterpart.

### 2.1 Heterogenous Beliefs under the Assumption of Identical Information

Our general setup is akin to that in Lazear and Rosen (1981). The specificity of our model lies in the beliefs of **L** and **S**:

Agent **L** believes all luck components to be independent s.t.  $\epsilon_{L/L} \sim N(0, \frac{\sigma^2}{L})$  and  $\epsilon_{S/L} \sim N(0, \frac{\sigma^2}{L})$

Furthermore, the following general assumptions apply:

We consider a single tournament round.

The cost function  $C(\cdot)$  is quadratic and not a source of agent heterogeneity.

The firm derives a marginal social return  $V$  from each unit of effort that an agent exerts, and acts in a perfectly competitive market.

We denote the tournament prize spread by  $W = W_1 - W_2$  where  $W_1$  and  $W_2$  are the winner and loser prizes, respectively.

Before we move to the analysis of the game, we introduce the notion of a performance gap in this tournament.

**Definition** A performance gap exists if  $L \notin S$ .

If equilibrium effort choices differ between agents, and  $W > 0$ , this results in a performance gap, as different levels of effort exertion imply different probabilities of winning the tournament. The probability of winning the tournament is equal to:

$$\text{prob}_i(q_i > q_j) = \text{prob}_i(\epsilon_j > \epsilon_i) \quad (2)$$

where  $i \in j$ .

Given the above-mentioned distributional assumption,  $E[\epsilon_j - \epsilon_i] = 0$ , with the variance depending on the beliefs of the respective player ( $L, S$ ). If  $\frac{2}{L} < \frac{2}{S}$ , agent  $S$  underestimates the impact of effort on actual performance. As we shall see, the equilibrium investment in effort is a function of  $\text{prob}_S(q_S > q_L) = g(S - L)$  for  $S$  and  $\text{prob}_L(q_L > q_S) = h(L - S)$  for  $L$ . Here,  $g(S - L)$  and  $h(L - S)$  are the probability density functions of a normal distribution with zero mean and variance  $2 \frac{2}{S}$  and  $2 \frac{2}{L}$ , respectively, so this is the channel through which the perceived variance of the luck component impacts effort choice.

From Lazear and Rosen (1981) we know that a decrease in the precision with which the agents understand the effort-reward relationship leads to reduced effort provision by risk averse agents. In the case of risk neutrality, however, this effect could be offset by an increase in the prize spread, assuming homogenous agents. Hence, in Lazear and Rosen (1981), for risk neutral agents with homogenous beliefs about the error term, the optimum investment in effort does not vary with the variance of the luck component.

Given that in our model we have two types of agents with heterogeneous beliefs, this result does not hold. Prize spreads cannot be optimally adjusted for both groups at the same time, and thus, even under risk neutrality, we expect a worse understanding of the effort-reward relationship to result in less effort. Accordingly, we assume risk neutrality, and continue with the analysis of the game.

Unlike agent S, agent L perfectly observes the variance (this assumption can be relaxed, as we simply require L's belief to be closer to the firm's reality than S's belief), but both agents assume identical information conditions, i.e.,  $\pi_{x,y}$  and  $\pi_{y,y}$  for  $x, y \in \{L, S\}$ ,  $x \neq y$  have the same distribution. In this setup, a performance gap follows from Lazear and Rosen (1981). The proof of the following proposition is in Appendix A.

**Proposition 1** If  $\sigma_L^2 < \sigma_S^2$  and both agents assume that each of them faces identical information conditions, a performance gap exists s.t.  $s_S < s_L$ .

Agent S does not invest efficiently and  $s_S < s_L$ , i.e., the equilibrium investment in effort of L is greater than that of S. This is due to the fact that S underestimates the responsiveness of pay to effort, whereas L knows the correct distribution of the luck component. Hence, there is a performance gap in equilibrium, and S is less likely to win the tournament than L.



that  $\sigma_S < \sigma_L$  as long as  $W_2 < \frac{4}{L} \ln \frac{e_S}{L} \frac{P}{V}$ , and both agents invest inefficiently. With full updating and  $e_S^2 = \frac{\sigma^2}{L}$  for  $S$ , the performance gap vanishes.

### 2.2.2 Informational Injustice and Fairness Considerations

Given our proposed information conditions (with one group being worse informed than the other), it is conceivable that particularly the informationally disadvantaged agents might deviate from the behavior laid out above, and – instead of acknowledging that their perceived variance of the luck component is an upper bound – feel discouraged, which could in turn lead to a worsening of the perceived effort-reward relationship. That is, the informationally disadvantaged group could implicitly derive disutility in the form of a **higher** perceived variance of the luck component, discouraging effort and therefore smothering economic prospects. For simplicity, we assume that  $L$  does not exhibit positive inequity aversion (which is an extreme case of the typical assumption that agents care more about negative than about positive inequity). Then, denote by  $\sigma_S$  agent  $S$ 's perceived variance incorporating the option to rationally update her beliefs, but adjusted by a penalty (leading to a higher variance) due to negative inequity aversion:

$$\begin{aligned} \sigma_S^2 &= \frac{\sigma^2}{L} + \max\left(\frac{\sigma^2}{S}, e_S^2; 0\right) - \max\left(\frac{\sigma^2}{S}, e_S^2; 0\right) \\ &= \frac{\sigma^2}{L} + (\alpha) \max\left(\frac{\sigma^2}{S}, e_S^2; 0\right); \end{aligned} \quad (3)$$

here  $\alpha \in \mathbb{R}^+$  are weights for negative inequity aversion and rational variance correction, respectively, and  $\frac{\sigma^2}{L} e_S^2 < \frac{\sigma^2}{S}$  with  $e_S^2$  as  $S$ 's updated estimate of the actual variance  $\frac{\sigma^2}{L}$ .

We have already covered the cases here in Proposition 2a, so we are left with  $\alpha > 0$ , which implies that  $\sigma_S^2 > \frac{\sigma^2}{L}$ . In the next proposition, we demonstrate that even with full updating the performance gap persists if  $S$  exhibits negative inequity aversion and  $L$  does not take it into account. This setup can be interpreted as follows:  $S$  has a small data sample suggesting some  $\frac{\sigma^2}{S} > \frac{\sigma^2}{L}$ , but – given that she realizes that her perceived variance of the luck component is an upper bound – fully updates her beliefs to  $e_S^2 = \frac{\sigma^2}{L}$ .  $S$  exhibits negative inequity aversion because she knows that the provided information is less precise. This leads to the following proposition, with the corresponding proof in the Appendix.

**Proposition 2b** If  $\frac{\sigma^2}{L} < \frac{\sigma^2}{S}$  but (1) the players fully update their beliefs such that  $e_S^2 = \frac{\sigma^2}{L}$



As in Section 2.2.1, the long-run tendency of the performance gap will be to shrink when  $L$  becomes a large fraction of  $S$ .

can be larger when the agents are aware of the informational differences than when they assume identical information conditions.

one person per pair received information on the large sample and the other person in the pair received information on the small sample, and this was common knowledge. We refer to this as **different-information tournament**.

After an initial practice round, the task was repeated four times (with a different letter matrix and word list in every round). Subjects remained in the same pair for the duration of the experiment. In rounds 1 and 2, subjects were confronted with a wide range of potential bonus values from 0 to 100. In rounds 3 and 4, we decreased the range of bonus values by limiting them to be between 30 and 70. Performance is likely responsive to both experience with the task and the range of potential bonus values (as predicted by the theory). At the end of each round, subjects were informed of their task score, their final score, their counterpart's final score, and the tokens they won. They did not receive information on their counterpart's task score, and were thus unable to determine with certainty whether they won/lost because of their counterpart's performance or the random draw on bonus. As an example, Appendix B provides the instructions for **S**-players in the different-information tournament.

Besides the subjects' performance on the word-find task, we collected three additional pieces of information.

for a study that lasted one hour.

We ran the experiments in the Harvard Decision Science Laboratory in the spring of 2010. 20 subjects participated in nine sessions with 22 or 24 subjects in each of them, and we have valid score data for 812 individual outcomes.<sup>5</sup>

## 4 Results

We first report descriptive statistics. Then, we examine our central prediction, Implication 1: agents who are provided with a smaller sample of information on possible bonus values (**S**-players) perform worse than their counterparts with more precise information (**L**-players), and this effect is due to the perceived variance of the bonus component. Finally, we test Implications 2a and 2b, i.e., whether the performance gap varies depending on whether subjects assume identical information conditions (in the identical-information tournament) or are aware of informational differences (in the different-information tournament).

[Insert Figure 1 about here]

On average, subjects found 10.13 words (with a standard deviation of 3.88) out of a total of 20 words available in a given letter matrix. Women and men differed slightly in their performance, with women marking 10.35 words correctly and men finding 9.78 words on average ( $p < 0.05$ ). This difference was entirely driven by performance in the first round, and women and men did not differ at all in their performance in the remaining three rounds. Figure 1 presents the distribution of the number of words people found in the pooled sample. Typical outcomes ranged from 5 to 15 words per matrix. Four participants, i.e., roughly 2% of our subjects, found the maximum of 20 words in at least one round.

Examining Implication 1, we first review differences in the mean number of words found by **L**- and **S**-players. Table 1 reports the data pooled across both treatments (cf. first panel) and separately for each treatment condition (cf. second and third panels). Within each panel, in the first row we present performance levels aggregated over all four rounds, in the second for the wide-range rounds (rounds 1 and 2), in the third for the narrow-range rounds (rounds 3 and 4), and in the last row for the rounds where people had already gained one round's experience within a given range condition (rounds 2 and 4). **L**-players found about one word more than **S**-players on average ( $p < 0.01$ ).

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<sup>5</sup>We dropped all scores of a subject after incidents involving IT or other problems during the experiment, which explains the loss of 12 out of 824 outcomes.

[Insert Table 1 about here]

Considering identical-information and different-information tournaments separately in the second and third panels, the performance gap between **L**- and **S**-players is exacerbated in the different-information tournament. In the third panel, **L**-players found 1.3 cards more than **S**-players on average, which corresponds to an increase of one-third of a standard deviation. Experience increased the performance gap to 1.8 cards in rounds 2 and 4. On average (cf. first row of the second and third panels), the performance gap was mainly driven by **S**-players who performed significantly worse when competing against **L**-players rather than against identically informed counterparts ( $p < 0.05$ ). In contrast, the better informed group was not differentially affected by the two treatment conditions.

[Insert Table 2 about here]

People's scores improved over time, but no clear learning pattern is observable (see Table 2, which presents mean scores by round). In particular, scores decreased between rounds 2 and 3 for **S**-players in the identical-information and for **L**-players in the different-information tournament, refuting simple learning but suggesting the existence of adjustment costs to the new bonus range in round 3. We do not assign particular importance to this, other than noting that learning alone cannot explain the dynamics we observe. On average, performance levels were significantly higher in the narrow-bonus-range rounds 3 and 4 as compared to the wide-range rounds 1 and 2, which

Subjects reported the range to be 0.50 (with perceived, normalized mean bonus values of 0.51 and 0.45, respectively).<sup>7</sup> To more easily interpret the effect on performance, we include **1**

Having shown that informational differences impact performance through the perceived variance of the bonus component, we now discuss Implications 2a and 2b, namely whether the performance gap shrinks or widens when informational differences are public information. Based on the theoretical discussion in Section 2.2, we hypothesize that the difference in perceived variance in the different-information tournament is not the same as the one in the identical-information tournament.

Given the mean scores in Table 1, informational injustice and fairness considerations (as in Implication 2b) might affect performance directly rather than through a rational understanding of the effort-reward relationship.

to perceived informational injustice, leading to a larger performance gap in the different-information than in the identical-information tournament, is supported.

[Insert Table 4 about here]

In order to explore whether there is an differential impact of the different- vs. identical-information treatment operating directl through the sample sizes rather than indirectl through **Perceived range** e also consider the reduced-form estimation (i.e., regressing scores on the large-sample indicator and the remaining variables included in Table 3a) in Table 4 . Columns 1 to 3 demonstrate that our results regarding Implication 1 are robust to the inclusion of multiple controls: **L**-players outperformed **S**-players overall. Column 4 shows that while **L**-players outperformed **S**-players in the different-information tournament (the sum of the coefficients of Large sample and Large sample Different info is significant at the 2 level), the performance difference – albeit positive – does not significantl exceed that in the identical-information tournament. Thus, rational updating in the absence of negative inequit aversion is unlikel to explain our findings, as the performance gap is not smaller in the different-information than in the identical-information tournament. Either the two channels of influence discussed in Propositions 2a and 2b do not matter, or they cancel each other out.

## Concluding remarks

This paper explores the impact of noise in people’s perceptions of the effort-reward relationship on their performance in a tournament setting, and demonstrates how informational differences can translate into differences in performance. In our laboratory experiment, we implement a new mechanism to manipulate beliefs about the role of luck for tournament outcomes by varying the amount of information people received on the latter, building on the simple statistical idea that smaller samples are noisier than larger samples. We show that receiving more information on the role of luck improves the understanding of the effort-reward relationship, and leads to significantl better performance. This has broader implications, and could help explain how beliefs about one’s initial conditions may influence one’s future labor market outcomes.

Consider our findings in the context of a well-known labor market phenomenon, namely the (rigidity of the) underrepresentation of women in top management positions. Women only hold a small fraction of leadership positions in the corporate world (Bertrand and Hallock 2001). At the Fortune 500 companies in 2010, 2.4 percent of the CEOs, 14.4 percent of the executive officers, and



15.7 percent of the board members were female.<sup>11</sup> Most notably, women are also consistently more likely to attribute success to luck rather than individual effort (Fisman and O’Neill 2009).

Our paper suggests how this might be the case, and hints at a potential mechanism underlying the persistence of gender gaps at the top: when people (have to) source career-relevant information on the effort-reward relationship from similar others, women being in the minority in top management positions are at a disadvantage because the size of the group of similar others determines how precise the information received is. As a consequence, women might end up overestimating the importance of luck in the effort-reward relationship and, thus, put forth less effort in the workplace. This in turn affects their likelihood of success under performance pay schemes and eventual promotion in an organization.

The theoretical framework in this paper fits gender imbalances in organizations quite nicely, as gender gaps are most pronounced in senior positions characterized by competitive work environments where managers are involved in promotion tournaments with substantial uncertainty about how effort translates into rewards. As in our model, promotion tournaments involve unique prize schemes, e.g., wages are often defined for different career stages and hardly vary among individual employees within a given slate. Tournaments tend to be particularly harsh at the top of the wage distribution, given that the loser prize typically decreases across the wage distribution. An extreme example is the up-or-out system implemented by firms in very competitive industries – e.g., consulting, investment banking, or legal practices – and in academia such that candidates below a certain percentile in the performance ranking are dismissed (corresponding to a loser prize of  $W_2 = 0$  in our model, which is reminiscent of Proposition 2a and the discussion in Section 2.2.1, where we have shown that an upper bound on  $W_2$  is a sufficient condition for a performance gap), while the remaining employees are promoted.

For our model to apply in this context, some aspects of career-relevant information must be gender-specific.<sup>12</sup> Informal accounts suggest this is the case. The scarcity of senior colleagues of the same sex puts female junior managers at a disadvantage: junior women “have inadequate information about acceptable (or successful) modes of behavior...” (Blau et al. 2005, p. 177). Similarly, Ibarra (1992, p. 7) argued that “organizational demography” constrains women’s available set of comparable others to learn from: “Women and minorities usually have a much smaller set of ‘similar others’ with whom to develop professional relationships based on identity-group homophily.” Such

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<sup>11</sup> <http://www.catalyst.org/publication/132/us-women-in-business>

<sup>12</sup> In addition, the career relevance of such information must be independent of whether the firm discriminates in any form against any group, or whether returns to information vary between groups, which seems plausible.

networks matter: examining the effectiveness of same-sex networks in a professional service firm where only a small minority of women held senior management positions, Ibarra (1993) found that men reaped greater benefits from their larger same-sex networks than women.

The patterns of behavior for the informationally advantaged and disadvantaged groups found in our experiment are compatible with other laboratory and field observations based on women and men. Gneezy et al. (2003) as well as Booth and Dolan (2009) present experimental evidence suggesting that the gender performance gap is particularly pronounced in mixed or male-dominated competitive environments as compared to same-sex competitions. Reminiscent of our findings, gender differences in performance were also driven by women – or, in our case, the informationally disadvantaged group – adjusting their behavior to the different environments: women performed better in same-sex than in mixed-sex competitions, while men’s performance was not affected by the gender composition (Gneezy et al. 2003). A similar pattern has been found in performance evaluations in an organization where women were in the minority, namely among officers in the Israeli military: women were evaluated more positively the larger their relative share in a group was, whereas men’s evaluations were invariant to the gender balance (Paz and Oron 2001). More generally, our findings relate to earlier work in sociology and political science, “critical mass theory,” suggesting the importance of relative group size for economic success (Kanter 1977).

Clearly, the gender balance in organizations may affect women’s and men’s productivity through a multitude of channels. For instance, a larger share of women in an organization might be correlated with a larger share of women in the talent pool of organizationally relevant professions, thereby increasing the firm’s economic benefits of adjusting working conditions to women’s needs (see Bertrand et al. 2010 for a discussion). In addition, an increased proportion of women in counter-stereotypical positions may also affect implicit biases, changing women’s and men’s beliefs about career trajectories (Beaman et al. 2009). More generally, differences in the evaluations of women and men based on the gender composition of the group are also compatible with statistical discrimination and information asymmetries where the employer is worse informed about the productivity of the minority group than of the majority group (Coate and Loury 1993), or where the minority group has invisible abilities (Milgrom and Oster 1987).

Our paper suggests an additional mechanism through which differences in performance, pay, and representation in leadership positions can emerge – informational differences due to the relative size of one’s group. Organizational demography may thus be an important determinant of the productivity, promotion likelihood, and pay outcomes of an organization’s employees.

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## Tables

**Table 1:** Differences in Mean Scores

Treatment	Rounds	Large sample (N = 102)	Small sample (N = 104)	Difference
All	All	10.37 [3.83]	9.32 [3.87]	1.005*** [0.27]
All	1 & 2	10.134 [3.59]	9.203 [3.2]	0.931*** [0.3]
All	3 & 4	11.14 [4.00]	10.03 [4.08]	1.083*** [0.40]
All	2 & 4	11.280 [3.9]	9.9 [4.05]	1.314*** [0.0]
Treatment	Rounds	Large sample (N = 46)	Small sample (N = 48)	Difference
Identical info	All	10.793 [3.85]	10.138 [3.90]	0.5 [0.40]
Identical info	1 & 2	10.231 [3.72]	9.800 [3. ]	0.431 [0.54]
Identical info	3 & 4	11.375 [3.92]	10.479 [4.11]	0.89 [0.0]
Identical info	2 & 4	11.231 [4.13]	10.505 [4.05]	0.72 [0.0]
Treatment	Rounds	Large sample (N = 56)	Small sample (N = 56)	Difference
Different info	All	10.509 [3.82]	9.205 [3.81]	1.304*** [0.3]
Different info	1 & 2	10.055 [3.50]	8.9 [3.52]	1.358*** [0.47]
Different info	3 & 4	10.94 [4.08]	9.714 [4.04]	1.249** [0.55]
Different info	2 & 4	11.321 [3.84]	9.509 [4.00]	1.812*** [0.53]

**Notes (Tables 1 and 2):** In the first two columns, standard deviations are in parentheses. The third column indicates the results of a two-sided difference-in-means test (with standard errors in parentheses) here \*/\*\*/\*\* denote significance at the 10 /5 /1 level, respectively.

**Table 2:** Differences in Mean Scores b Rounds

Treatment	Round	Large sample (N = 102)	Small sample (N = 104)	Difference
All	1	9.554 [3.57]	9.08 [3.48]	0.48 [0.27]
All	2	10.720 [3.54]	9.337 [3.75]	1.383*** [0.51]
All	3	10.439 [3.57]	9.524 [3.8 ]	0.915* [0.53]
All	4	11.840 [4.29]	10.02 [4.25]	1.238** [0.0]
Treatment	Round	Large sample (N = 46)	Small sample (N = 48)	Difference
Identical info	1	9.75 [3.4]	9.851 [3.2]	-0.09 [0.7 ]
Identical info	2	10.9 [3.78]	9.750 [3.73]	0.94 [0.78]
Identical info	3	10.953 [3.30]	9.81 [3.85]	1.273* [0.7 ]
Identical info	4	11.778 [4.43]	11.277 [4.2 ]	0.501 [0.91]
Treatment	Round	Large sample (N = 56)	Small sample (N = 56)	Difference
Different info	1	9.393 [3.54]	8.411 [3.25]	0.982 [0.4]
Different info	2	10.741 [3.35]	8.982 [3.77]	1.759** [0.8]
Different info	3	10.03 [3.75]	9.393 [3.89]	0.44 [0.73]
Different info	4	11.891 [4.22]	10.03 [4.20]	1.855** [0.80]

**Table 3a:** Determinants of Perceived Variance of Bonus Component (First Stage)



**Table 3b:** Determinants of Task Performance (Second Stage)

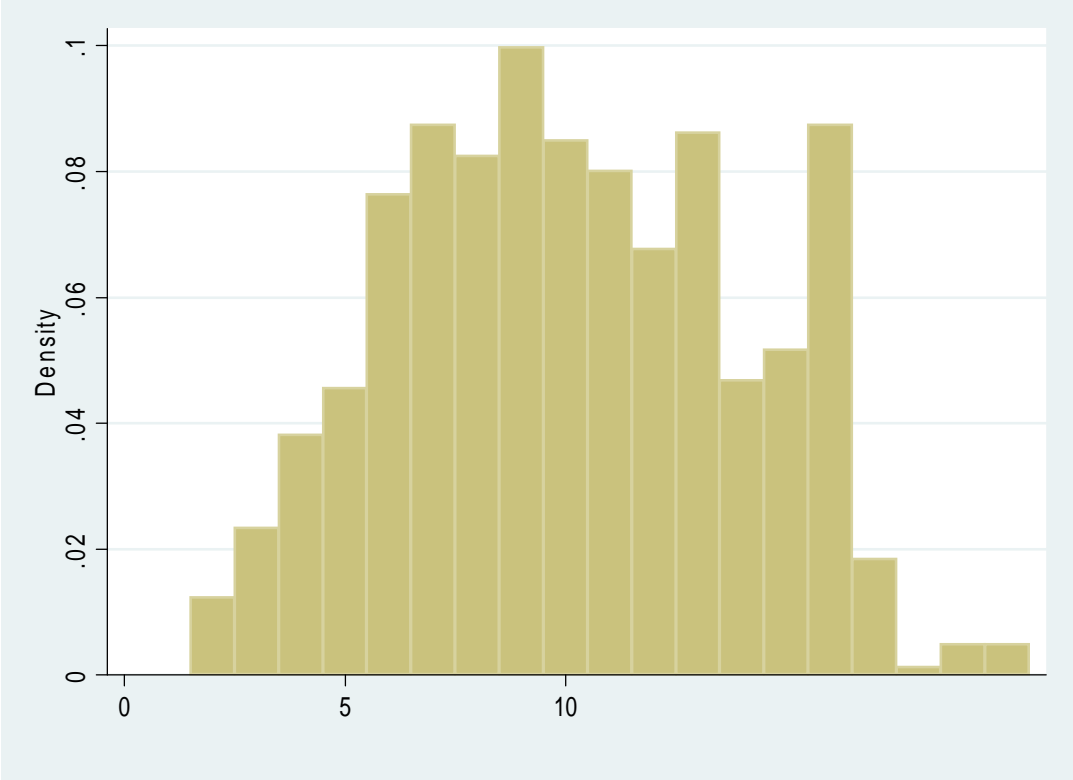
**Table 4:** Determinants of Task Performance (Reduced Form)

Dependent variable: <b>Score</b>				
Large sample	1.005** [0.45]	1.007** [0.45]	1.117** [0.51]	0.498 [0. 8]
Diff. info			-0.541 [0.48]	-1.179* [0. 7]
Large sample    Diff. info				1.217 [0.92]
Rounds 2 & 4		0.972*** [0.19]	1.080*** [0.21]	1.080*** [0.21]
Rounds 3 & 4		0.932*** [0.1 ]	0.771*** [0.19]	0.7 7*** [0.19]
Female			0.32 [0.49]	0.290 [0.49]
Student			1. 9 *** [0.5 ]	1. 02*** [0.5 ]
Constant	9. 32*** [0.34]	8. 79*** [0.34]		
Economic-background FE	o	o	Yes	Yes
Risk-aversion FE	o	o	Yes	Yes
# of observations	812	812	37	37

**Notes:** \*/\*\*/\*\* denote significance at the 10 /5 /1 level, respectively. In the linear regressions, standard errors are given in parentheses, and are clustered at the pair level. Self-reported economic

# Figures

Figure 1: Histogram of Scores (Pooled)



# Appendix A

## Proofs

Proof of Proposition 1 (follows from Lazear and Rosen 1981)      The optimum investment in effort  $e_i$  ( $i = L; S$ ) will be a function of  $W$ , the prize spread, and the variance of the net dose of bad luck ( $\sigma^2$ )

Recall that  $V$  depends on  $W$ , so the corresponding FOC is:

$$(V - C'(W)) \frac{\partial}{\partial W} = 0, \quad V = C'(W). \quad (4.9)$$

Combining (4.6), (4.7), and (4.9), one finds:

$$W = \frac{V}{h'(0)} = \frac{W_1 + W_2}{2 h'(0)}. \quad (4.10)$$

Given that  $C(\cdot)$

and  $L$ -players are unaware of this learning process on the part of the  $S$ -players, the performance gap is characterized by the difference  $h(l - s) - g(0) > 0$  here  $g(0) > g(0)$  and  $s < s$ , so the performance gap remains but becomes smaller.

With full updating,  $S$ -players will update their beliefs s.t.  $e_S^2 = \frac{2}{L}$ , and  $L$ -players will be aware of this, so that  $s = l = \dots$ .

**Proof of Proposition 2b**  $L$ 's beliefs reflect the standard Nash-Cournot case, whereas  $S$  – given her negative inequity aversion – feels discouraged and powerless, as reflected by a **higher** perceived variance of the luck component. Thus, the performance gap is characterized by the difference  $h(0) - \bar{g}(l - s)$  here  $\bar{g}(\cdot)$  is the probability density function of a normal distribution with variance  $\frac{2}{S}$  and  $s$  is  $S$ 's optimal effort given  $l$  and  $\bar{g}(\cdot)$ . Hence, as long as  $L$  knows that  $S$  is worse informed (but does not incorporate  $S$ 's inequity aversion), there will be a performance gap because  $h(0) - \bar{g}(l - s) > 0$ .

Finally, to see that the performance gap exceeds the one in Proposition 1:

$$p \frac{1}{4 - \frac{2}{S}} > p \frac{1}{4 - \frac{2}{S}} \exp\left(-\frac{(l - s)^2}{4 - \frac{2}{S}}\right) = h(0) - \bar{g}(l - s) > h(0) - g(0).$$

## Appendix B

### Letter Matrix (Example: Nations of the World)

B T U W T T B P M S K L L L T W Q N B V	ALGERIA
O O M E X J A E B K I D A M A R B H W Y	BELGIUM
F F H N G N G Y O M U H J I U T K U B W	CANADA
W C P I A Y L S T A K C S A R I V Y B P	EGYPT
S Z E M U T P E V I R T K Q P E G I M X	FINLAND
R A A A L S B T U U A Z Q D A A G L A Q	GREECE
D N A L A E Z W E N I X W D V O N L E F	HONDURAS
S B V V T W U A I R N X N J U W R I A B	INDONESIA
N G Y K H Y D F T B E A R C B V V X G H	JAPAN
S F T V A R Y B R L W Y A O I I N T M Y	KOREA
A G D D I M D G U R A U S E D E C J A U	LATVIA
R U W P L B G Z X G Q M T F M A J I X W	MALTA
U D B N A C O T S Z U N P E N U S D F H	NEW ZEALAND
D H N X N O I D B H A R Y A P E K I I U	PANAMA
N O C P D O M X V M G P D G N O N V R K	RWANDA
O Q L L J M H I B R A A H O R L Q T T R	SINGAPORE
H F B V G R E E C E M V D E A J Q B L P	THAILAND
A B I T L K P H C W B N A N P J P G U O	UKRAINE
C X Q U G I Z F V J I C D O Z K N T I V	VIETNAM
B W Y L D I S I N G A P O R E V I D K M	YEMEN

## Experimental Instructions

You are participating in a study in which you will earn some money. The amount will depend on how well you do in a task plus a bonus (described below). At the end of the study, your earnings (1 token = \$1) will be added to a show-up fee, and you will be paid in cash.

**Main task** We will show you matrices containing letters. Some letters appear in random order



**Calculation of payout** The person getting the higher final point score in our pair will receive 10 tokens. The person with the lower final point score will receive 2 tokens.

**How the study is conducted** It is conducted in five stages.

**Stage 1** You will be informed of the lowest and the highest possible bonus ( $X$  and  $Y$ ) contained in a given hat and the

**Specific instructions for how to mark the words** Once we start, you will see a letter matrix on our screen. You can highlight the words you find by marking them with our mouse. Your task is to mark as many correct words as possible. We will practice this in a trial round.