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More effort or better technologies?
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Abstract

Relative performance feedback (RPF) allows agents to compare their performance to that of others. Current theory assumes that RPF affects performance by changing the optimal level of effort. We introduce a *technology* channel in which agents use RPF to improve their technologies. We compare the effort and technology channels by combining three elements: an extensive review, an original model and two field experiments. Under the technology channel, we highlight that RPF increases performance even at the *bottom* of the distribution and has a *cumulative* effect across periods. We draw implications for education and social norms.

Keywords: Relative performance feedback, rankings, technology improvement, Education, Social Norms.

JEL Classification: D83, D84, D91

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1 Introduction

Relative performance feedback (RPF henceforth) consists of information, such as rankings, that enables individuals to compare their own performance to that of others. RPF is ubiquitous in the economy: employers provide information on worker's relative productivity, academics are able to compare themselves using publicly-available citation indices, the TripAdvisor website publishes rankings of hotels, students are sometimes told their rank as well as their grades, and so on. The effect of RPF on performance is, however, still open to debate.

We are specifically interested in what agents can learn from RPF in order to take optimal decisions. To date, the effect of RPF on performance has always been examined with the assumption that the only choice variable affecting performance is *effort*. We refer to this as the effort channel. The novel approach of this paper is to introduce the possibility that RPF may also trigger a change in *technology* by helping to identify better technologies. We refer to this as the technology channel.

Consider the example of a student competing in a selective University-entrance exam which takes place over several rounds. On the one hand, RPF gives her information about the payoff of her effort. If she learns that she is close to making the cut, she may work harder; if she instead learns that she ranks poorly, she may scale back her effort. On the other hand, RPF provides information about the quality of her (learning) technology. If she ranks badly, she may realize that there exist better technologies and change the way in which she prepares for the exams (e.g. studying in a group rather than alone), which may produce substantially better performance. The introduction of a technology channel in the analysis of the effect of RPF brings about a significant departure from the predictions of the effort channel, which should be particularly notable in situations in which technology likely has a large effect on performance. In what follows, we refer to these situations, in which agents can change to a better technology (and have the time necessary to do so), as having large *room for improvement*.

To assess the economic relevance of the technology channel, we combine three elements. First, we systematically *re-evaluate existing evidence* on the effect of RPF to establish whether the specific setting in each study has any scope for technological change, considering the task and the timing of feedback. We find that controlling for room for improvement allows us to make sense of otherwise conflicting evidence on the effect of RPF on performance. For instance, all of the analyses involving a task with room for improvement find a positive performance effect for low performers (while this effect is mixed when there is no room for improvement). Second, we *propose an original model* of technology improvement and contrast its predictions regarding the effect of RPF to those from a standard model of effort choice under tournament incentives. Last, since few experiments have been designed to compare the effect of RPF with and without room for improvement, we consider the results from *two experiments*: one in which the technology channel is shut down, so as to leave effort as the only active channel for performance improvement, and the other in which there is clear room for improvement. The first experiment uses a task (counting numbers) in which little technological improvement is expected. In contrast, the second experiment involves pupils who have to perform several math tests. The experiment took place over several weeks so as to allow improvement over time. Both experiments consist in comparing performance with and without RPF under tournament incentives.

Our main finding is that the three elements (review, model and experiments) complement each other and underline two important differences between the effort and technology channels. (1) The effect of RPF on low performers is strikingly different when there is room for technological improvement (while there are only small differences for top or average performers): in general, low performers benefit from exposure to RPF when there is room for improvement. On the contrary, the effect of RPF is expected to be zero or negative when technological change is not an option. The effect of RPF thus depends crucially on the availability of alternative technologies to carry out the task. (2) Repeated exposure to RPF produces a *cumulative* effect over time when there is room for improvement; In contrast, when effort is the only source of performance improvement the RPF effect is expected to be constant over time. The effect of repeated exposure has rarely been analyzed to date and, to the best of our knowledge, the present work is the first to explain why the effect of repeated exposure may depend on the room for improvement. While a complete analysis of the effect of repeated exposure to RPF is beyond the scope of the present paper, we nonetheless emphasize the dynamic aspect of feedback as a blind spot in the literature.

When should RPF be provided? Considering a technology channel, in addition to the traditional effort channel, suggests that the answer to this question should depend on the nature of the task to be performed (i.e. the possibility of technological improvement), an element that is so far absent from analysis. A clear argument can be made for the use of RPF in tasks with room for improvement. Our approach can explain the large performance improvement of low-ability students that is often documented in the empirical RPF literature. Rank feedback may indeed help students to improve their learning technology, and in particular those who initially rank poorly.[1] It is noteworthy that providing (private) RPF, for instance to students, entails a negligible cost.

The remainder of this paper is organized as follows. In Section 2 we review the empirical evidence on the effect of RPF on performance and show that we are able to organize this literature neatly by controlling for the room for improvement. Section 3 then reviews the existing theoretical models of the effect of RPF on performance, and presents our own model of technological change. In Section 4 we present the two experiments we carried out, which differ in their scope for technological innovation - i.e. the room for improvement. Section 5 concludes.

2 A review of the effect of RPF through the lens of the technology channel

In this section we review the empirical evidence on the performance effect of RPF. The novelty of this review is to distinguish between tasks with little room for improvement and those with greater scope for technological innovation. We show that the effort channel to be dominant when there is little room for improvement, while the technology channel becomes relevant when there is more room for improvement. We will present forest plots separating high and low performers, and show that RPF has strikingly different effects towards the bottom of the distribution.

[1] The results presented do not require that feedback be public. In particular, the feedback can be sent privately so as to avoid the effect of public shaming.

2.1 Paper selection

We consider all references in the extensive and very-recent review of Villeval (2020) on performance feedback. We select all of the contributions in this review that satisfy the following three conditions:

(1) The experiment includes a control group that does not receive any RPF. For instance, Genakos and Pagliero (2012) is not included as all subjects received an interim ranking, so that there is no control group without ranking.[2]

(2) There is a clear measure of performance. For example, Wozniak et al. (2014); Banerjee et al. (2018); Danz (2020) focus on the effect of RPF on competitiveness, rather than performance per se. We also exclude Ertac (2011); Mobius et al. (2011); Ertac et al. (2016); Zimmermann (2018), which focus on beliefs about performance. Jalava et al. (2015) is also excluded, as they look at the effect on performance of making rankings public and not the effect of receiving ranking information itself.

(3) The same incentive scheme is used in the control and treatment groups. We only include papers comparing the effect of RPF while holding the incentive scheme constant. Incentive schemes include tournaments, piece-rate, flat-rate, and so on. We exclude for example Casas-Arce and Martínez-Jerez (2009), who provide flat-rate incentives to the control group while the treatment group with RPF takes part in a tournament.

We are left with 42 papers after excluding those that do not satisfy all three criteria. As some of these include multiple treatments, our final analysis is of 66 different treatments, which are summarized in Tables A.1 to A.5.

2.2 Classification

(1) Incentive scheme. We sort the treatments according to the four incentive schemes subjects may face: piece rate, flat-rate, tournament, and grades.[3]

[2] Other papers excluded for the same reason are Gill and Prowse (2012); Buser et al. (2018); Haenni (2019).

[3] We consider grades separately, as the associated incentives are ambiguous. Grades may be equivalent to piece-rate incentives (when the individual's payoff increases proportionally to the grade), but may have a tournament aspect (when rank matters for future opportunities) or could work like a flat rate (when the student attaches little importance to them).

(2) Room for improvement We separate the treatments into two categories: little and large room for improvement. This depends both on the timing of feedback and the nature of the task that subjects carry out. While there is some degree of subjectivity in this classification, it is straightforward in most cases: it is unlikely that subjects can quickly change their technology to improve their performance when feedback is given with little or no time for adjustment. This is the case for subjects who see their competitors while running (Fershtman and Gneezy, 2011) or the scores of other participants while adding or multiplying numbers (Eriksson et al., 2009; Kuhnen and Tymula, 2012). On the other hand, there is greater room for improvement in tasks that are new to subjects, where there exist a number of potential technologies to complete the task, and when subjects have sufficient time to revise their technology (Azmat and Iriberri, 2010; Blanes i Vidal and Nossol, 2011; Tran and Zeckhauser, 2012).

We consider three outcome variables: the average effect, and the effect at the top and the bottom of the performance distribution. To enable comparisons across studies, results are normalized using Cohen's d-statistic. "Top" and "Bottom" are roughly defined, as it is not always possible to obtain information for the exact same sub-group (like, say, the top and bottom quartiles). Despite our best efforts, the definition of "top" and "bottom" does then vary across papers.

2.3 Results

We present three graphs that summarize the existing empirical evidence on the effect of RPF. A first result is that for top performers the effect is positive in most treatments. As can be seen in Figure 1, only two treatments find a significant negative effect with little room for improvement and one with large room for improvement. The incentive scheme does not appear to play a clear role. In contrast, room for improvement is associated with a larger and more-frequently positive effect of RPF.

An even sharper difference can been seen when we consider the bottom of the distribution in Figure 2. Intuition suggests that poor performers may be harmed by RPF, becoming discouraged and dropping out when they realize that they are performing poorly. This intuition may well hold when there is little room for improvement, and we see a significant share of experiments in which the effect is negative. In sharp contrast, when there is more room for improvement,

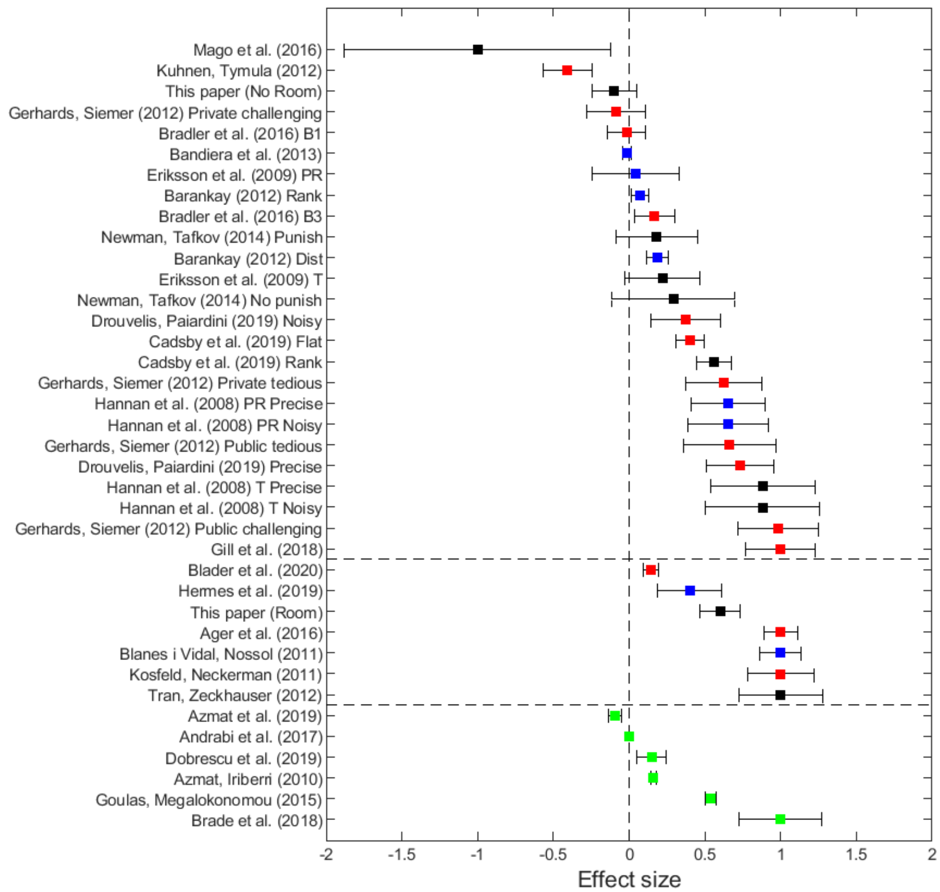


Figure 1: Forest plot of the effect of RPF at the top of the distribution

Note: Each square represents an effect size at the top of the performance distribution for each of the treatments, and the bars the confidence intervals. The colors represent the incentive schemes: flat (red), grades (green), piece-rate (blue) and tournament (black). There is little room for improvement in the treatments above the first dashed line, and large room for improvement below. The treatments are ranked by effect size in each category (room vs. no room for improvement). The grade treatments appear separately below the second dashed line. For visibility, the effect sizes are truncated to lie within the [-1,1] range.

the effect is always positive. We suggest that subjects benefit from RPF as they realize that there exist better technologies, which they can use to improve their performance. Again, while room for improvement appears to play a role, the incentive scheme does not have a clear and predictable effect.

We now consider the average effect of RPF on performance.[4] We observe, as in the previous figures, that the incentive scheme does not have a univocal performance effect. We also confirm that the RPF performance effect can be negative. The effect is more often positive when there is more as opposed to less room for improvement, although this gap is less marked for the average than for the top or bottom of the distribution.

Unfortunately, the existing evidence on the effect of RPF over a number of periods is too scarce to provide a clean picture. We contribute to the discussion about the cumulative effect of RPF, with or without room for improvement, in the Sections below.

[4]The overall distribution of performance is not simply the sum of the top and bottom effects in the previous figures, as we now include performance close to the median.

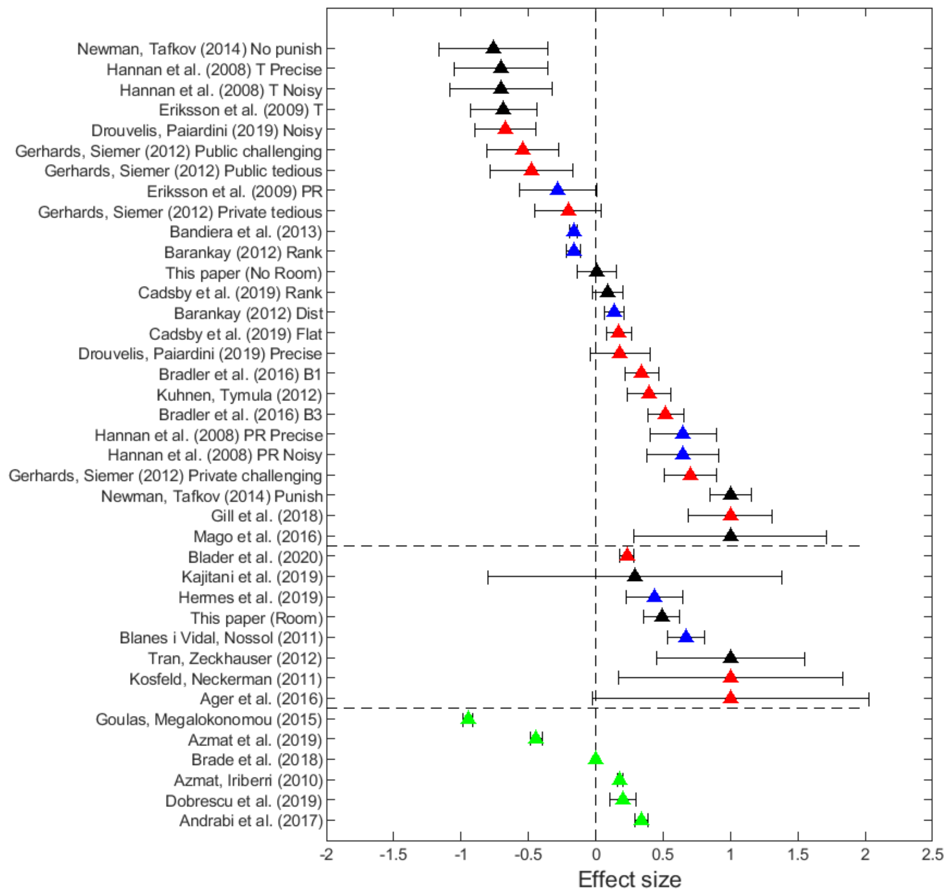


Figure 2: Forest plot of the effect of RPF at the bottom of the performance distribution

Note: Each triangle represents the effect sizes at the bottom of the performance distribution for each of the treatments, and the bars the confidence intervals. The colors represent the incentive schemes: flat (red), grades (green), piece-rate (blue) and tournament (black). There is little room for improvement in the treatments above the first dashed line, and large room for improvement below. The treatments are ranked by effect size in each category (room vs. no room for improvement). The grade treatments appear separately below the second dashed line. For visibility, the effect sizes are truncated to lie within the [-1,1] range.

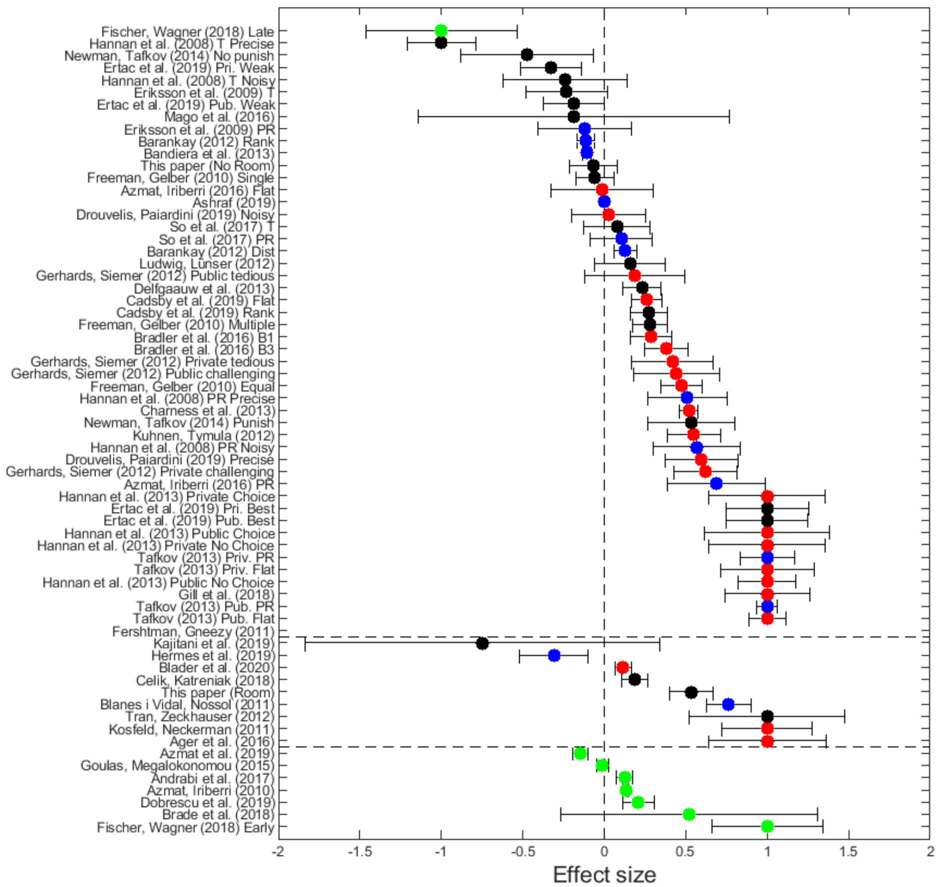


Figure 3: Forest plot of the average RPF effect

Note: Each circle represents the average RPF effect size, and the bars the confidence intervals. The colors represent the incentive schemes: flat (red), grades (green), piece-rate (blue) and tournament (black). There is little room for improvement in the treatments above the first dashed line, and large room for improvement below. The treatments are ranked by effect size in each category (room vs. no room for improvement). The grade treatments appear separately below the second dashed line. For visibility, the effect sizes are truncated to lie within the [-1,1] range.

3 Theory: The effect of RPF on performance.

This section provides a theoretical analysis of the effect of RPF on performance. After briefly reviewing the literature, we present a theoretical model of the effect of RPF on performance. In our setting, RPF improves the agent's information about their performance in the presence of aggregate uncertainty.

In subsection 3.2 we consider the effect of RPF when the only choice variable is effort. In subsection 3.3 we contrast this with the case when there is room for improvement through technological innovation. This is a novel contribution, and introduces the possibility of RPF allowing agents to identify better technologies. The two models can be understood as polar cases. The effort model, at one extreme, assumes that all agents have the same technology and only decide on the effort to exert; the technology model, at the other extreme, assumes that all agents exert the same effort but choose which technologies to use.

There are two major differences between the effort and technology approaches. The first regards the influence of performance from one period to the next. Under the effort channel, performance in one period does depend on the level of effort in previous periods.[5] By way of contrast, technological change is persistent. The second difference relates to the cost: we assume that effort is costly but that technological change is costless.

3.1 Related theoretical literature

There is a small theoretical literature on the effect of RPF on performance in two-player tournament settings: Ederer (2010); Aoyagi (2010); Goltsman and Mukherjee (2011); Gershkov and Perry (2009). These contributions consider how RPF information affects effort incentives, and do not predict that this is unambiguously positive: if subjects increase their effort for some feedback values, they necessarily must reduce it for other values, in line with the law of total expectation. Feedback will discourage effort when the agent learns that this effort is unlikely to improve their chance of winning. For individual incentives, Fuchs (2007) analyzes a principal-agent setting where the principal privately observes output and may have an incentive to give

[5] However, the outcome of previous periods may affect the nature of the incentives in subsequent periods, and thus moderating the optimal effort (see below).

dishonest feedback to reduce the agent's pay. When agents have the option to choose and discard technologies, the riskiness of their output changes. This connects our work to the literature on risk-taking in contests (Hvide, 2002; Anderson and Cabral, 2007; Seel and Strack, 2013), who point out that agents who lag behind in a contest tend to benefit from increased risk-taking.

The idea that agents learn over time about the quality of the technology they use, and may learn from the performance of others appears in the strategic-experimentation literature. The closest paper to ours is Halac et al. (2017), who consider the optimal feedback and prize structure in an innovation contest. As in our model, feedback allows agents to learn about the quality of the technology they use, and their chance of winning the contest. However, there is only one technology which all agents use and about which they become increasingly pessimistic. The agent only has the choice of how much and for how long to invest in the technology, but cannot switch to a different one. The possibility of RPF allowing agents to improve the technology they use has rarely been analyzed . One exception is Wirtz (2016), who focuses on the strategic interaction of two agents. The technology model in section 3.3 applies this idea to a linear incentives and a stylized tournament with many participants.

For simplicity, we consider a stylized model with a continuum of agents. This has two effects: Fist, rank feedback allows the agents to infer their individual performance precisely. Second, tournament incentives are reduced to a non-strategic setting, where an individual agent knows precisely the performance necessary to obtain a reward. While it significantly simplifies the analysis, the results would not change qualitatively if this assumption was relaxed. Moreover, our analysis is more applicable to real world settings in education where there are typically many competitors than a two-person setting which is often studied in the theoretical literature.

3.2 Effort choice

In this section we consider a model where agents choose effort to maximize their payoff. There is a continuum of identical agents.[6] Each agent is assigned to one of two groups: the

[6]In our model, we abstract away from differences in ability between agents. Ederer (2010) finds that, when ability is unknown and affects the productivity of effort, relative performance feedback increases effort for the leader and decreases effort for the follower. This aligns with empirical (non experimental) evidence for a positive effect of rank information at the top of the distribution and a negative or no effect at the bottom (Goulas and Megalokonomou, 2021; Elsner et al., 2021; Murphy and Weinhardt, 2020). In contrast, if ability is known or does

control or treatment (RPF) group. In each period $t = 1, \dots, T$, an agent produces output

$$x_t = e_t + b_t + \varepsilon_t.$$

where e_t denotes effort, which is provided at cost $c(e_t) = \frac{e_t^2}{2}$. b_t denotes a common shock, which affects all agents in a group in the same way, and is independently and identically distributed (*iid*) across periods, according to the cumulative density function (CDF) $F_b(\cdot)$ and the density $f_b(\cdot)$. ε_t denotes an individual error term, which is *iid* across agents and periods, with CDF $F_\varepsilon(\cdot)$ and density $f_\varepsilon(\cdot)$. Both densities are unimodal at 0 and twice continuously-differentiable. We denote the sequence of common shocks and individual errors up to period t as $b^t \equiv b_1, \dots, b_t$ and $\varepsilon^t \equiv \varepsilon_1, \dots, \varepsilon_t$.

The agent's payment $g(x)$ depends on her aggregate output $x \equiv \sum_{t=1}^{T} x_t$. We assume $g'(\cdot) \geq 0$ and $\mathbb{E}[g''(\cdot)] < 1$.[7] In each period, the agent chooses effort to maximize her expected payoff, which is given by the expected payment minus the cost of effort:

$$U = \mathbb{E}\left[g(x) - \sum_{t=1}^{T} c(e_t)\right]$$

After each period, the agent receives feedback about her performance. Both the RPF and the control group learn their individual performance x_t after each period. At the beginning of period t the agent thus knows her performance in all previous periods, summarized as $\boldsymbol{x}^{t-1} \equiv x_1, \dots, x_{t-1}$. If the agent is in the RPF group, she additionally learns her rank r_t for each period, where the highest rank is 1 and the lowest rank 0. We assume that there is no information spillover between groups. The information the agent derives from all past rankings at the beginning of period t is denoted by $\boldsymbol{r}^{t-1} \equiv r_1, \dots, r_{t-1}$.

3.2.1 Average effects

Lemma 1. The agent can infer the values of b_t and ε_t from her rank r_t.

not affect the efficacy of effort there should be no effect of relative performance feedback on effort provision.

[7]The first assumption excludes that payment falls in output; the second ensures that the first-order condition identifies the maximum.

Proof of Lemma 1. In period 1, all agents exert the same effort, since they have no prior information. In addition, the common shock b_1 affects all agents in the same way. Differences in performance are then entirely due to the respective draws of the individual error term ε_1. The agent's rank is given by: $r_1 = F_\varepsilon(\varepsilon_1)$. The agent can thus derive $\varepsilon_1 = F_\varepsilon^{-1}(r_1)$ and $b_1 = x_1 - e_1 - \varepsilon_1$. For subsequent periods, let output net of the aggregate shock in period t be given by: $y_t \equiv x_t - b_t = e_t + \varepsilon_t$. All agents exert optimum effort, given the information they have received. The agent can therefore predict the equilibrium distribution of y_t for all agents across the continuum: F_{y_t}. Rank is given by: $r_t = F_{y_t}(e_t + \varepsilon_t)$. We have $\varepsilon_t = F_{y_t}^{-1}(r_t) - e_t$ and $b_t = x_t - e_t - \varepsilon_t$.

Proposition 1. When the choice variable is effort, there is no effect of RPF on expected average performance.

Proof of Proposition 1. We define total output net of effort in period t as $x_{-t} \equiv x - e_t$. The optimal effort in period t then satisfies:

$$e_t^* = \mathbb{E}\left[g'(x_{-t} + e_t^*)\right].$$

A control-group agent knows her previous performances $\boldsymbol{x}^{t-1}$. Her optimal effort in period t is thus:

$$e_t^C = \mathbb{E}\left[g'(x_{-t} + e_t^C)\middle|\boldsymbol{x}^{t-1}\right].$$

A RPF-group agent additionally knows her previous rankings $\boldsymbol{r}^{t-1}$. Her optimal effort in period t is then:

$$e_t^R = \mathbb{E}\left[g'(x_{-t} + e_t^R)\middle|\boldsymbol{x}^{t-1}, \boldsymbol{r}^{t-1}\right].$$

According to the law of total expectation, we have

$$\begin{aligned}\mathbb{E}\left[e_t^C\right] &= \mathbb{E}\left[\mathbb{E}\left[g'(x_{-t} + e_t)\middle|\boldsymbol{x}^{t-1}\right]\right] = \mathbb{E}\left[g'(x_{-t} + e_t)\right]\\ &= \mathbb{E}\left[\mathbb{E}\left[g'(x_{-t} + e_t)\middle|\boldsymbol{x}^{t-1}, \boldsymbol{r}^{t-1}\right]\right] = \mathbb{E}\left[e_t^R\right].\end{aligned}$$

Average effort in the RPF and treatment groups is then identical in expectation.[8]

Preferences for rank. While theory predicts no effect of RPF on expected average performance if agents care only about their payment, a number of contributions find evidence of this effect. Some papers have addressed this by introducing an *ad hoc* term into the payoff function, to reflect a *taste for rank*. The idea is that, when agents receive RPF, they start caring about rank per se in addition to the payment.[9] The expected payoff function takes the following form:

$$\mathbb{E}\left[g(x) + \mathbb{1}_{RPF}\sum_{1}^{T} h(r_t) - \sum_{1}^{T} c(e_t),\right] \tag{1}$$

where the taste for rank in period t is denoted by $h(r_t)$ and only enters the payoff function once RPF is received. We assume that the payoff weakly increases in rank $(h'(\cdot) \geq 0)$,[10] and that rank weakly increases in effort $(r_t'(e_t) \geq 0)$.

Lemma 2. With a taste for rank there is a positive effect of RPF on average performance in expectation.

Proof of Lemma 2. With a taste for rank, the optimal effort $\hat{e}_t^R$ of an RPF-group agent in period t is:

$$\hat{e}_t^R = \mathbb{E}\left[g'(x_{-t} + \hat{e}_t^R) + h'(r_t)r_t'(\hat{e}_t^R)\middle|\boldsymbol{x}^{t-1}, \boldsymbol{r}^{t-1}\right].$$

As the additional term is positive, the optimal effort of an RPF-group agent rises with the taste for rank:

$$\begin{aligned}\hat{e}_t^R &= \mathbb{E}\left[g'(x_{-t} + \hat{e}_t^R) + h'(r_t)r_t'(\hat{e}_t^R)\middle|\boldsymbol{x}^{t-1}, \boldsymbol{r}^{t-1}\right] \\ &\geq \mathbb{E}\left[g'(x_{-t} + e_t^R)\middle|\boldsymbol{x}^{t-1}, \boldsymbol{r}^{t-1}\right] = e_t^R.\end{aligned}$$

Meanwhile, the optimal effort of a control-group agent $\hat{e}_t^C$ is unchanged by a taste for rank,

[8] This holds as long as $c'''(\cdot) = 0$. For $c'''(\cdot) > 0$ (< 0), the average effort in the RPF group is lower (higher) in expectation. This is analogous to Proposition 1 in Ederer (2010).

[9] In an alternative specification, the agent also cares about rank when she does not receive RPF, but the payoff increases in the precision of the information. The results are qualitatively identical.

[10] Recall that $r_t \in [0, 1]$, where 1 is the highest rank.

as she does not receive information about her rank: $\hat{e}_t^C = e_t^C$. We thus have

$$\mathbb{E}\left[\hat{e}_t^C \middle| \boldsymbol{x}^{t-1}\right] = \mathbb{E}\left[e_t^C \middle| \boldsymbol{x}^{t-1}\right] = e_t^R \leq \hat{e}_t^R,$$

which proves the result. Taste for rank increases the marginal return of effort for the RPF group relative to the control group.

3.2.2 Distribution effects

While RPF is predicted to have no effect on average performance without the taste for rank, we are interested in the effect of RPF along the performance distribution. The prediction here will depend on the shape of the payment function $g(\cdot)$. We consider examples of individual and tournament incentives, as these are the most common incentive schemes in the empirical literature. We first consider individual incentives in the form of a linear payment scheme, where $g(x) \equiv ax$, with $a > 0$.

Proposition 2. With a linear payment scheme, RPF has no effect on expected future performance anywhere in the distribution.

Proof. In this case, the optimal effort is $e_t = a$, independent of feedback and everywhere on the performance distribution.

Second, we consider a stylized model of tournament incentives with $T = 2$ periods. We denote the aggregate output net of the aggregate shock by: $y \equiv \sum_{t=1}^{T} y_t \equiv \sum_{t=1}^{T} x_t - b_t$. The agent receives a prize of 1 if this value exceeds a threshold of s, with the payoff of losing being normalized to zero. With a continuum of agents, this is equivalent to some share $\hat{s}$ of agents with the highest total output winning the prize.[11] We assume that the threshold s is restrictive, i.e. it is high enough that the share $\hat{s}$ of agents that attain it is under $\frac{1}{2}$. The expected payoff

[11] As the aggregate shock b_t affects all agents, it is irrelevant for the outcome of the tournament. All agents exert optimum effort, given the information they have received. The agent can therefore predict the equilibrium distribution of output net of the aggregate shock y_t for all agents across the continuum: F_{y_t}. If the share $\hat{s}$ of agents with the highest total output wins the prize, the agent can derive the threshold s she has to attain to win from: $1 - F_y(s) = \hat{s}$.

function then takes the following form:

$$U = \mathbb{E}\left[\mathcal{P}(y > s) - c(e_1) - c(e_2)\right] = \mathbb{E}\left[1 - F_\varepsilon(s - e_1 - e_2 - \varepsilon_1) - \frac{1}{2}\left(e_1^2 + e_2^2\right)\right],$$

where $\mathcal{P}(y > s)$ denotes the probability that the agent's output reach the threshold. Optimal effort in period t is

$$e_t^* = \mathbb{E}\left[f_\varepsilon(s - \varepsilon_1 - e_{-t} - e_t^*)\right],$$

where e_{-t} denotes the effort level in the other period. As shown in Lemma 1, a RPF group agent can derive ε_1 after receiving feedback on r_1. Her optimal effort in period 2 is thus:

$$e_2^R(\varepsilon_1) = f_\varepsilon(s - e_1 - e_2^R(\varepsilon_1) - \varepsilon_1).$$

Meanwhile, her optimal effort in period 1 is:

$$e_1^R = \mathbb{E}\left[f_\varepsilon\left(s - e_1^R - e_2^R(\varepsilon_1) - \varepsilon_1\right)\right].$$

We therefore have $e_1^R = \mathbb{E}\left[e_2^R\right]$: A RPF-group agent's first-period effort is equal to her expected second-period effort. First-period effort is the same for all RPF-group agents, as everyone has the same information at the start of period one.

A control-group agent only learns her output x_1 after period 1. Her optimal effort in period 2 is thus:

$$e_2^C = \mathbb{E}\left[f_\varepsilon\left(s - e_1 - e_2^C - \varepsilon_1\right)\middle| x_1\right].$$

Meanwhile, her optimal effort in period 1 is:

$$e_1^C = \mathbb{E}\left[f_\varepsilon\left(s - e_1^C - e_2^C(\varepsilon_1) - \varepsilon_1\right)\right].$$

We thus have $e_1^C = \mathbb{E}\left[e_2^C\right]$: A control-group agent's first-period effort is equal to her expected second-period effort, and first-period effort is identical for all control-group agents. In addition, first-period effort is equal for the control and RPF groups and second-period effort is equal in expectation, as we have:

$$
\begin{aligned}
e_1^C &= \mathbb{E}\left[\mathbb{E}\left[f_\varepsilon\left(s-e_1-e_2-\varepsilon_1\right)\middle|x_1\right]\right] = \mathbb{E}\left[f_\varepsilon\left(s-e_1-e_2-\varepsilon_1\right)\right] \\
&= \mathbb{E}\left[\mathbb{E}\left[f_\varepsilon\left(s-e_1-e_2-\varepsilon_1\right)\middle|x_1, r_1\right]\right] = e_1^R.
\end{aligned}
$$

This confirms that expected average effort is equal for both groups with tournament incentives, as stated generally in Proposition 1.

Proposition 3. For tournament incentives, RPF has a positive effect on expected future performance at the top of the distribution and a negative effect at the bottom.

Proof. As all agents exert the same level of effort in period 1, the first-period error term ε_1 drives the differences in first-period performance and, consequently, in second-period effort. We first consider second-period effort in the RPF group. As the mode of f_ε is at 0, maximal second-period effort is exerted when ε_1 satisfies $s - e_1 - e_2 - \varepsilon_1 = 0$. As ε_2 is distributed symmetrically around 0, this agent has a winning probability of $\frac{1}{2}$. This would be the case for the agent whose first-period error term is $1 - F_\varepsilon(\varepsilon_1) = \hat{s}$. Given that we assume that the tournament is restrictive, i.e. $\hat{s} < \frac{1}{2}$, the highest effort is exerted by an agent on the top half of the distribution. Second-period effort is monotonically decreasing both up and down the distribution starting from $\hat{s}$. In the control group, maximal effort is necessarily lower, as $E\left[f_\varepsilon\left(s-e_1-e_2-\varepsilon_1\right)\middle|x_1)\right] < f_\varepsilon\left(0\right)$ for all x_1. Since expected effort is equal for both groups, it is necessarily the case that, for ε_1 low enough, expected effort is higher for the control group. Thus, the expected treatment effect is positive at the top and negative at the bottom of the distribution.

3.3 Technology choice

This section introduces a model in which RPF affects performance through the improved identification of good *technologies*. Instead of choosing effort, agents have to make decisions about the technologies they use. Technologies are ways of working that could either improve or worsen performance. In the context of education, examples could be taking notes on a computer, studying with classmates, drinking coffee, or studying late the night before the exam. The impact of these technologies could be positive or negative, and is ex ante uncertain. As in Section 3.2, there is a continuum of identical agents who carry out the same task over T periods. Agents draw technologies θ from a normal distribution with mean zero and variance 1, with CDF $F_\theta(\cdot)$ and density $f_\theta(\cdot)$. The technology drawn in period t is denoted by θ_t. Technologies are *iid* across agents and periods. Output in period t is affected by a common shock B_t, which affects all agents in the same way. This takes the form of a random walk with increments b_t, which are *iid* according to a normal distribution with mean zero and variance σ^2, with CDF $F_b(\cdot)$ and density $f_b(\cdot)$.[12] The agent makes two decisions in each period: $d_t \in \{0,1\}$ and $k_t \in \{0,1\}$. At the start of period $t \in [1,T]$, she decides whether to draw a new technology θ_t ($d_t = 1$) or not ($d_t = 0$). At the end of the period $t \in [1,(T-1)]$, she decides whether to keep the technology she just tried out for future periods ($k_t = 1$) or to drop it ($k_t = 0$).[13] We assume that this decision is final, and that the agent keeps the technology when she is indifferent. Output in period t is determined by the technologies currently in use:

$$x_t = \sum_{r=1}^{t-1} \left(\theta_r \cdot \mathbb{1}_{(k_r=1)}\right) + \theta_t \cdot \mathbb{1}_{(d_t=1)} + B_t.$$

Aggregate output is given by the sum of per-period outputs:

$$x = \sum_{t=1}^{T} x_t = \sum_{t=1}^{T} \theta_t \left[\mathbb{1}_{(d_t=1)} + \mathbb{1}_{(k_t=1)}(T-t) + B_t\right]$$

In each period, the agent chooses k_t and d_t to maximize expected payoff, given by $U = \mathbb{E}\left[g(x)\right]$. As in Section 3.2, agents in the control group only learn their own output x_t at the end of period t, while RPF-group agents additionally learn their rank r_t.

Lemma 3. The agent can infer the values of B_t and θ_t from her rank r_t.

Proof of Lemma 3. In period 1, the common shock B_1 affects all agents in the same way. Dif-

[12]Modelling the common shock as a random walk is convenient, as the agent only updates her beliefs about the value of the technology once, after the realization of x_t. In the subsequent periods this belief will remain constant as long as the agent keeps the technology.

[13]For coherence, it must be the case that if $(d_t = 0)$ then $(k_t = 0)$. If the agent did not draw a new technology in period t, it cannot be used in future periods.

ferences in performance are therefore entirely due to the individual technology draws θ_1. The agent's rank is then given by: $r_1 = F_{x_1}(x_1) = F_\theta(\theta_1)$. The agent can thus derive $\theta_1 = F_\theta^{-1}(r_1)$ and $B_1 = x_1 - \theta_1$. In subsequent periods, let output net of the aggregate shock in period t be given by:

$$y_t \equiv x_t - B_t = \sum_1^{t-1} \left(\theta_r \cdot \mathbb{1}_{(k_r=1)}\right) + \theta_t \cdot \mathbb{1}_{(d_t=1)}.$$

All agents drop technologies below a certain threshold $\bar{\theta}_t$. The agent can therefore predict the equilibrium distribution of y_t for all agents across the continuum: F_{y_t}. Rank is given by:

$$r_t = F_{y_t}\left(\sum_1^{t-1} \left(\theta_r \cdot \mathbb{1}_{(k_r=1)}\right) + \theta_t \cdot \mathbb{1}_{(d_t=1)}\right).$$

The agent can thus derive

$$\theta_t = F_{x_t}^{-1}(r_t) - \sum_1^{t-1} \left(\theta_r \cdot \mathbb{1}_{(k_r=1)}\right) \quad \text{and} \quad B_t = x_t - \sum_1^{t-1} \left(\theta_r \cdot \mathbb{1}_{(k_r=1)}\right) - \theta_t \cdot \mathbb{1}_{(d_t=1)}.$$

Lemma 4. For agents in the control group, the updated belief of the value of the technology after observing output $\theta_t | x_t$ is distributed normally with mean $\frac{x_t - x_{(t-1)}}{1+\sigma^2}$ and variance $\frac{\sigma^2}{1+\sigma^2}$, where we define $x_0 = 0$.

Proof. We denote $\Delta x_t \equiv x_t - x_{(t-1)}$. According to Bayes Rule, we have:

$$\begin{aligned} f_{\theta|\Delta x_t}(\theta_t) &= \frac{f_{\Delta x|\theta_t}(\Delta x_t) \cdot f_\theta(\theta_t)}{f_{\Delta x}(\Delta x_t)} = \frac{f_b(\Delta x_t - \theta_t) \cdot f_\theta(\theta_t)}{f_{\Delta x}(\Delta x_t)} \\ &= \frac{\frac{e^{-\frac{(\Delta x - \theta_t)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}} \cdot \frac{e^{-\frac{\theta_t^2}{2}}}{\sqrt{2\pi}}}{\frac{e^{-\frac{(\Delta x)^2}{2(1+\sigma^2)}}}{\sqrt{2\pi(1+\sigma^2)}}} = \frac{e^{-\frac{(\theta - \frac{\Delta x_t}{1+\sigma^2})^2}{\frac{\sigma^2}{1+\sigma^2}}}}{\sqrt{2\pi\frac{\sigma^2}{1+\sigma^2}}}. \end{aligned}$$

The updated distribution of the technology θ_t, given output x_t, has the CDF $F_{\theta_t|x_t}(\cdot)$ and density $f_{\theta_t|x_t}(\cdot)$. We next analyze the agent's optimal technology decisions for the cases of individual and tournament incentives.

3.3.1 Individual incentives

We first consider individual incentives in the form of a linear payment scheme, where $g(x) \equiv ax$, with $a > 0$.

Lemma 5. For agents in the RPF group, we have $k_t = 1$ iff $\theta_t \geq 0$ and $d_t = 1$ always.

Proof. As shown in Lemma 3, agents who receive RPF can deduce the value of θ_t. Keeping a technology increases the expected payoff by $a\theta_t(T-t)$. The agent therefore keeps any technology with a positive value ($\theta_t \geq 0$) and discards any technology with a negative value. Taking a new draw in period t has no effect on the expected payoff in this period, as $\mathbb{E}(\theta_t) = 0$. However, since the agent only keeps technologies with a positive value, the effect on the expected aggregate payoff is positive:

$$a(T-t)\mathbb{E}(\theta_t|\theta_t > 0) = a(T-t)\sqrt{\frac{2}{\pi}} > 0.$$

The agent therefore always takes a new draw.

Lemma 6. For agents in the control group, we have $k_t = 1$ iff $x_t \geq x_{(t-1)}$ and $d_t = 1$ always.

Proof. Agents in the control group use the updated belief about technology θ_t given output x_t to make decisions. Keeping a technology increases increase expected payoff by

$$a(T-t)\mathbb{E}(\theta_t|x_t) = a(T-t)\frac{x_t - x_{(t-1)}}{1+\sigma^2}.$$

The agent therefore keeps any technology with a positive expected value, which is the case when the output increases over the previous period: $x_t \geq x_{(t-1)}$. Similarly to RPF-group agents, control-group agents always draw new technologies. Taking a new draw in period t has no effect on expected output in this period, as $\mathbb{E}(\theta_t) = 0$. However, since the agent only keeps technologies with a positive expected value, the effect on aggregate output, and thus the payoff, is positive:

$$a(T-t)\mathbb{E}(\theta_t|x_t > x_{(t-1)}) = \sqrt{\frac{2\sigma^2}{\pi(1+\sigma^2)}} > 0.$$

The agent therefore always takes a new draw.

Proposition 4. When the agent can explore new technologies and faces linear incentives, there is a positive effect of RPF on expected performance. The treatment effect is positive everywhere along the distribution of prior performance, and is symmetric around the mean.

Proof. Since both the RPF and the Control group draw a new technology in every period, this decision should not affect the treatment effect. Due to the imprecise information about the value of θ_t, some control-group agents will, however, take sub-optimal decisions about keeping or dropping their technology when $b_t \neq 0$. Consider first the case $\theta_t > 0$. For values of the common shock such that $(\theta_t + b_t < 0)$, the agent's output declines $(x_t < x_{(t-1)})$ even though the technology has a positive value. Therefore, control-group agents will *not keep* the technology $(k_t = 0)$ when the the common shock is low enough. The expected output is reduced by θ_t relative to RPF-group agents in all $(T - t)$ future rounds. The probability of treatment is $\mathcal{P}\left(\theta_t + b_t < 0\right)$. The expected average treatment effect over all future periods, given a technology $\theta_t > 0$, is therefore therefore positive and given by:

$$\mathbb{E}\left(TE|\theta_t > 0\right) = (T-t)\theta_t \cdot \mathcal{P}\left(\theta_t + b_t < 0\right) = (T-t)\theta_t \cdot F_b\left(-\theta_t\right) > 0.$$

Second, consider the case $\theta_t < 0$. For values of the common shock such that $(\theta_t + b_t > 0)$, the agent's output increases $(x_t > x_{(t-1)})$ even though the technology has a negative value. Therefore, control-group agents will *keep* the technology $(k_t = 1)$ when the the common shock is high enough. The expected output is reduced by $-\theta_t$ relative to RPF-group agents in all $(T - t)$ future rounds. The probability of treatment is $\mathcal{P}\left(\theta_t + b_t > 0\right)$. The expected average treatment effect over all future periods, given a technology $\theta_t > 0$, is therefore therefore positive and given by:

$$\begin{aligned}\mathbb{E}\left(TE|\theta_t < 0\right) &= (T-t)(-\theta_t) \cdot \mathcal{P}\left(\theta_t + b_t > 0\right) = (T-t)(-\theta_t)\left[1 - F_b\left(-\theta_t\right)\right] \\ &= (T-t)|\theta_t| F_b\left(\theta_t\right) > 0.\end{aligned}$$

In both cases, the average performance of control-group agents falls relative to the treatment group. The expected treatment effect is equal for an agent with technology above the median $(\theta_t > 0)$ and the corresponding agent with a technology which is equidistant below the median $\theta_t' = -\theta_t < 0$. The expected treatment effect must therefore be equal at the top and the bottom of the distribution of prior performance. In summary, the treated segment is $\theta_t \in (\min\{-b_t, 0\}, \max\{-b_t, 0\})$ and, if treated, the treatment effect for a given technology θ_t is its absolute value. The only case when all agents agent make the optimal decision k is when $b_t = 0$. The expected treatment effect over the whole distribution of θ_t is positive and given by:

$$\mathbb{E}(TE) = \sum_{t=1}^{T}(T-t)\int_{-\infty}^{\infty}|\theta_t| F_b\left(\theta_t\right) d\theta = \frac{\sigma^2}{8}T(T-1) > 0.$$

Over time, the possibility of trying new technologies leads to an increase in expected performance for both groups. However, the increase is greater for the RPF group since they are better able to distinguish productive from unproductive technologies than the control group. Consequently, they only keep productive technologies, whose positive effect persists for all future periods.

3.3.2 Tournament incentives

Second, we consider the stylized tournament incentives introduced in Section 3.2.2. For simplicity, we analyze the case of $T = 2$ periods. Aggregate output net of the aggregate shock is given by:

$$y = \sum_{t=1}^{2} x_t - B_t = \theta_1(1 + \mathbb{1}_{(k=1)}) + \mathbb{1}_{(d=1)}\theta_2.$$

The agent receives a prize of 1 if this value exceeds a threshold of $s > 0$, with the payoff of losing being normalized to zero. The expected payoff function takes the following form:

$$U = \mathcal{P}\left[y \geq s\right] = 1 - \Phi\left(\frac{s - \mathbb{E}[y]}{\sqrt{Var[y]}}\right).$$

Lemma 7. For agents in the RPF group, we have $k = 1$ iff $\theta_1 \geq 0$ and $d = 1$ iff $\theta_1 < \frac{s}{2}$.

Proof. As shown in Lemma 3, agents who receive RPF after period 1 can infer the value of θ_1. If the technology has a positive value ($\theta_1 \geq 0$), keeping it clearly increases the probability that total net output y will exceed the threshold s. Therefore, the agent keeps any technology with a positive value and discards technologies with negative value.

Next, we consider the decision whether to take a new draw in period 2. When $2\theta_1 \geq s$, the probability of reaching the threshold is 1 if the agent does not draw a new technology. However, the probability drops to $1 - F_\theta(s - 2\theta_1)$ if the agent takes another draw. Therefore, the agent never takes a new draw when $\theta_1 \geq \frac{s}{2}$. When $2\theta_1 < s$, the probability of reaching the threshold is 0 if the agent does not draw a new technology. However, the probability rises to $F_\theta\left(s - \theta_1\left(1 + \mathbb{1}_{(k=1)}\right)\right)$ if the agent takes another draw. Therefore, the agent takes a new draw in period t when $\theta_1 < \frac{s}{2}$.

We define $\underline{x} \equiv -\frac{s}{3}\left(\sigma^2 + \sqrt{\left(1+2\sigma^2\right)\left(1+5\sigma^2\right)} - 1\right)$ and $\overline{x} \equiv \frac{s}{2}(1+\sigma^2)$.

Lemma 8. For agents in the control group, the optimal technology choices are

$$\begin{cases} k = 1, d = 0 \quad \text{for} \quad x_t \geq \overline{x} \\ k = 1, d = 1 \quad \text{for} \quad \overline{x} > x_t \geq \underline{x} \\ k = 0, d = 1 \quad \text{for} \quad x_t < \underline{x}. \end{cases}$$

Proof. The probabilities that the agent attain the threshold given her first-period output x_1 for all possible combinations of her decisions k and d are given by:

$$\mathcal{P}\left(y > s | x_1, k = 1, d = 0\right) = 1 - \Phi\left(\frac{s - \frac{2x_1}{1+\sigma^2}}{\sqrt{4\frac{\sigma^2}{1+\sigma^2}}}\right)$$
$$\mathcal{P}\left(y > s | x_1, k = 1, d = 1\right) = 1 - \Phi\left(\frac{s - \frac{2x_1}{1+\sigma^2}}{\sqrt{4\frac{\sigma^2}{1+\sigma^2} + 1}}\right)$$
$$\mathcal{P}\left(y > s | x_1, k = 0, d = 1\right) = 1 - \Phi\left(\frac{s - \frac{x_1}{1+\sigma^2}}{\sqrt{\frac{\sigma^2}{1+\sigma^2} + 1}}\right)$$
$$\mathcal{P}\left(y > s | x_1, k = 0, d = 0\right) = 1 - \Phi\left(\frac{s - \frac{x_1}{1+\sigma^2}}{\sqrt{\frac{\sigma^2}{1+\sigma^2}}}\right)$$

The maximum probability of reaching the threshold depending on first-period output x_1 is:

$$\begin{cases} \mathcal{P}\left(y > s | x_1, k = 0, d = 1\right) & \text{for } x_1 < \underline{x} \\ \mathcal{P}\left(y > s | x_1, k = 1, d = 1\right) & \text{for } \underline{x} \leq x_1 < \overline{x} \\ \mathcal{P}\left(y > s | x_1, k = 1, d = 0\right) & \text{for } \overline{x} \leq x_1. \end{cases}$$

Note that $\underline{x} < 0$: The threshold for keeping a technology is below zero. This means that the agent will keep technologies with an expected value slightly below zero. The reason is that the agent has a bias for more-variable output in the tournament setting. She does not care about her expected output, but only about the probability of crossing a high threshold. This probability increases when the output has a higher variance, which is achieved by keeping the technology. The agent is willing to trade off a slight decrease in expected output for a higher variance.

Proposition 5. When the agent can explore new technologies and faces tournament incentives, there is a positive effect of RPF on expected performance. The treatment effect is positive everywhere along the distribution of prior performance and larger at the bottom.

Proof. Due to imprecise information about the value of θ_1, some control-group agents will take sub-optimal decisions about keeping or dropping their first-period technology when $b_t \neq x_1$. First, consider the case $\theta_1 > 0$. These agents performed above the median in period 1. For values of the common shock such that $(\theta_1 + b_1 < \underline{x})$, the agent's output is below the threshold $(x_1 < \underline{x})$, even though, unbeknownst to the agent, the technology θ_1 has a positive value. Therefore, control-group agents will *not keep* the technology $(k = 0)$ when the common shock is low enough. The expected output in all future rounds is reduced by the value of θ_1 relative to RPF-group agents. The probability of treatment is $\mathcal{P}\left(\theta_1 + b_1 < \underline{x}\right)$. Thus, the expected treatment effect for a technology $\theta_1 > 0$ is:

$$\mathbb{E}\left(TE^{+}\right) = \theta_1 \cdot \mathcal{P}\left(\theta_1 + b_1 < \underline{x}\right) = \theta_1 \cdot F_b\left(\underline{x} - \theta_1\right) > 0.$$

Second, consider the case $\theta_1 < 0$. These agents performed below the median in period 1. For values of the common shock such that ($\theta_1 + b_1 \geq \underline{x}$), the agent's output is above the threshold ($x_1 \geq \underline{x}$), even though the technology θ_1 has a negative value. Therefore, control-group agents will *keep* the technology ($k = 1$) when the common shock is high enough. The expected output in all future rounds is reduced by the value of $-\theta_1$ relative to RPF-group agents. The probability of treatment is $\mathcal{P}(\theta_1 + b_1 \geq \underline{x})$. The expected treatment effect, for a technology $\theta_1 < 0$ is thus:

$$\mathbb{E}\left(TE^-\right) = (-\theta_1) \cdot \mathcal{P}(\theta_1 + b_1 \geq \underline{x}) = (-\theta_1)\left[1 - F_b\left(\underline{x} - \theta_1\right)\right] > 0.$$

The expected performance of control-group agents is reduced relative to the treatment group, both for agents who performed above the median in period 1 ($\theta_1 > 0$) and those who performed below ($\theta_1 < 0$). Moreover, provided an agent is treated, the size of the treatment effect is equal for agents with technology above the median ($\theta_1 > 0$) and agents with a technology that is equidistant below the median $\theta_1' = -\theta_1$. However, the probability that the respective agents are treated is different. Since f_b is symmetric around zero and $\underline{x} \leq 0$, it is less likely that the agent above the median is treated.

$$\begin{aligned}\mathcal{P}(\theta_1' + b_1 < \underline{x}) = F_b\left(\underline{x} - \theta_1\right) &= 1 - F_b\left(-\underline{x} + \theta_1\right) \\ &\leq 1 - F_b\left(\underline{x} - \theta_1'\right) = \mathcal{P}(\theta_1' + b_1 \geq \underline{x})\end{aligned}$$

It is more likely that a control-group agent keeps a technology with a negative value ($\theta_1 < 0$) than that she discards a technology with a positive value ($\theta_1 > 0$). Therefore, the expected treatment effect is larger at the bottom of the distribution.

In summary, the treated segment is $\theta_1 \in (\min\{\underline{x} - b_1, 0\}, \max\{\underline{x} - b_1, 0\})$ and, if treated, the treatment effect for a given technology θ_1 is its absolute value. The only case when all agents agent make the optimal decision k is when $b_1 = \underline{x}$. The expected treatment effect is positive at the top and the bottom of the distribution of first-period performance ($\theta_1 > 0$ and $\theta_1 < 0$). Thus, the expected treatment effect over the whole distribution is also positive, and is given by:

$$\mathbb{E}(TE) = \int_{-\infty}^{0} (-\theta_1)\left[1 - F_b\left(\underline{x} - \theta_1\right)\right] d\theta + \int_{0}^{\infty} \theta_1 \cdot F_b\left(\underline{x} - \theta_1\right) d\theta > 0.$$

The decision whether to draw a new technology in period 2 does not affect expected total output in the two-period scenario, as the expected value of the new technology is zero.

3.4 Comparison

In summary, our model predicts that when agents choose effort there is no effect of relative performance feedback on expected average performance (Proposition 1), unless an *ad hoc* preference for rank is introduced (Lemma 2). If agents face linear individual incentives, no effect is expected anywhere on the distribution (Proposition 2). If agents face tournament-style incentives, a positive effect of RPF is expected at the top of the distribution, while that at the bottom of the distribution is expected to be negative (Proposition 3).

Meanwhile, when agents can explore new technologies, RPF helps to distinguish good and bad technologies and there is a positive treatment effect everywhere on the distribution (Propositions 4 and 5). When agents face tournament-style incentives, the effect is expected to be larger at the bottom of the distribution (Proposition 5). We can also conclude that the specific incentive scheme makes little difference for the RPF effect on average performance, in particular when there is little room for improvement.

Finally, the effort and technology channel differ in the influence of RPF on performance over time. Under the effort channel, exerting effort in one period does not carry over to the subsequent period. By contrast, technological change is persistent. For linear incentives, we show that there is a cumulative treatment effect. RPF group agents are better able to correctly identify a productive or unproductive technology, and the effect carries over to all future periods.

4 Empirics

We now describe two field experiments in which the tasks to be performed differ according to the possibility of improving performance by changing technology, i.e. in terms of room for improvement. In the first experiment the task consists in counting 1's in a matrix over a short time period. In line with the theoretical predictions for the effort channel, we find no particular effect of RPF, except perhaps at the top of the distribution. In the second experiment the task consists in maths tests at one-week intervals. In sharp contrast to the first experiment, this task leaves ample room for improving technology. We find that RPF speeds up learning, and there is performance improvement all along the distribution. As will be explained in more details, the two experiments provide similar incentives and mainly differ in the nature of the task. However, we note that subject pools differ (Students vs Turkers) between the two experiments. There is however no reason to believe that differences between treatments would be qualitatively affected.

4.1 Experiment 1: No room for improvement

4.1.1 Experimental design

The experiment was run on Amazon Mechanical Turk (AMT). The task consisted in counting the number of 1's in grids containing only 0's and 1's. Each grid had 6 rows and 6 columns as in Figure 4. The experiment consisted of four rounds. In each round, subjects had 180 seconds to count as many grids as they can. Remaining time is displayed on the screen.

All participants received a flat payment of \$2 and could receive an additional bonus payment of \$8, depending on their performance. Each correct answer is rewarded with 1 point, each incorrect answer costs 1/2 a point. The first round is an unincentivized trial. If the total points from Rounds 2 to 4 is above a certain threshold, the participant received the bonus payment. The threshold was set according to the score at the 5th percentile of a previous trial group.[14]

0	0	0	0	1	1
0	1	0	1	0	0
1	1	0	1	0	0
1	1	0	1	1	0
1	0	1	0	0	0
1	1	0	0	0	1

Figure 4: Screenshot of a typical grid used

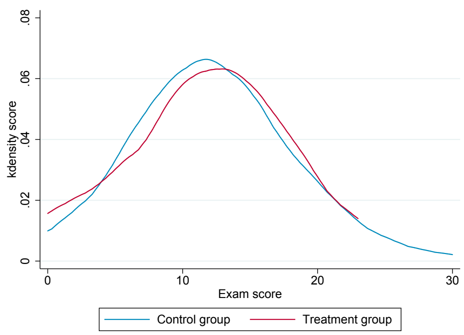
All subjects received feedback about their performance between rounds. In the control

[14]The trial group consisted of 50 participants on AMT. Their performance was recorded prior to the experiment, with subjects receiving a piece rate. This procedure was followed as it is not feasible to stipulate simultaneous participation on AMT.

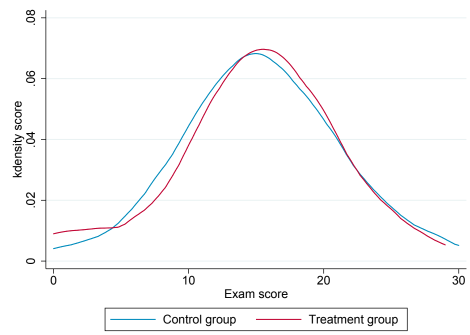
group, subjects were only told their individual score; in the treatment group, subjects were told both their individual score and their rank in comparison to the trial group. A total of 204 subjects participated in the experiment on AMT in March 2020, with 96 subjects in the treatment and 108 in the control group. On average subjects received $2.3 for an experiment that lasted no more than 20 minutes (which is relatively high compared to standard earnings on AMT, Hara et al. (2018)).

4.1.2 Results

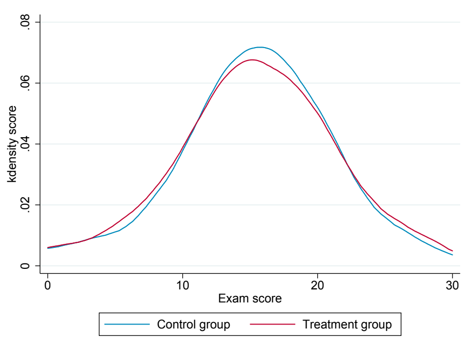
The distribution of scores by round is shown in Figure 5. In line with our expectations, RPF appears to have no significant effect on performance and the treatment effect does not vary over time.



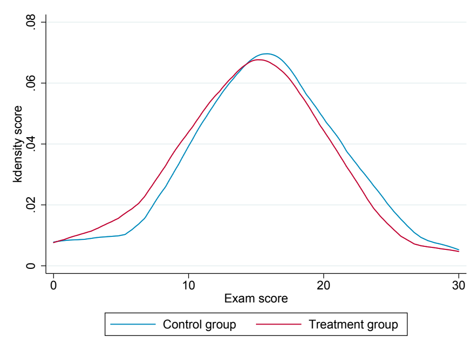
(a) Round 1 (trial)



(b) Round 2



(c) Round 3



(d) Round 4

Figure 5: The change in the densities of performance over time for the control (blue) and treatment (red) groups

The evolution of average performance in the treatment and control groups over rounds is shown in Figure 6. Note that Round 1 is a trial round that does not count towards the aggregate score. This figure illustrates that (1) RPF has no effect on performance, and (2) the effect does not vary over time. The absence of a significant difference between the RPF and control group is even more striking in column 1 of Table 1, in which we show the results from a difference-in-difference estimation (Equation 2).

$$Performance_{it} = \alpha_0 + \beta_1 Treatment_i + \sum_{t=2}^{4} \gamma_t Period_t * Treatment_i + \delta_t + \eta X_i + \varepsilon_{it} \quad (2)$$

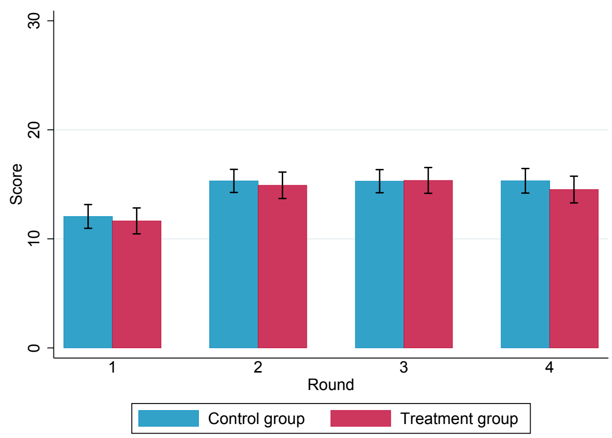


Figure 6: Evolution of average performance across rounds

In line with the theoretical predictions, there might be, if anything, a slight effect of RPF at the very top of the distribution, with slightly more subjects reaching the threshold in the treatment group relative to the control group (4 out of 96 in the treatment group, 4.2%, vs. 3 out of 108 in the control group, 2.8%). The average performance of the top 5% in Round 4 is also slightly higher in the treatment group (27.9 points vs. 26.8 points), although this difference is not statistically significant. The results from quantile regressions in columns 2 and 3 of Table 1 show that RPF has no effect both at the first and last quartile.

Overall, the results from this first experiment confirm our theoretical predictions: when there is little room for improvement, RPF has a very small effect on performance, except perhaps at the very top of the distribution, and the effect does not vary by round.

4.2 Experiment 2: Large room for improvement

4.2.1 Experimental design

For the second experiment, subjects were Eighth-grade students at two girls' schools in Iran, with an average age of 14. There were three classes per school and around 30 students per class. The students took a series of four weekly maths exams, which were framed as part of the curriculum. The experiment was run with tournament incentives: in each class, the two best performers received a significant prize of 1.000.000 Iranian Rials.[15] The students were ranked according to the sum of their scores over the last three exams. The first exam was conceived as a trial-run and did not count for the final score.

In the control group, students only received feedback about their individual grade after each exam. In the treatment group, students additionally received feedback about their rank within the class. The total number of students in the control group was 91, with 83 in the treatment group. In order to prevent spillovers of information, all students from one school were allocated to the control group while all students from the second school were allocated to the treatment group. As there was a significant distance between the schools, there was little chance of the students realizing that a similar (but different) tournament was being organized in another school. To ensure comparability, we ran a pilot study to identify schools that were sufficiently similar.

Each exam consisted of 40 multiple-choice questions. The difficulty of the questions was evaluated using a pilot study, to ensure that the grades across the tests were comparable. Any improvement across rounds should therefore be attributed to better performance rather than changes in difficulty. For each question there were four answer options, with only one correct choice. Four points were awarded for a correct answer, while one point was subtracted for an incorrect answer. Unanswered questions were not penalized. There was a one-week gap between each exam, and students received feedback the day after each exam, to ensure that they had time to react.

[15] At the time roughly equivalent to 50€, about one week's wages for a low-skilled worker.

4.2.2 Results

Figure 7 shows the histograms of student scores in the treatment and control groups. These show that (1) there is a strong positive effect of RPF on average exam scores and (2) students who receive RPF continually improve, as the treatment effect rises over time.

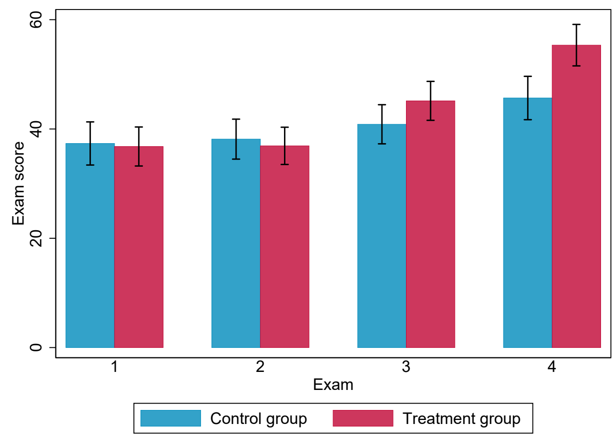


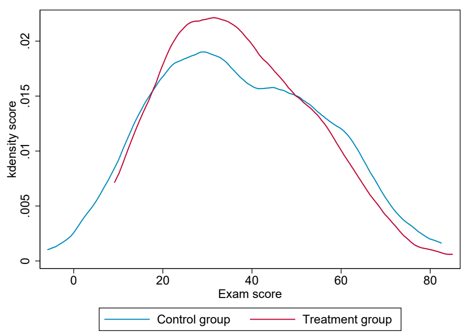
Figure 7: The evolution of average exam scores over time for the control and treatment groups.

Moreover, as indicated in Figure 8, RPF appears to shift the entire distribution upwards.

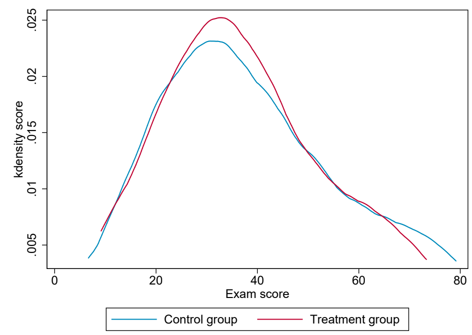
We confirm these observations via a standard difference-in-differences regression (Equation 2: the coefficients of interest are the γ_t's). The results in column 4 of Table 1 confirm that the size of the RPF effect is large (in exam 4 approximately 10 points out of a maximum score of 160 points, corresponding to an increase of 0.56 standard deviations) and robust to the introduction of the available controls (parents' education and number of siblings).

The performance of low-performing students deserves particular attention. It is often assumed that RPF will harm weaker students. Across rounds, some students are less and less likely to have a chance to win any prize. However, we observe that the score at the bottom of the distribution does improve (see Figure 9). Figure 9 also suggests that RPF has a homogeneous effect across the performance distribution.

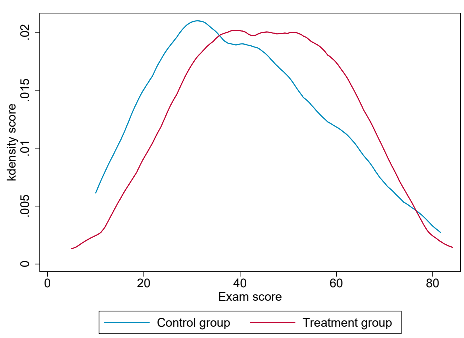
To test the homogeneity of the RPF performance effect, we run quantile regressions at the 25th, 50th and 75th percentile. The results in columns 5 and 6 of Table 1 indicate that the effect is statistically significant over the entire distribution. The effect is not statistically different



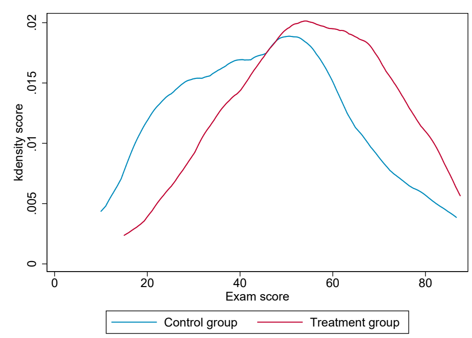
(a) Exam 1



(b) Exam 2



(c) Exam 3



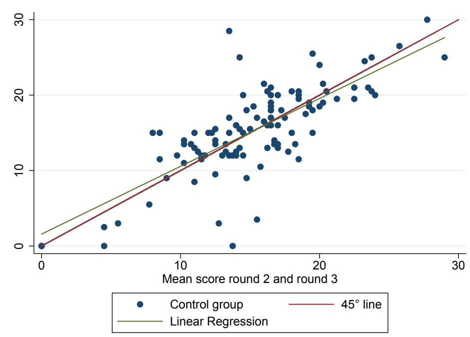
(d) Exam 4

Figure 8: The change in the densities of exam scores over time for the control (blue) and treatment (red) groups

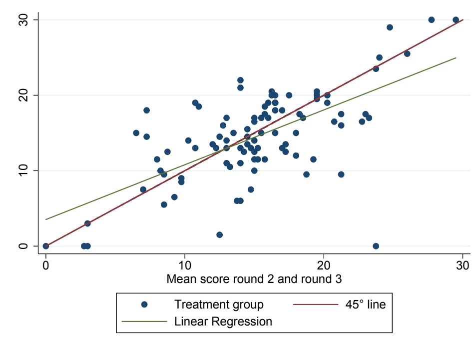
between the first and the last quartile, although the coefficient is slightly larger in the former.

Overall, our empirical findings fit the predictions of the technology channel well: the treatment effect increases across periods. This feature is hard to explain through the effort channel alone. The fact that the treatment effect is found over the whole performance distribution matches the predictions of the technology model. Since there obviously is room for improvement in this experiment, we conjecture that students improved their performance by gradually improving their learning technology.

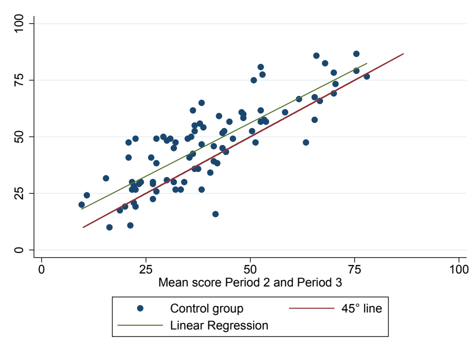
4.3 Comparison between the two experiments



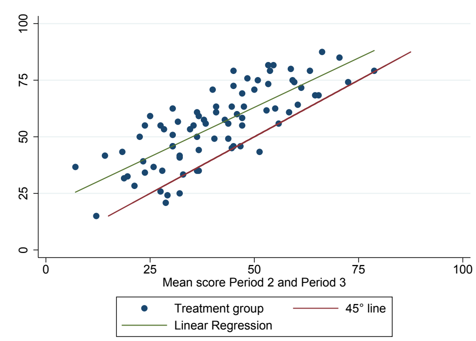
(a) Control group without room for improvement



(b) Treatment group without room for improvement



(c) Control group with room for improvement



(d) Treatment group with room for improvement

Figure 9: Comparison of the score in Round 4 (Y-axis) to that in Rounds 2 and 3 (X-axis). Each dot represents a subject. Figures 9a and 9b show performance in the experiment without room for improvement, and Figures 9c and 9d performance in the experiment with room for improvement.

Table 1 shows the results from both experiments, which allows us to draw three conclusions.

Average effect Without room for improvement, there does not seem to be an average performance effect. When there is considerable room for improvement, however, there is a substantial and significant positive average effect of RPF on performance.

Distribution effect Comparing the effects at the bottom of the distribution (the first quartile in columns 2 and 5 in Table 1), we can see that there is, after a few rounds, a substantial difference between the results of the two experiments. There is no effect in the experiment without room for improvement, but a positive significant effect with room for improvement. At the top of the distribution (the top quartile in columns 3 and 6 of Table 1), we see a similar pattern of a positive effect with room for improvement and no effect without room for improvement.

Cumulative effect The third and final empirical difference between the two experiments concerns the difference in the provision of RPF over several rounds. There does not seem to be a performance effect after providing the information just once. However, after a number of RPF a significant difference between the two experiments appears, with a clear positive effect all along the performance distribution in the experiment with large room for improvement, but none in the experiment without room for improvement.

Table 1: Effect of RPF on performance without (columns 1 to 3) or with (columns 4 to 6) room for improvement

	No Room for Improvement			Large Room for Improvement		
	ATE	Bottom	Top	ATE	Bottom	Top
	(1)	(2)	(3)	(4)	(5)	(6)
Round=2	3.259***	2.827***	2.839***	1.385	5.256**	-3.833
	(.448)	(.668)	(.762)	(1.508)	(2.470)	(2.479)
Round=3	3.231***	3.837***	2.455***	4.014**	6.282**	2.167
	(.621)	(.781)	(.696)	(1.580)	(2.782)	(2.520)
Round=4	3.269***	3.431***	3.514***	8.681***	9.936***	6.000**
	(.510)	(.689)	(.749)	(1.806)	(2.660)	(2.525)
Treatment=1	-.459	-.634	-.398	-4.301	1.474	-7.833**
	(.813)	(1.467)	(.866)	(2.800)	(3.303)	(3.344)
Round=2 x	.006	.931	.054	-1.256	-4.231	-.500
Treatment=1	(.665)	(1.330)	(1.070)	(2.127)	(3.350)	(3.153)
Round=3 x	.482	.188	.729	5.223**	3.269	7.500**
Treatment=1	(.872)	(1.823)	(.965)	(2.397)	(3.438)	(3.495)
Round=4 x	-.394	.050	-.568	10.013***	9.231**	11.333***
Treatment=1	(.835)	(1.554)	(1.053)	(2.517)	(3.657)	(3.790)
Constant	14.515***	11.139***	18.018***	29.579***	12.051***	42.333***
	(1.775)	(2.091)	(1.591)	(4.779)	(3.923)	(6.093)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.064	.060	.059	.174	.158	.161
No. obs	816	816	816	641	641	641

* p<0.10 ** p<0.05 *** p<0.01. The dependent variable for columns 1 to 3 is performance in counting matrices, for columns 4 to 6 the dependent variable is exam scores. Standard errors (in parentheses) are clustered at the individual level. The “bottom” and “top” columns represent quantile regressions at the bottom and top quartiles. In the first three columns, the controls are education and age; in the last three columns, controls are parents’ education and number of siblings.

5 Conclusion

The main claim of this paper is that RPF provides information about peers' performance which helps to better - and faster - identify good technologies. In particular, low performers can benefit from RPF, an effect that has been consistently observed but poorly explained. A common explanation is that agents have an intrinsic taste for ranking (e.g. self-image concerns). In this paper we propose a less *ad hoc* and more satisfactory explanation based on technology improvement.

At a more general level, considering a technology channel suggests that for the assessment of the RPF effect it is crucial to know whether the task at hand offers a possibility of technological improvement, which we call room for improvement. Surprisingly enough, the nature of the incentives (tournament, individual, etc) appear to be of lesser importance. Indeed, even when rank has no influence on payoffs, as with individual incentives, agents may nonetheless use the feedback to improve their technology. Section 2 confirms that the specific incentive scheme does not make a great difference to the RPF effect, in particular when there is little room for improvement. RPF is provided in countless situations, and the focus on the technological aspect of RPF makes it possible to shed new light on two branches of the literature: education and social norms.

In education, teachers are often reluctant to provide rankings to young pupils, as RPF is thought to affect poor performers negatively, for instance by lowering their self-image. A better understanding of the role of RPF suggests, on the contrary, that providing *private* rankings is likely to trigger technological improvement, while avoiding public shaming. This is indeed what some work has concluded: Hannan et al. (2013) and Gerhards and Siemer (2016) find a positive effect of (private) ranking on performance, even for low performers. Differently from previous work, this paper does not rely on an *ad hoc* "taste for ranking" to account for this improvement.

Social norms are usually thought to influence behavior by specifying what is acceptable and what is not in a society or a group. Informing agents that a large fraction of their peers respect a particular norm is often taken as a way of increasing compliance. It is usually assumed that agents have a preference for compliance, or that they try to avoid the possible costs of deviating from the norm. Our work here suggests an alternative interpretation. Informing agents about compliance to a given social norm provides information about the behavior of others. This information is a form of feedback which may, in fact, trigger learning about new technologies. One good example is electricity consumption. Electricity consumers have been found to reduce their consumption when provided with information about their consumption relative to that of similar households in their neighborhoods (Goldstein et al., 2008; Schultz et al., 2007). Agents who consume more than their neighbors may realize, thanks to RPF, that it is possible to use electricity in a more efficient way. Agents may thus comply with the norm (i.e. reduce their consumption), not (only) because they wish to comply *per se* or to avoid costs imposed on deviators, but because they learn about better technologies.

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Appendices

A Description of the papers included in the empirical literature review

Table A.1: Papers included in this review with large room for improvement (1)

Paper	Task	Nature of Feedback	Incentives	N	Average effect	Effect at bottom	Effect at top
Ager et al. (2016)	Pilot fighters	Praise in Armed Force Bulletin	Flat	5081	+	+	+
Andrabi et al. (2017)	Tests	Quintile rank + mean score	IG	12110	+	+	0
Azmat and Iriberri (2010)	Tests	Class average	IG	3414	+	+	+
Azmat et al. (2019)	Tests	Decile rank every 6 months	IG	977	-	-	0
Blader et al. (2015)	Transport	Ranking	Flat	5000	+	0	+
Blanes i Vidal, Nossol (2011)	Wholesale retail	Ranking	PR	63	+	+	+
Brade et al. (2018)	Tests	Distance median 80th percentile	IG	1609	+	0	+
Celik Katreniak (2018)	Tests	Performance few classmates + ranking	T	7150	+		

This table lists papers in which the task is considered by the authors as having large room for improvement. Papers are ranked alphabetically. PR: Piece-rate; IG: Individual grades; T: Tournament

Table A.2: Papers included in this review with large room for improvement (2)

Paper	Task	Nature of Feedback	Incentives	N	Average effect	Effect at bottom	Effect at top
Dobrescu et al. (2019)	Tests	Ranking	IG	1101	+	+	+
Fischer and Wagner (2018)	Tests	Early	IG	123	+		
Goulas and Megalokonomou (2015)	Tests	Ranking	IG	45746	-	0	+
Hermes et al. (2019)	Tests	Class ranking improvement	PR	378	+	+	0
Kajitani et al. (2020)	Tests	Ranking	T	255	0	+	-
Kosfeld and Neckermann (2011)	Data entry	Announce of best	Flat Flat	184	+	0	+
This paper (Room)	Tests	Ranking	T	172	+	+	+
Tran and Zeckhauser (2012)	Tests	Ranking	T	124	+	-	+

This table lists papers in which the task is considered by the authors as having large room for improvement. Papers are ranked alphabetically. PR: Piece-rate; IG: Individual grades; T: Tournament

Table A.3: Papers included in this review with no room for improvement (1)

Paper	Task	Nature of Feedback	Incentives	N	Average effect	Effect at bottom	Effect at top
Ashraf (2019)	Sweater production	Private ranking	PR	366	0+		
Azmat and Iriberri (2016)	Adding numbers	Average	Flat	156	0		
			PR	160	+		
Bandiera et al. (2015)	Fruit	Team ranking	PR	656	-	-	0
Barankay (2011)	Image class. Amazon MT	Ranking	PR	147	-	-	0
Barankay (2012)	Furniture salesmen	Ranking + Distrib.	PR	1754	+	+	+
		Ranking	PR	1754	-	-	0
Bradler et al. (2016)	Data entry	Best 1	Flat	82	+	+	0
		Best 3		95	+	+	0
Cadsby et al. (2019)	Adding numbers	Ranking	Flat	560	+	+	+
			T	560	+	0	+
Charness et al. (2014)	Encryption	Distrib.	Flat	585	+		
Delfgaauw et al. (2013)	Sales	Team ranking	T	128	+		
Drouvelis and Paiardini (2019)	Encryption	Noisy	Flat	248	0	-	0
		Precise		248	+	0	+
Eriksson et al. (2009)	Adding numbers	Ranking	PR	88	0	-	0
			T	120	0	-	0

This table lists papers in which the task is considered by the authors as having little room for improvement. Papers are ranked alphabetically. PR: Piece-rate; IG: Individual grades; T: Tournament

Table A.4: Papers included in this review with no room for improvement (2)

Paper	**Task**	**Nature of Feedback**	**Incentives**	**N**	**Average effect**	**Effect at bottom**	**Effect at top**
Ertac et al. (2019)	Effort task	Private	Best link	165	+		
			Weak link	165	-		
		Public	Best link	165	+		
			Weak link	165	0		
Fershtman and Gneezy (2011)	60m races	Continuous feedback	T	471		-	+
Fischer and Wagner (2018)	Tests	Late	IG	117	-		
Freeman and Gelber (2010)	Mazes		Flat	156	+		
			T	156	+		
			T	156	0		
Gerhards and Siemer (2016)	IQ	Private	Flat	50	+	+	0
		Public	Flat	45	0	-	+
	Slider task	Private	Flat	50	+	0	+
		Public	Flat	45	0	0	+
Gill et al. (2018)	Verbal / maths		Flat	306	+	+	+
Hannan et al. (2008)	Production game	Noisy	PR	23	+	+	+
			T	22	0	-	+
		Precise	PR	21	+	+	+
			T	22	-	-	+

This table lists papers in which the task is considered by the authors as having little room for improvement. Papers are ranked alphabetically. PR: Piece-rate; IG: Individual grades; T: Tournament

Table A.5: Papers included in this review with no room for improvement (3)

Paper	Task	Nature of Feedback	Incentives	N	Average effect	Effect at bottom	Effect at top
Hannan et al. (2013)	Verbal and maths						
	(choice)	Private ranking	Flat	15	+		
	(no choice)			15	+		
	(choice)	Public ranking		15	+		
	(no Choice)			15	+		
Kuhnen and Tymula (2012)	Multiplications	Ranking	Flat	54	+	+	-
Ludwig and Lünser (2012)	Effort task	Distribution	T	72	0		
Mago et al. (2016)	Effort task	Distribution	T	240	0	+	-
Newman and Tafkov (2014)	Production game	Ranking	T	40	-	-	+
			T	40	+	+	+
So et al. (2017)	Multiple cue learning task	Ranking	PR	84	0		
			T	76	0		
Tafkov (2013)	Multiplications	Private ranking	Flat	20	+	+	-
			PR	20	+	+	0
		Public ranking	Flat	20	+	+	-
			PR	20	+	+	0
This paper (No Room)	Counting task	Ranking	T	204	0	0	0

This table lists papers in which the task is considered by the authors as having little room for improvement. Papers are ranked alphabetically. PR: Piece-rate; IG: Individual grades; T: Tournament

B Instructions given to participants

B.1 No Room for Improvement (Experiment 1)

Thank you for taking part in this experiment.

To thank you for your participation, we give you $2, regardless of your performance in this experiment. In addition to this amount, we give you the opportunity to earn more money.

Your task consists in counting the number of 1s in grids containing only 0s and 1s. Each grid has 6 rows and 6 columns as in the example below.

0	0	0	0	1	1
0	1	0	1	0	0
1	1	0	1	0	0
1	1	0	1	1	0
1	0	1	0	0	0
1	1	0	0	0	1

This experiment will consist in 4 rounds. For each round, you will have 60 seconds to count as much grids as you can.

The remaining time is displayed at the top left of the screen.

When you have counted the number of 1s in the grid, you will need to enter your answer in the box next to the grid.

After entering your answer, you will have to click outside the input area to enable the “Next grid” button.

In each round, you will be rewarded with 1 point for each correct answer. However, wrong answers will be penalized.

For each incorrect answer, you will lose 1/2 point. It is therefore very important that you give your best for every grid.

The first round will be a trial.

Your point totals for rounds 2, 3 and 4 will give you the grand total of points you have earned. This grand total will be compared to that of 50 other persons, randomly chosen among those who have already participated in the same experiment.

If your grand total (the sum of your points in round 2, 3 and 4) is higher than that of 95% of others (i.e. you are in the top 3), you will earn an extra $8.

At the end of each round, we will display the number of points you have earned during the round and all previous rounds.

At the end of each round, we will display the number of points you have earned during the round and all previous rounds. We will also display your rank among the 50 others for this round.

B.2 Room for Improvement (Experiment 2)

Answer sheet of Math Exam n°4

Seat Number: **First Name – Last Name:**

The duration of the test is 40’.
Please indicate the correct answer using an X.
For each correct answer, 1 point will be awarded. For each incorrect answer, 1/3 point will be removed.

	1	2	3	4
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	1	2	3	4
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38				
39				
40				

Final grade:	Number of unanswered questions:	Number of incorrect answers:	Number of correct answers:

پاسخنامه آزمون ریاضی ۴

نام ونام خانوادگی : **شماره صندلی :**

- وقت آزمون ۴۰ دقیقه می باشد.
- گزینه صحیح را باعلامت × مشخص نمایید.
- هرپاسخ صحیح ۱ نمره مثبت و هر پاسخ نادرست $\frac{1}{3}$ نمره منفی دارد .

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صحیح :	نادرست :	نزده :	نمره :