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## Inequality of Opportunity and Income Redistribution

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# Inequality of Opportunity and Income Redistribution\*

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August 31, 2022

## Abstract

This paper examines how people redistribute income when there is uncertainty about the role luck plays in determining opportunities and outcomes. We introduce a portable experimental method that generates exogenous variation in the probability that real workers' earnings are due to luck, while varying whether luck interacts with effort in the earning process. Then, we elicit redistribution decisions from a U.S.-nationally representative sample who observe worker outcomes and whether luck magnified workers' effort ("lucky opportunities") or determined workers' income directly ("lucky outcomes"). We find that participants redistribute less and are less reactive to changes in the importance of luck in environments with lucky opportunities. We show that individuals rely on a simple heuristic when assessing the impact of unequal opportunities, which leads them to underappreciate the extent to which small differences in opportunities can have a large impact on outcomes. Our findings have implications for models that seek to understand and predict attitudes toward redistribution, while helping to explain the gap between lab evidence on preferences for redistribution and real-world inequality trends.

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# 1 Introduction

Individuals who hold meritocratic fairness ideals tolerate inequalities that are due to differences in effort but prefer to redistribute income differences that are due to luck. Experimental evidence shows that the majority of Americans hold such ideals ([Almås et al., 2020](#)). However, the popularity of meritocratic principles documented in empirical work is difficult to reconcile with the recent trends in income inequality in the United States. Americans accept more inequality today than in previous decades, even though equality of opportunity has not improved.<sup>1</sup> The impact of circumstances beyond people’s control has risen over the past decades ([Chetty et al., 2014](#)), and the U.S. remains the most unequal country in the OECD, while also ranking relatively low on equality of opportunity ([Corak, 2013](#); [Mitnik et al., 2020](#)).

We propose that this disconnect between empirical work and real-world redistribution trends is partly due to the difficulty of assessing the source of inequality when luck is experienced through unequal opportunities. In this case, luck and effort are intertwined, and individuals might wrongly ascribe differences in outcomes as driven by effort, not appreciating the role opportunities had in generating those outcomes. To illustrate this point, consider the case of Microsoft founder Bill Gates—one of the wealthiest individuals alive. Is Bill Gates’ success mainly due to effort or luck? On the one hand, he was fortunate to attend one of the few high schools that offered unlimited access to a computer programming terminal. This is just one of many lucky breaks in Gates’ career ([Frank, 2016](#)). On the other hand, Gates is known for a fierce work ethic, famously stating that he “didn’t believe in weekends; didn’t believe in vacations.” Both luck and effort were instrumental in his professional success, and attributing his success to only one of these factors would be misleading.

This paper examines whether individuals’ redistribution decisions depend on whether luck creates income inequality through unequal opportunities that amplify workers’ effort (“lucky opportunities”). We compare this to a setting in which luck directly selects outcomes at random (“lucky outcomes”), the type of luck on which most of the existing literature has focused on. We implement a novel experimental design that enables us to control the importance of luck in determining outcomes, regardless of how it interacts with effort in the earning process. We find that the type of luck affects how much inequality individuals

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<sup>1</sup>[Saez and Zucman \(2020\)](#) show that inequality has been rising in the U.S. [Ashok et al. \(2015\)](#) show that support for redistribution has not increased in recent decades, implying increased tolerance for inequality.

are willing to tolerate. Redistribution is lower when luck stems from unequal opportunities rather than affecting outcomes directly, holding fixed its importance. Importantly, we find that individuals appear to underestimate how small changes in opportunities can lead to large changes in outcomes.

To motivate our experimental design and empirical approach, we develop a stylized model of redistribution that places lucky opportunities and lucky outcomes in a common framework. An impartial spectator decides how to allocate total earnings between two workers who compete at a task for a fixed prize in a winner-takes-all environment. Spectators observe workers' returns to effort and who won the competition, but not actual effort. Optimal redistribution depends on the spectators' preferences about the fair income share for the worker who exerted more effort and the likelihood that the worker who won is the one who exerted more effort. We denote this probability by  $\pi$ , so that  $(1 - \pi)$  is the likelihood that the outcome is due to luck. In other words,  $\pi$  provides a direct measure of how important luck was in determining worker outcomes. This variable allows us to link the two experimental paradigms.

We recruited 2,400 Amazon Mechanical Turk (mTurk) workers to perform an encryption task and randomly paired them to compete in a winner-takes-all environment. Then we asked approximately 1,200 individuals ("spectators") from the Survey of Consumer Expectations—a U.S.-nationally representative panel—to choose the final earnings allocation for pairs of workers. Spectators redistribute earnings under two different forms of luck: outcome and opportunity. In the lucky outcomes environment, we select the winner of each worker match by a coin flip (CF) with probability  $q$  and by the number of encryptions with probability  $1 - q$ . In the lucky opportunities environment, the winner of each match is the worker with the higher score, given by the number of encryptions completed times a randomly assigned effort multiplier. We generate inequality of opportunity (IOp) by exogenously varying worker multipliers. We implement within-spectator variation in the importance of luck in determining the winner,  $\pi$ , across worker pairs by varying  $q$  in the CF condition or the ratio between workers' multipliers in the IOp condition.

We report two main differences in spectators' behavior between the outcome and opportunity luck environments. First, average redistribution is 4.3 percentage points (or 15.3 percent) lower in the IOp condition than in the CF condition. On average, spectators redistributed 27.6 percent of earnings from the winner to the loser in CF and 23.3 percent in IOp. Second,

the elasticity of redistribution with respect to  $\pi$  is lower in IOp than in CF. A 10 percentage point increase in the likelihood that luck determined the winner leads to a 3.7 percentage point increase in the share of earnings redistributed in the CF condition but only a 1.9 percentage point increase in the IOp condition.

We decompose these differences in redistribution between the two conditions into an extensive margin (i.e., whether or not spectators redistribute any earnings) and an intensive margin (i.e., the amount spectators redistribute, conditional on redistributing anything). We find that lower average redistribution in the IOp condition is driven by both a higher fraction of spectators who do not redistribute any earnings at all and more tolerance toward inequality among the spectators who redistribute. Importantly, we continue to find that redistribution is less elastic to changes in luck in the IOp condition when excluding spectators who never redistribute.

To understand the mechanisms that drive the differences in redistribution that we observe across our luck environments, we implement two additional between-subjects treatments. First, we vary the timing of when luck is realized to examine if differences in perceived worker effort across environments can explain our results. In the baseline IOp condition, workers learn their multiplier before starting the encryption task. Hence, they could adjust their labor supply in response to a low or a high multiplier, possibly affecting how much spectators want to redistribute if they also anticipate an effort response. We introduce an “ex-post” IOp condition in which workers learn about their multiplier *after* they have finished the task. We find that average redistribution and the elasticity of redistribution with respect to luck are economically and statistically equal in the baseline and ex-post conditions.

Second, we examine whether differences in redistribution persist when we provide information about the likelihood that the outcome is due to luck,  $\pi$ . In the CF condition, estimating  $\pi$  is relatively simple; it is linearly related to the probability that a coin flip determined the winner. In the IOp condition, estimating  $\pi$  is more complex, since it is a convex function of the ratio of multipliers. Differences in redistribution might be due to spectators finding it more difficult to assess the importance of luck in one of the luck environments. Our information treatment allows us to investigate the potential role of inaccurate beliefs about  $\pi$  in driving differences in redistribution across CF and IOp.

We find that informing spectators of  $\pi$  leads to a significant decrease in average redistri-

bution in both conditions. This is driven by changes in the intensive margin, as the share of spectators who do not redistribute any earnings does not change. However, the difference in the average level of redistribution across our CF and IOp conditions remains unchanged in the information treatment. We also find that redistribution is more elastic to changes in  $\pi$  in both luck environments when we provide information about  $\pi$ . However, we again find no differential change in the average elasticity between the two luck environments.

Taken together, these results suggest that individuals hold different preferences for redistribution when there is outcome versus opportunity luck, leading them to lower levels of redistribution and less responsiveness to changes in luck. To understand what drives these preferences, we examine how people incorporate unequal opportunities into their redistribution decisions. The impact of worker multipliers on  $\pi$  is highly convex, and previous work has found that individuals often struggle to estimate nonlinear relationships (Larrick and Soll, 2008; Levy and Tasoff, 2016; Rees-Jones and Taubinsky, 2020). We find that spectators rely on a simple heuristic based on the linear multiplier difference when factoring the impact of opportunities into their redistribution decisions. This implies that spectators underappreciate the extent to which small differences in opportunity can have a large impact on outcomes. When we provide information about  $\pi$ , spectators reduce, but do not eliminate, their reliance on this linear approximation.<sup>2</sup> That spectators put weight on the multiplier differences beyond their impact on  $\pi$  is consistent with findings from psychology showing that people care about the process by which an outcome arrives (Lind and Tyler, 1988).

This paper contributes to the literature that studies how the source of inequality affects redistribution. Evidence from empirical work using observational data (Corneo and Grüner, 2000; Fong, 2001; Alesina and La Ferrara, 2005) and experimental data (Cappelen et al., 2010, 2013; Durante et al., 2014; Mollerstrom et al., 2015; Cappelen et al., 2020; Almås et al., 2020; Cappelen et al., 2022; Andre, 2022; Cappelen et al., 2022) shows that support for redistribution depends on whether inequality is due to differences in luck or effort. We show that the whether luck interacts with effort in the earning process plays an important role in shaping these decisions: People are more willing to support redistribution when luck directly

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<sup>2</sup>Previous work has shown that Americans tend to be overly optimistic about social mobility, believing that disadvantages early in life can be overcome with sufficient effort (Alesina et al., 2018). This work also finds that correcting these perceptions leads to negligible changes in support for redistribution. This is consistent with the results of our information treatment and the conclusion that people’s support for redistribution under unequal opportunities depends partially on nonstandard factors.

affects outcomes than when it emerges through unequal opportunities. More generally, our work relates to the literature on the determinants of support for redistribution ([Charness and Rabin, 2002](#); [Cappelen et al., 2007](#); [Fisman et al., 2015](#); [Kuziemko et al., 2015](#)).

Our results replicate and extend several findings from the literature. First, our CF results replicate the nonlinear relationship between redistribution and  $\pi$  found by [Cappelen et al. \(2022\)](#). The authors explain this nonlinearity as a consequence of risk aversion. However, we find that the relationship becomes approximately linear in our information treatment, which suggests that spectators might make inferential mistakes absent precise information about the role of luck. Second, we echo the null effect that the timing of luck has on redistribution found by [Andre \(2022\)](#). Unlike [Andre \(2022\)](#), we examine redistribution in a winner-takes-all setting in which there are no effort responses. We show that the insensitivity of redistribution to the timing of when luck is realized extends to settings in which effort is not observed and there is uncertainty about the role of luck versus effort in determining outcomes.

Finally, our results contribute to the literature that studies heuristics and biases in the inference process. Previous work demonstrates that individuals often fail to solve even simple Bayesian updating problems ([Benjamin, 2019](#)). We contribute by documenting the consequences of inappropriate inference in an important economic setting. We also show that more numerate individuals are less likely to rely on heuristics when assessing the importance of unequal opportunities for outcomes. This is consistent with some spectators making errors in statistical reasoning.

## 2 Theoretical Framework

In this section, we analyze a simple model of spectators’ redistribution decisions in the presence of uncertainty about worker effort. The model setup closely follows that of [Cappelen et al. \(2022\)](#) but extends the framework to allow for differences in the source of luck across environments. The goal of the model is to provide a common framework for quantifying the impact of luck on outcomes, regardless of whether luck interacts with effort in the earning process. We use this framework to clarify our main experimental hypotheses and to guide the interpretation of our results.

Consider an impartial spectator who observes initial earnings in a winner-takes-all environment in which two randomly paired workers compete at a task for a fixed amount of

income. Spectator  $i$ 's task is to choose  $r_i$ , the fraction of income to redistribute from the winner to the loser. Some spectators may never redistribute regardless of the importance of luck, so that  $r_i = 0$ . The setting below focuses on spectators who do redistribute some positive amount. For this group of spectators,  $r_i$  can be characterized by their preferences and beliefs about the impact of luck. Formally, let  $f_i$  denote the share of total income for the lower-effort worker that spectator  $i$  deems to be fair, and let  $1 - f_i$  denote the fair share for the higher-effort worker.<sup>3</sup> Spectator  $i$  chooses  $r_i$  to minimize differences between the fair allocation  $(f_i, 1 - f_i)$  and the actual allocation  $(r_i, 1 - r_i)$  as captured by the following utility function:

$$U(r_i, f_i) = -(r_i - f_i)^2. \quad (1)$$

If spectators know with certainty that the winner was the worker who exerted more effort, then they implement the fair allocation,  $r_i^* = f_i$ . However, in the real world and in our experiment, spectators do not observe each worker's effort level. Given this uncertainty, spectators maximize the expected utility

$$\mathbb{E}(U(r_i, f_i)) = -\pi(r_i - f_i)^2 - (1 - \pi)(r_i - (1 - f_i))^2, \quad (2)$$

where  $\pi$  denotes the probability that the winner of the match exerted more effort. Conversely,  $1 - \pi$  is the probability that the worker who exerted less effort won, and thus that luck determined the winner. In an interior solution, the optimal level of redistribution is

$$r_i^* = \pi f_i + (1 - \pi)(1 - f_i). \quad (3)$$

Equation (3) highlights that redistribution depends on both preferences about the fair share for the lower- and higher-effort worker ( $f_i$ ) and the impact of luck ( $\pi$ ) provided  $f_i < 1/2$ . The key inferential hurdle spectators face is forming beliefs about  $\pi$ . As is often the case in reality, spectators do not directly observe  $\pi$ . Instead, they must form an estimate of  $\pi$  based on noisy signals about the importance of luck. We investigate two environments that differ

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<sup>3</sup>The literature has identified three main types of redistribution preference types or “fairness ideals”: egalitarians, libertarians, and meritocrats (see Cappelen et al., 2007, 2022). In the presence of inaccurate beliefs or other biases, choices may not provide a direct reflection of preferences. We therefore abstract from these labels and instead refer to spectators in terms of their observable behavior.



in terms of how spectators must infer  $\pi$ .

In the *outcome* luck environment, there is a  $q$  probability that a coin flip determines the winner and a  $1 - q$  probability that we select the worker with the higher number of completed encryptions as the winner. To infer  $\pi$  from  $q$ , spectators must use Bayesian updating, which implies  $\pi = 1 - 0.5q$ . In the *opportunity* luck environment, we randomly assign productivity multipliers  $m_k$  to each worker  $k \in \{1, 2\}$  and determine the winner by comparing the final scores, given by  $m_k$  times the number of completed tasks,  $e_k$ . Without loss of generality, assume that worker 1 wins, which means  $m_1 e_1 > m_2 e_2$ . Spectators must form an estimate of  $\pi$  using information about the relative magnitudes of  $m_1$  and  $m_2$  and their perceived distribution of effort. Formally, the probability that the higher-effort worker is the winner given the information spectators observe is

$$\pi = \Pr(e_1 \geq e_2 | m_1 e_1 > m_2 e_2, m_1, m_2). \quad (4)$$

Spectators must consider two cases. First, if  $m_1 \leq m_2$ , then  $\pi = 1$ . Intuitively, if worker 1 wins despite having a lower (or the same) multiplier, then they must have exerted more effort than worker 2. Conversely, if  $m_1 > m_2$ , equation (4) becomes

$$\pi = \frac{\Pr(e_1 \geq e_2 | m_1, m_2)}{\Pr(m_1 e_1 > m_2 e_2 | m_1, m_2)} \geq 0.5. \quad (5)$$

Notably, expression (5) depends on the relative multiplier  $m_1/m_2$ . Moreover,  $\pi$  is convex and decreasing in  $m_1/m_2$  if effort is normally distributed. This is because even a small multiplier advantage has a big impact on who wins if worker effort tends to be similar.

The spectator's estimate of  $\pi$  may not be accurate for several reasons. When there is outcome luck, the spectator may fail to perform basic Bayesian updating. When there is opportunity luck, they might not appreciate that a small multiplier advantage can correspond to a significant change in  $\pi$ . Relatedly, spectators may resort to simple heuristics such as comparing multiplier differences rather than assessing how multiplier ratios translate to differences in  $\pi$ . Since a spectator's estimate of  $\pi$  may deviate from the truth, we use  $\tilde{\pi}_i$  to denote spectator  $i$ 's subjective estimate of  $\pi$ . Then, spectator  $i$ 's redistribution decision

becomes

$$r_i^* = \tilde{\pi}_i f_i + (1 - \tilde{\pi}_i)(1 - f_i). \quad (6)$$

Let  $p$  denote the fraction of spectators who do not redistribute anything in the environment under consideration and let  $F$  denote the distribution of fairness preferences,  $f_i$ , among those who do redistribute some amount. Assuming that  $f_i$  and  $\tilde{\pi}_i$  are independent, the average level of redistribution in the population is given by:

$$\bar{r}^* = (1 - p) (\tilde{\pi} f + (1 - \tilde{\pi}) (1 - f)), \quad (7)$$

where  $\tilde{\pi}$  is the average estimate of  $\pi$  and  $f$  is the average share of earnings that spectators deem fair for the less productive worker among spectators who choose to redistribute some positive amount. In the remainder of this section, we use equation (7) to derive our main theoretical predictions.

## 2.1 Predictions and Comparative Statics

Our main research question concerns how spectators' redistribution decisions depend on whether luck interacts with effort in the earning process. To facilitate comparing predictions across conditions, we add a subscript  $\tau \in \{IOp, CF\}$  to  $p$ ,  $\tilde{\pi}$ , and  $f$  as these terms may depend on whether luck is manifested through inequality of opportunity (IOp) or a coin flip (CF).

First, we compare the average level of redistribution in IOp and CF. Equation (7) highlights that average redistribution depends on three factors: the share of spectators who do not redistribute any earnings ( $p_\tau$ ), the average fair-share among those who do redistribute ( $f_\tau$ ), and subjective beliefs about the importance of luck ( $\tilde{\pi}_\tau$ ). Thus, average redistribution may differ across luck environments due to differences in any of these three factors. First, a different share of individuals might decide not to redistribute any earnings across environments; we refer to this as differences in the “extensive margin” of redistribution. For example, spectators might hold different fairness views regarding the two forms of luck, and, therefore, might be against any redistribution regardless of how important luck is in one environment but support it in another.

Average redistribution may also differ due to changes in the average amount redistributed among spectators who redistribute a strictly positive amount; we refer to this as the “intensive margin” of redistribution. Intensive margin responses can arise from differences in the fair-share across environments or because spectators hold different beliefs about the role of luck across environments. For example, spectators may overestimate the importance of luck when it interacts with effort,  $\tilde{\pi}_{IOp} > \tilde{\pi}_{CF}$ , which would increase the amount of redistribution in IOp relative to CF.

Second, we explore the elasticity of redistribution to changes in luck across environments. We use equation (7) to obtain the effect of a marginal increase in  $\pi$ :

$$\frac{\partial \bar{r}^*}{\partial \pi} = -2(1 - p_\tau) \left( \frac{1}{2} - \bar{f}_\tau \right) \frac{\partial \tilde{\pi}_\tau}{\partial \pi}. \quad (8)$$

Equation (8) shows that the average level of redistribution is decreasing in  $\pi$  in general. The term  $\partial \tilde{\pi}_\tau / \partial \pi$  accounts for the possibility that subjective beliefs may not respond one-to-one to changes in the objective value of  $\pi$ .

Equation (8) also highlights why the elasticity of redistribution with respect to luck may differ across environments. First, the larger the share of spectators who do not redistribute anything, the less sensitive redistribution is to changes in the importance of luck. Second, the more spectators who do redistribute decide to allocate to the lower-effort worker on average, the less responsive redistribution is to changes in the importance of luck. Finally, the elasticity of redistribution depends on how subjective beliefs respond to changes in the true importance of luck. For example, if spectators underestimate the importance of a small multiplier difference, then redistribution will be less responsive to changes in  $\pi$  in IOp than in CF.

Equations (7) and (8) form the basis of our primary empirical hypotheses. Both equations are determined by spectator preferences and subjective beliefs. To isolate the role of preferences, we consider an information intervention in which we tell spectators the value of  $\pi$ . This allows us to shut down the role of inaccurate beliefs in evaluating the differences in redistribution between opportunity and outcome luck.

We can further investigate the extent to which spectator beliefs are biased by examining how information affects the elasticity of redistribution with respect to luck. Formally, this elasticity becomes  $\partial \bar{r}^* / \partial \pi = -(1 - p_\tau)(1 - 2\bar{f}_\tau)$ . This term is greater in magnitude than the

analogue expression for the no information treatment if  $\partial \tilde{\pi}_\tau / \partial \pi < 1$ . In other words, if the information treatment makes spectators more responsive to changes in luck, this implies that they were underestimating its importance in the absence of information.

### 3 Experimental Design

The experiment follows the impartial-spectator paradigm in [Cappelen et al. \(2013\)](#) and is divided into three stages: a production stage, an earnings stage, and a redistribution stage.<sup>4</sup> In the production stage, workers engage in a real-effort task for a fixed amount of time. In the earnings stage, we randomly pair workers and determine the winner based on varying degrees of worker effort and chance. In the redistribution stage, impartial third-party spectators make decisions about earnings redistribution between pairs of workers. Our research questions concern the redistribution decisions of spectators. Therefore, we limit our discussion of the production and earnings stage to the key elements that are relevant to spectators’ redistribution decisions.

The experiment embeds between-subject variation in whether luck interacts with effort in the earning process (lucky opportunities vs. lucky outcomes), timing of when luck is revealed to the workers (before vs. after), and information available to spectators about the importance of luck (full vs. partial). We also implement within-subject variation in the importance of luck in determining the winner, that is, variation in the probability that the higher-effort worker won,  $\pi \in [0.5, 1]$ .

#### 3.1 Production and Earnings Stage

In the production stage, workers engage in a real-effort task in which they encrypt three-letter “words” into numerical code ([Erkal et al., 2011](#)). They have five minutes to correctly encrypt as many words as possible using a dynamic and randomly generated codebook for each word ([Benndorf et al., 2019](#)). We provide an example of a word encryption in Appendix Figure C1. Panel A of Appendix Figure A1 plots the distribution of worker performance.

In the earnings phase of the study, we randomly pair workers and determine the winner based on some combination of effort and luck. Winners are initially allocated earnings of \$5

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<sup>4</sup>We designed all experimental programs in oTree ([Chen et al., 2016](#)).

and losers are allocated \$0. The exact interaction between luck and effort, and the overall importance of luck form our main experimental treatments, which we describe in Section 3.3.

### 3.2 Redistribution Stage

In the redistribution stage, spectators can redistribute earnings between a pair of real workers. The spectator’s task is to choose how much income to redistribute from the winner to the loser. Spectators make a total of 12 redistribution decisions involving different real pairs of workers, with each decision varying in the importance of luck involved in the worker-pair outcome.

Spectators can choose to redistribute any amount from \$0 to \$5 in \$0.50 increments. We present each decision in the form of an adjustment schedule (see Appendix Figure C2 for an example of a redistribution choice). For example, an adjustment of \$1.50 implies \$3.50 for the winner and \$1.50 for the loser. The first option is always a \$0.00 adjustment and is labeled as a “no”-adjustment choice. The remaining  $\{\$0.50, \dots, \$5.00\}$  redistribution choices are labeled as a “yes”-adjustment choice, and denote the final earnings for both the winner and the loser: that is,  $\{(\text{winner gets}, \text{loser gets})\} = \{(\$4.50, \$0.50), (\$4.00, \$1.00), \dots, (\$0.50, \$4.50), (\$0.00, \$5.00)\}$ .<sup>5</sup>

To give spectators an incentive to respond truthfully and accurately, we randomly select one of their 12 decisions and implement it. In other words, one of the spectator’s decisions determined the final, adjusted earnings of a real pair of workers. We emphasize to spectators that they should treat each decision as if it is real, since they do not know which decision we will randomly draw. We also assure spectators that while workers know a third party may influence their final earnings, the spectator’s identity is completely anonymous to the workers.

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<sup>5</sup>We included several design features to combat the influence of framing effects in these redistribution choices. First, we included choices beyond the egalitarian redistribution preferences of \$2.50 to the winner and loser—that is, \$3.00 or more to the loser and \$2.00 or less to the winner. Second, we inform spectators that workers are not told whether they won or lost nor the exact amount they will earn in each case. Spectators know that workers were informed that they could earn up to \$5 and that winning against their randomly assigned opponent increases their chances of earning more. This design intentionally removes any confounding issues relating to spectators’ unwillingness to take earnings away from what workers might already expect.

### 3.3 Spectator Treatments

Spectators always have some signal about the importance of chance in determining outcomes. However, we randomly vary between subjects whether luck interacts with effort, the timing of when it occurs, and the information available to spectators about the importance of chance in driving outcomes.

#### 3.3.1 Lucky Outcomes vs. Lucky Opportunities

We assign spectators to redistribute earnings under two different luck environments: outcome and opportunity. In our outcome luck condition, we select the winner by a coin flip (CF) with probability  $q$  and by the number of correct encryptions with probability  $1 - q$ . Thus, the effect of luck is independent of worker effort when there is outcome luck. In our opportunity luck condition, we generate inequality of opportunity (IOp) by randomly assigning effort multipliers to workers. For example, a worker with a multiplier of 1.2 who solved 20 encryptions would have a final score of 24, while a worker with a multiplier of 3.0 who solved 10 encryptions would have a final score of 30. The winner in each pair is the worker who has the higher final score. Thus, effort and luck interact when there is opportunity luck. We draw the multiplier for each worker  $i$  from the distribution:  $m_i = 1$  with probability 0.05,  $m_i = 4$  with probability 0.05, and  $m_i \sim U(1, 4)$  with probability 0.9. We round all multipliers to the nearest 0.1. Henceforth, we label our outcome luck environment CF and our opportunity luck environment IOp.

We never inform spectators about the actual effort level of the workers. We do provide some information about the importance of luck in each condition. In the CF condition, spectators know the probability  $q$  that we determine the winner by a coin flip, but not whether a coin flip actually determined the winner. Spectators also know that we do not reveal this probability to workers, though workers do know that there is some unstated chance that a coin flip determines their outcomes.

Appendix Figure C3 provides an example of a CF redistribution decision. We randomly assign one-third of spectators to the CF treatment. In the IOp treatment, spectators know the multiplier of the worker who won and of the worker who lost. We inform spectators that workers only know of their own multiplier and do not know anything about the worker

they compete against.<sup>6</sup> Appendix Figure C3 provides an example of an IOp redistribution decision. We randomly assign two thirds of spectators to the IOp treatment.

### 3.3.2 Importance of Luck in Determining the Winner

We implement within-subject variation in the importance of luck across worker pairs. We tightly control for the importance of luck by introducing a common metric that is portable across environments: the probability that the winner in a given pair completed more encryptions ( $\pi$ ). In other words,  $\pi$  measures the likelihood that outcome differences are due to effort rather than luck.

The key information we present on each trial is the multiplier of each worker pair,  $(m_i, m_j)$ , or the ex-ante probability that the winner was determined by a coin flip,  $q$ . It is therefore necessary to map each  $\pi$  value to a corresponding  $(m_i, m_j)$  or a coin-flip probability  $q$ . Mapping  $\pi$  to  $q$  is straightforward and is given by the formula  $\pi = 1 - 0.5q$ . Mapping  $\pi$  to a multiplier pair,  $(m_i, m_j)$ , is less straightforward. To estimate  $\pi$  for a given relative multiplier,  $m \equiv \max\{m_i, m_j\} / \min\{m_i, m_j\}$ , we examine all possible worker pairs and compute the fraction of times that the winner was the worker who solved more encryptions. With 800 workers per condition, there are  $\binom{800}{2} = 319,600$  possible pairings. Since we can assign the higher multiplier to either worker, that creates 639,200 observations that we can use to calculate  $\pi$  for each relative multiplier,  $m$ . Using this method, we compute, for each  $m$ , the fraction of all possible pairings in which the winner completed more encryptions. This yields an estimate of  $\pi$  for each  $m$ , providing a mapping from  $m$  to  $\pi$  (depicted in Panel B in Appendix Figure A1). For a given  $\pi$ , we then select a random worker pairing with a corresponding relative multiplier.

Spectators make decisions for a total of 12 worker pairs and each pair varies in the probability that the worker who solved the most encryptions was the winner,  $\pi$ . Each worker pair corresponds to a unique value of  $\pi$  drawn from one of the following 12 bins:

$$\pi \in \left\{ \underbrace{\{0.50\}}_{\text{Bin 1}}, \underbrace{\{0.51, \dots, 0.54\}}_{\text{Bin 2}}, \underbrace{\{0.55, 0.56, \dots, 0.59\}}_{\text{Bin 3}}, \dots, \underbrace{\{0.95, 0.96, \dots, 0.99\}}_{\text{Bin 11}}, \underbrace{\{1\}}_{\text{Bin 12}} \right\}. \quad (9)$$

For each spectator, we randomly draw one value of  $\pi$  from each of the 12 bins. This

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<sup>6</sup>Workers also know the distribution from which we draw multipliers.

ensures that every spectator makes a decision with  $\pi = 0.5$ ,  $\pi = 1$ , and that the remaining values are evenly distributed throughout the support of  $\pi$ . We present the 12 trials in random order.

### 3.3.3 Timing of Opportunity Luck

We also randomly vary the timing of when luck is realized. In our baseline IOp condition, we inform workers of their multipliers before they begin working on the encryption task. In the ex-post (EP) IOp condition, workers learn their multipliers after they complete the task. We randomly assigned half of the spectators in the opportunity luck treatment to baseline IOp and the other half to EP-IOp.

### 3.3.4 Information Intervention

We randomly assign half of spectators in each treatment to receive precise information about  $\pi$  (INFO). In the IOp-INFO condition, we present the following additional text on the redistribution decision screen: “Based on historical data for these multipliers, there is a  $[\pi]$  chance that the winner above completed more transcriptions than the loser.” In the CF-INFO condition, the equivalent text is: “There is a  $[\pi]$  chance that the winner above completed more encryptions than the loser.” As noted above, the value of  $\pi$  varies from trial to trial. Appendix Figure C3 provides an example of the decision screens for the CF-INFO and IOp-INFO treatments.

### 3.3.5 Workers’ Awareness about Rules

Finally, we vary the timing of when workers learn about how luck is experienced. In the Rules-Before condition, we inform workers that there will be score multipliers or a coin flip that influences the final outcomes *before* they start their task. In the Rules-After condition, we inform workers that there will be multipliers or a coin flip that influences the final outcomes *after* they complete the task. We randomly assign half of the participants in the EP-IOp and CF treatments to Rules-Before and half to Rules-After. We assign all participants in baseline IOp to Rules-Before. Spectators have full information about when workers learned how we determine the winner.



### 3.4 Comprehension Checks and Elicitation of Beliefs

To ensure that spectators understand the details of the design, we implement a number of comprehension questions after they see the initial instructions about the worker task. These questions test spectators’ understanding of how luck can affect outcomes, as well as their awareness of when workers learn about the importance of luck. Spectators cannot continue until they select the correct answer, and we provide a brief explanation about why the answer is correct once they submit it. Therefore, these questions serve as both a comprehension check and as reminders that reinforce the critical aspects of the worker task.

After spectators finish the 12 redistribution decisions, they complete a brief exit survey. The first part of the exit survey consists of three questions. First, we randomly select one of the 12 decisions that spectators made and present the same information to them. We then ask them to provide their estimate of  $\pi$ : that is, how likely they think it is that the winner completed more encryptions than the loser. Second, we ask spectators in the CF condition how many encryptions they think workers solved on average. For spectators in the IOp treatments, we randomly draw a multiplier and ask how many encryptions they think workers with that multiplier solved on average. Finally, we ask them how much they would allocate to the winner if they knew for sure that they had solved more encryptions. See Appendix Figures C4 and C5 for the first part of the exit survey.

The second part of the exit survey asks spectators to select their level of agreement with a number of belief statements in a five-point Likert scale grid. It probes their views on various topics relating to income redistribution and the role of the government. We also embed an attention check in one of the rows that states: “Select disagree if you are reading this.” See Appendix Figure C6 for the second part of the exit survey.

### 3.5 Recruitment

#### 3.5.1 Workers

We recruited 2,416 participants on Amazon Mechanical Turk to participate in the worker task. Participants were U.S.-based, had a 95 percent minimum approval rate, and at least 500 approved human intelligence tasks (HITs). We excluded 16 participants who completed less than one encryption per minute for a final sample of 2,400 workers. We paid all workers

a fixed participation fee of \$2 upon task completion. Workers also received an additional payment of up to \$5 based on the decision of a randomly chosen spectator approximately six weeks after the workers completed the task.

### 3.5.2 Spectators

Our sample of spectators contains 1,170 panelists from the Federal Reserve Bank of New York’s *Survey of Consumer Expectations* (SCE). This survey targets a nationally representative panel of U.S. heads of households ([Armantier et al., 2017](#)). Our experimental interface was mobile-friendly to encourage hard-to-reach demographic groups to participate in our experiment. The median spectator spent 15 minutes on the survey; 89 percent of them passed the attention check, and 77 percent passed all four comprehension questions on their first attempt. No spectator failed to answer more than two comprehension questions. We paid all respondents a \$5 Amazon gift card for completing the survey.

Table 1 reports descriptive statistics for the spectator sample.<sup>7</sup> The average spectator is 49 years old; 52 percent are female, 62 percent are married, and 14 percent are non-white. More than 62 percent of spectators attained a college degree, 58 percent work full-time, 15 percent work part-time, and 20 percent are retired. About a quarter (24 percent) of spectators have a household income below \$40,000 per year. Our sample includes individuals living in all 50 states plus Washington DC. About 23 percent of spectators live in the Midwest, 21 percent in the Northeast, 35 percent in the South, and 22 percent in the West. Columns 2–5 show that spectator characteristics are similar across conditions.

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<sup>7</sup>See Appendix Table A1 for summary statistics on our sample of workers.

Table 1: Average spectator characteristics by treatment condition

	All (1)	Baseline condition			INFO condition		
		CF (2)	IOp (3)	EP−IOp (4)	CF (5)	IOp (6)	EP−IOp (7)
Panel A. Demographic characteristics and race							
Age	49.10	49.50	50.08	47.35	48.68	49.63	49.37
Male	0.48	0.50	0.47	0.48	0.48	0.52	0.45
Married	0.62	0.61	0.63	0.68	0.57	0.66	0.60
Nr. of children under 18	0.60	0.51	0.56	0.61	0.53	0.74	0.62
White	0.86	0.82	0.88	0.84	0.84	0.88	0.90
Black	0.08	0.12	0.06	0.07	0.07	0.07	0.07
Hispanic	0.08	0.09	0.08	0.09	0.08	0.08	0.06
Panel B. Education and employment							
Completed college	0.62	0.62	0.62	0.65	0.60	0.67	0.58
Numeracy index	4.09	4.00	4.12	4.16	4.11	4.15	4.03
Works full-time	0.58	0.62	0.53	0.64	0.55	0.56	0.58
Works part-time	0.15	0.15	0.14	0.13	0.18	0.14	0.15
Retired	0.20	0.16	0.22	0.19	0.19	0.23	0.22
Homeowner	0.73	0.68	0.77	0.70	0.69	0.74	0.77
Panel C. Household Income							
Income below 40k	0.24	0.25	0.22	0.19	0.23	0.24	0.27
Income btw. 40k and 75k	0.28	0.30	0.27	0.28	0.28	0.25	0.26
Income btw. 75k and 100k	0.16	0.17	0.14	0.15	0.17	0.15	0.17
Income over 100k	0.32	0.25	0.36	0.38	0.31	0.36	0.28
Panel D. Region							
Lives in the Midwest	0.23	0.30	0.20	0.26	0.20	0.20	0.20
Lives in the Northeast	0.21	0.20	0.20	0.19	0.23	0.22	0.23
Lives in the South	0.35	0.32	0.30	0.36	0.31	0.36	0.43
Lives in the West	0.22	0.18	0.30	0.19	0.25	0.22	0.15
Used a mobile device	0.37	0.38	0.39	0.35	0.42	0.31	0.38
Minutes spent in experiment	14.72	14.67	15.06	13.62	14.83	15.37	15.09
Passed attention check	0.89	0.86	0.84	0.91	0.93	0.91	0.88
Number of spectators	1,170	197	194	193	197	196	193

**Notes:** This table shows the demographic make-up of our spectator sample by percentage, comparing spectators treated with and without information about  $\pi$  (the likelihood that the winner performed better than the loser), between outcome luck (CF, columns (2) and (5)), opportunity luck (IOP, columns (3) and (6)), and ex-post opportunity luck (EP-IOP, columns (4) and (7)) conditions.

## 4 Main Results

This section investigates how both the level and the elasticity of redistribution depend on whether luck interacts with effort when creating income inequality. We also explore whether any differences that we observe stem from changes in the intensive or extensive margin of redistribution. When comparing redistribution across different environments, we examine spectators' decisions as a function of the likelihood that the winner is the worker who exerted more effort ( $\pi$ ). The primary outcome we examine is the fraction of earnings,  $r_{ip}$ , that spectator  $i$  redistributes from the winner to the loser in worker pair  $p$ . We refer to the

“winner” as the worker who initially receives the total earnings and the “loser” as the worker who initially receives no earnings. When  $r_{ip} = 0$ , the loser gets none of the total earnings and the winner retains all of the earnings. If  $r_{ip} = 0.5$ , both workers receive half of the total earnings.

#### 4.1 Redistribution under Opportunity and Outcome Luck

Panel A of Table 2 reports the average level of distribution across our luck treatments. When chance creates inequality by affecting outcomes directly (the CF condition), spectators redistributed 27.6 percent of earnings from the winner to the loser on average. However, when luck affected outcomes by providing workers with unequal opportunities (the IOp condition), spectators redistributed only 23.4 percent of earnings on average. In other words, spectators redistributed 4.2 percentage points less of total income when luck was experienced indirectly through opportunities than when it stemmed directly from outcomes ( $p < 0.01$ , column 3). This difference equates to a 15.3 percent decrease in the final earnings for the worker who lost.

We also compare differences in the level of redistribution separately for the different likelihoods that luck determined the outcome. For this, we compute average redistribution for each experimental  $\pi$  bin, as defined in equation (9). Let  $b \in \{1, \dots, 12\}$  index the 12 experimental  $\pi$  bins. Recall that each spectator made a redistribution decision for a value of  $\pi$  from within each of these 12 bins. In Panel C of Table 2, we estimate regressions of the form:

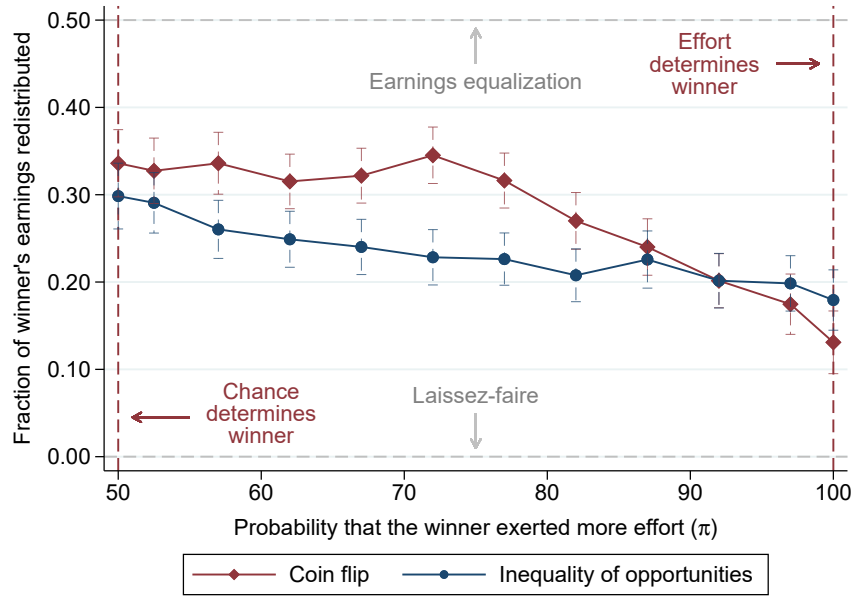
$$r_{ib} = \sum_{b=1}^{12} \gamma_b \pi_b + \varepsilon_{ib}, \quad (10)$$

where  $\pi_b$  is an indicator that equals one if  $\pi_{ip}$  is in bin  $b$ . We estimate equation (10) separately for each treatment as well as interacting the bins with treatment dummies to assess whether mean redistribution is the same across luck treatments at a given  $\pi$  bin. We cluster standard errors at the spectator level in all specifications.

Figure 1 plots the mean redistribution in the CF and IOp conditions against  $\pi$  for each bin. Each point is our estimate of  $\gamma_b$  for a given bin and treatment. Figure 1 reveals two striking patterns. First, average redistribution in IOp is lower than in CF across most  $\pi$  bins. For  $\pi \leq 0.85$ , average redistribution is higher in CF than in IOp. For  $\pi \in (0.85, 1)$ , average

redistribution is statistically equal in the two conditions. For  $\pi = 1$ , average redistribution is higher in IOp than in CF, although the difference is not statistically significant at the 10 percent level. These results show that average redistribution in the CF condition is equal to or higher than average redistribution in the IOp condition for all situations in which luck played any role ( $\pi < 1$ ).

Figure 1: Redistribution and the probability that the winner completed more encryptions ( $\pi$ )



**Notes:** This figure shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) relative to the likelihood that the winner exerted more effort. Displayed are the two main experimental conditions: outcome luck (CF) and opportunity luck (IOp).

The second important difference is in the shape of the negative relationship between average redistribution and the likelihood that luck determined the winner. In both conditions, redistribution tends to decline in  $\pi$ . In the IOp condition, redistribution is approximately linear and downward sloping from  $\pi = 0.5$  to  $\pi = 0.85$ . However, spectators are unresponsive to incremental increases in  $\pi$  beyond that point: Redistribution is roughly flat from  $\pi = 0.85$  to  $\pi = 1$ . In the CF condition, we observe the opposite pattern: Spectators are unresponsive to changes in the importance of luck from  $\pi = 0.5$  to  $\pi = 0.75$ , but react strongly to incremental changes in  $\pi$  thereafter. Moreover, the downward-sloping relationship between redistribution and  $\pi$  is approximately linear for  $\pi \geq 0.75$ .

To summarize the relationship between average redistribution and  $\pi$  in each condition, we estimate linear models that relate the share of earnings that spectators redistribute to the

likelihood that the winner of match  $p$  exerted more effort,  $\pi_{ip}$ :

$$r_{ip} = \alpha + \beta\pi_{ip} + \varepsilon_{ip}, \quad (11)$$

where  $\varepsilon_{ip}$  is an error term. The main parameter of interest is  $\beta = \partial \mathbb{E}(r_{ip}) / \partial \mathbb{E}(\pi_{ip})$ , which measures the elasticity of redistribution with respect to  $\pi_{ip}$ . The exogenous within-subject variation in  $\pi_{ip}$  allows us to identify  $\beta$ .

Panel B of Table 2 presents estimates of  $\beta$  across the different luck environments. Spectators redistribute more as the likelihood that the outcome is due to luck increases. A 10 percentage point decrease in  $\pi$  leads to a 2.0 percentage point increase in redistribution in the IOp condition. However, redistribution is more elastic to changes in  $\pi$  in the CF condition: A ten percentage point decrease in  $\pi$  leads to a 3.7 percentage point increase in the share of earnings redistributed in the CF condition. To formally test for differences in how spectators react to changes in  $\pi$ , we estimate the following specification:

$$r_{ip} = \alpha_0 + \beta_0\pi_{ip} + \alpha_1\mathbb{1}_{\text{IOp},i} + \beta_1\mathbb{1}_{\text{IOp},i}\pi_{ip} + \varepsilon_{ip}, \quad (12)$$

where  $\mathbb{1}_{\text{IOp},i}$  is equal to one if spectator  $i$  was in the IOp treatment group. The coefficient  $\beta_1$  measures the difference in the elasticity of redistribution with respect to  $\pi$  in the IOp versus CF treatment. Column (3) of Table 2 shows that this coefficient is economically and statistically significant ( $p < 0.01$ ). In other words, spectators in the IOp condition respond less to changes in the probability that the outcome is due to luck relative to the CF condition. This is despite the fact that changes in luck are observationally equivalent in terms of its impact on outcomes across the two conditions.

We observe redistribution under CF and IOp for two important boundary cases that are typical in much of the prior literature (Cappelen et al., 2007, 2013; Almås et al., 2020).<sup>8</sup> As shown in Figure 1, we find no significant differences in redistribution across the two environments in the cases where the winner was chosen by pure chance ( $\pi = 0.5$ ) or solely on merit ( $\pi = 1$ ). On the other hand, our experimental paradigm allows us to observe redistribution behavior as we vary the importance of luck for determining outcomes between these

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<sup>8</sup>A notable exception is Cappelen et al. (2022), who examine how redistribution behavior responds to changes in  $q$  in the CF environment. We replicate the concave relationship that they find when luck emerges through exogenous coin-flip probabilities.

Table 2: Fraction redistributed as a function of  $\pi$ 

	Outcome: Fraction of earnings redistributed		
	CF	Inequality of	Difference
	condition (1)	opportunities (2)	CF – IOp (3)
<b>Panel A. Average redistribution</b>			
Constant	0.276*** (0.010)	0.234*** (0.013)	0.042*** (0.016)
$N$ (Redistributive decisions)	2,364	2,328	4,692
<b>Panel B. Linear slope</b>			
$\pi$	-0.037*** (0.005)	-0.020*** (0.004)	-0.017*** (0.006)
Constant	0.368*** (0.016)	0.283*** (0.016)	0.085*** (0.023)
$N$ (Redistributive decisions)	2,364	2,328	4,692
<b>Panel C. Average redistribution across <math>\pi</math> bins</b>			
$\pi = 0.50$	0.336*** (0.020)	0.298*** (0.019)	0.038 (0.028)
$\pi \in (0.50, 0.55]$	0.327*** (0.019)	0.291*** (0.018)	0.037 (0.026)
$\pi \in (0.55, 0.60]$	0.336*** (0.018)	0.260*** (0.017)	0.076*** (0.025)
$\pi \in (0.60, 0.65]$	0.315*** (0.016)	0.249*** (0.016)	0.066*** (0.023)
$\pi \in (0.65, 0.70]$	0.322*** (0.016)	0.240*** (0.016)	0.082*** (0.023)
$\pi \in (0.70, 0.75]$	0.345*** (0.017)	0.228*** (0.016)	0.117*** (0.023)
$\pi \in (0.75, 0.80]$	0.316*** (0.016)	0.226*** (0.015)	0.090*** (0.022)
$\pi \in (0.80, 0.85]$	0.270*** (0.017)	0.208*** (0.015)	0.062*** (0.023)
$\pi \in (0.85, 0.90]$	0.240*** (0.017)	0.226*** (0.017)	0.014 (0.023)
$\pi \in (0.90, 0.95]$	0.202*** (0.016)	0.202*** (0.016)	-0.000 (0.022)
$\pi \in (0.95, 1.00]$	0.175*** (0.018)	0.198*** (0.016)	-0.024 (0.024)
$\pi = 1.00$	0.131*** (0.018)	0.179*** (0.018)	-0.048* (0.025)
$N$ (Redistributive decisions)	2,364	2,328	4,692

**Notes:** This table shows estimates of redistribution under outcome luck (column 1), opportunity luck (column 2), and the difference (column 3). Panel A shows the mean share of earnings redistributed. Panel B shows a linear approximation of the relationship between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker. Panel C shows the relationship between redistribution and the likelihood that the winning worker performed better is split into 12 bins. Omitted category is  $\pi = 0.50$ . Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

two extremes. We find that large differences in redistribution behavior between IOp and CF emerge between the boundary cases, especially over the range  $\pi \in [0.55, 0.85]$ . Therefore, our results highlight that varying the degree to which luck matters is important for understanding redistribution behavior: Focusing on only the two extreme cases would lead us to conclude that there are minimal differences in redistribution between outcome and opportunity luck.

Finally, results from a heterogeneity analysis reported in Appendix Table A3 highlight a number of relevant differences across spectators’ political and societal views. Most notably, people who self-reportedly side with republicans most of the time display less support for redistribution than those who do not. This is consistent with both survey and experimental evidence that finds that republicans are less likely to support redistribution (Ashok et al., 2015; Alesina et al., 2018; Almås et al., 2020). While we find that this difference persists in both luck environments, it is more pronounced when luck is experienced through unequal opportunities. This provides suggestive evidence that redistribution preferences are more dependent on political views when luck interacts with effort to determine outcomes. Focusing on environments with outcome luck might understate the political divide in support for redistribution if opportunity luck is the dominant driver of inequality in reality.

## 4.2 Extensive vs. Intensive Margin of Redistribution

We find that redistribution depends on whether luck creates income inequality indirectly through unequal opportunities or directly by selecting outcomes at random. To understand why we observe this gap in the overall level and slope of distribution, we distinguish between the intensive and extensive margins of redistribution. The extensive margin refers to whether or not spectators redistribute anything when luck influences outcomes. The intensive margin refers to how much spectators redistribute, conditional on redistributing anything. We investigate how both of these margins differ between luck environments.

We first explore whether spectators’ willingness to redistribute anything differs between opportunity and outcome luck. In Table 3, we estimate regressions where the outcome is a binary variable equal to one if a spectator never redistributes anything across all 12 decisions.<sup>9</sup> Column (1) shows that 9.6 percent of spectators never redistribute in CF. However,

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<sup>9</sup>In Table A2, we re-estimate these models under the assumption that someone who redistributed either once or twice made a mistake and never wanted to redistribute anything either. We find an even larger difference between luck environments under this assumption.



this fraction is significantly higher when workers faced unequal opportunities: On average, 15.9 percent of spectators do not redistribute in IOp. The difference of 6.3 percentage points is statistically significant ( $p < 0.01$ ) and equates to a 66 percent increase in the share of spectators who never redistribute. Thus, the extensive margin of redistribution is substantially lower when there are unequal opportunities than when outcomes are directly influenced by chance.

Table 3: Fraction of spectators who do not redistribute across conditions

	Outcome: = 1 if spectator does not redistribute in any round			
	(1)	(2)	(3)	(4)
IOp	0.063*** (0.024)	0.063*** (0.024)	0.063* (0.034)	0.064* (0.035)
Knows $\pi$		-0.011 (0.024)	-0.010 (0.030)	-0.014 (0.031)
IOp $\times$ knows $\pi$			-0.002 (0.048)	0.001 (0.049)
Constant	0.096*** (0.015)	0.102*** (0.019)	0.102*** (0.022)	0.121 (0.109)
$N$	9,408	9,408	9,408	9,384
Spectator-level controls	No	No	No	Yes

**Notes:** The dependent variable is the fraction of spectators who do not redistribute in any round. In column 4, we control for age, gender, marital status, number of children in the household, educational attainment, numerical literacy, race, indicators for working part-time and full-time, homeownership, income, region, the time spectators spent on the experiment, indicators for passing the comprehension and attention checks, an indicator that equals one if the spectator completed the survey on a mobile device, the probability that the winner exerted more effort on each worker-pair, and round number fixed effects (to control for possible fatigue effects). Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. \*\*\*, \*\* and \* denote significance at the 10%, 5% and, 1% level, respectively.

A higher share of spectators who never redistribute has two mechanical effects on redistribution. First, having fewer spectators who redistribute anything shifts the average level of redistribution down. Second, since these spectators never redistribute at any  $\pi$ , the slope flattens if there are more of them (see equation (8)). Thus, the change in the extensive margin of redistribution partly explains the changes in aggregate redistribution across our IOp and CF treatments.

Next, we analyze support for redistribution among the spectators who do redistribute in at least one of their 12 decisions and compare their decisions across our luck environments. Table 4 reproduces the analysis in Panels A–B of Table 2 but excludes spectators who do not redistribute anything in all 12 decisions. We continue to find differences in the average level of redistribution across the IOp and CF condition for this sub-sample: Spectators redistribute

30.7 percent on average in CF (column 1) and 28.0 percent on average in IOp (column 2). This difference is statistically significant at the 10 percent level (column 3).

We also continue to find that spectators in IOp are less sensitive to changes in the importance of luck. In Panel B, columns (1) and (2) show that a 10 percentage point increase in  $\pi$  reduces redistribution by 4.1 percentage points in the CF condition and by 2.4 percentage points in the IOp condition. This difference in slope is statistically significant ( $p < 0.01$ , column 3). Importantly, the magnitude of this difference is similar to the overall estimates in Table 2. Thus, the diminished overall sensitivity to luck that we observe for the IOp treatment is not merely due to the mechanical effect of more spectators deciding to redistribute nothing. Rather, it is largely driven by changes in the responsiveness to the importance of luck in determining workers' outcomes among spectators who do redistribute.

Table 4: Fraction redistributed as a function of  $\pi$  for spectators who redistribute something

	Outcome: Fraction of earnings redistributed		
	CF condition (1)	Inequality of opportunity (2)	Difference CF – IOp (3)
<b>Panel A. Average redistribution</b>			
Constant	0.307*** (0.009)	0.280*** (0.012)	0.027* (0.015)
$N$ (Redistributive decisions)	2,124	1,944	4,068
<b>Panel B. Linear slope</b>			
$\pi$	-0.041*** (0.005)	-0.024*** (0.004)	-0.018*** (0.007)
Constant	0.410*** (0.015)	0.339*** (0.016)	0.071*** (0.022)
$N$ (Redistributive decisions)	2,124	1,944	4,068

**Notes:** Panel A shows the mean share of earnings redistributed under outcome luck (CF, column 1), opportunity luck (IOp, column 2), and the difference (column 3). Panel B shows estimates of redistribution as a linear function of the probability that the winner was the worker who exerted more effort ( $\pi$ ) on each treatment. The sample is restricted to spectators who redistributed a strictly positive amount in at least one of their 12 decisions. Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

In summary, we find that support for redistribution is significantly more responsive to changes in the importance of luck when it is experienced directly through outcomes rather than indirectly through the rate of return to effort. This difference arises despite the fact that we hold fixed the importance of luck in determining workers' outcomes. The difference in the level of redistribution is driven by differences in both the intensive and extensive margins,

while the different elasticity of redistribution to changes in luck is due to differences in the intensive margin. In the following section, we explore several potential mechanisms that might drive this wedge in redistribution.

## 5 Mechanisms

We test two key mechanisms that may drive the patterns of redistribution that we observe across the outcome and opportunity luck environments. First, we investigate whether differences in actual or perceived worker effort across the environments can explain our main results. Second, we leverage our information intervention to test whether spectators have inaccurate beliefs about the role of luck in determining outcomes.

### 5.1 The Timing of Luck and Effort Responses

A key difference between our luck environments is that unequal opportunities are known before people exert effort, while direct outcome luck occurs afterward. This reflects how inequality of opportunities is commonly realized in real-life situations. This difference in the timing of luck could drive the differences in the redistribution decisions that we observe if spectators have different expectations about how workers may respond to getting a high or low multiplier.<sup>10</sup> For example, spectators may feel a greater need to hold workers accountable for overcoming their circumstances (by working harder) and decide to redistribute less,  $f_{IOp} < f_{CF}$ . Spectators could also express compassion for workers who put in effort despite a low multiplier and redistribute more,  $f_{IOp} > f_{CF}$ .

To test whether the timing of lucky opportunities affects redistribution, we compare spectators' redistribution decisions in the baseline IOp condition to those in the ex-post IOp condition. In both situations, workers in a pair face differential returns to their effort. However, in the baseline IOp condition, workers learn their multiplier *before* completing the encryption task, whereas in the EP-IOp condition they learn their multiplier only *after* they finished the

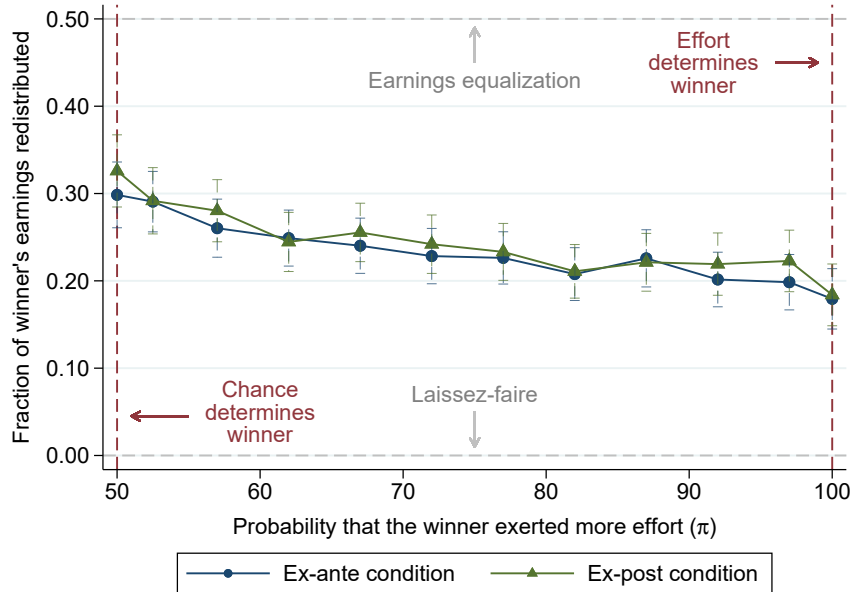
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<sup>10</sup>In practice, we do not find any evidence that worker effort responds to receiving a high or low multiplier (see Appendix Table A4). We also observe no differences in the overall distribution of effort across luck environments (see Appendix Figure A2). A Kolmogorov–Smirnov test for equality of distribution cannot reject the hypothesis that distribution of worker effort in the CF and IOp conditions are equal ( $p = 0.909$ ). We also cannot reject equality of distributions using pairwise distribution comparisons of worker effort between CF and baseline IOp ( $p = 0.359$ ) and between CF and EP-IOp ( $p = 0.393$ ). However, what matters for redistribution behavior are spectators' beliefs about effort, which may not align with reality.

task. Thus, our EP-IOP treatment aligns the timing of opportunity luck with that of outcome luck in the CF treatment.

In Appendix Table A5, we re-estimate the main specifications in Table 2, but compare redistribution between the baseline IOP and EP-IOP treatments. Redistribution is neither economically nor statistically different across the two treatments. We find no significant differences in the average level of redistribution across the IOP sub-treatments: The average amount of income redistributed was 23.4 percent in baseline IOP versus 24.4 percent in EP-IOP ( $p = 0.57$ ). We also find no significant differences in the elasticity of redistribution to changes in luck using a linear specification ( $p = 0.89$ ). Figure 2 plots our estimates of the average level of redistribution for both IOP treatments across each  $\pi$  bin. Across the entire range of  $\pi$  bins, we find no differences in the level of redistribution.

Figure 2: Redistribution and  $\pi$  in the baseline and ex-post IOP conditions



**Notes:** This figure shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) relative to the likelihood that the winner exerted more effort. Displayed are two variations of the opportunity luck condition (IOP): Workers in the baseline group are aware of their multiplier prior to their encryption task and workers in the EP group are aware of their multiplier after completing their encryption task.

To further assess whether spectators expected differential effort from workers who receive a low versus high multiplier, we elicited their stated beliefs about average worker effort across the multiplier distribution. Specifically, for each spectator in the baseline IOP treatment,

we randomly selected a multiplier and elicited their beliefs about the average number of encryptions completed by workers who received that multiplier. In Appendix Table A6, we regress spectator expectations on the randomly selected multiplier using a linear (column 1) or non-parametric (column 2) specification. We find no evidence that spectators expect a significant worker effort response due to receiving a high or low multiplier.

Finally, to rule out any potential anticipatory effort responses, we compare redistribution in our Rules-Before and Rules-After subtreatments. In the Rules-Before treatment, workers knew exactly how we would determine the winner before working on the task. In the Rules-After treatment, workers were only told that solving more encryptions would increase their chance of winning before they began the task. Crucially, spectators knew workers in the CF and EP-IOP had identical information prior to beginning the task. Comparing these two conditions eliminates any scope for differences in beliefs about the distribution of worker effort across the two luck environments. Appendix Figure B2 compares average redistribution in the CF and EP-IOP treatments for only the Rules-After subtreatments. It shows that even when workers faced identical information prior to exerting effort, spectators redistribute less and are less sensitive to changes in luck when there are unequal opportunities than when luck is direct via a coin-flip.<sup>11</sup>

Overall, we find no evidence that the timing of luck alters the redistribution behavior of spectators when there is opportunity or outcome luck. This implies that the extent to which luck and effort are separable is the primary driver of the differences in redistribution that we observe across the two luck environments. Our results are also broadly consistent with Andre (2022) who finds no differences in the redistribution decisions of spectators when wages are revealed before versus after workers complete their task.<sup>12</sup>

## 5.2 Information Provision Treatment

Spectators are less sensitive to changes in the importance of luck when it is experienced through unequal opportunities rather than directly by altering outcomes. This result per-

<sup>11</sup>We provide additional analysis of our Rules-Before and Rules-After sub-treatments in Appendix B.1.

<sup>12</sup>Unlike Andre (2022), we find that worker effort is inelastic to the productivity multipliers. We conjecture that this difference arises because our environment is a winner-takes-all tournament with a fixed working period, while Andre (2022) creates unequal opportunities via differential piece-rate wages and allows workers to choose how long they work for. Indeed, DellaVigna et al. (2022) find that higher incentives lead to higher output when workers can choose how long they work for but have no effect when the working period is fixed.

sists even when workers face identical information prior to beginning the task. One possible mechanism is that spectators find it more difficult to infer the importance of luck when it interacts with effort. In this section, we leverage our information provision treatment to examine whether support for redistribution becomes more elastic to changes in luck when spectators are informed about the value of  $\pi$ . We also examine whether the differences in redistribution across luck environments persist when we provide precise information about the importance of luck.

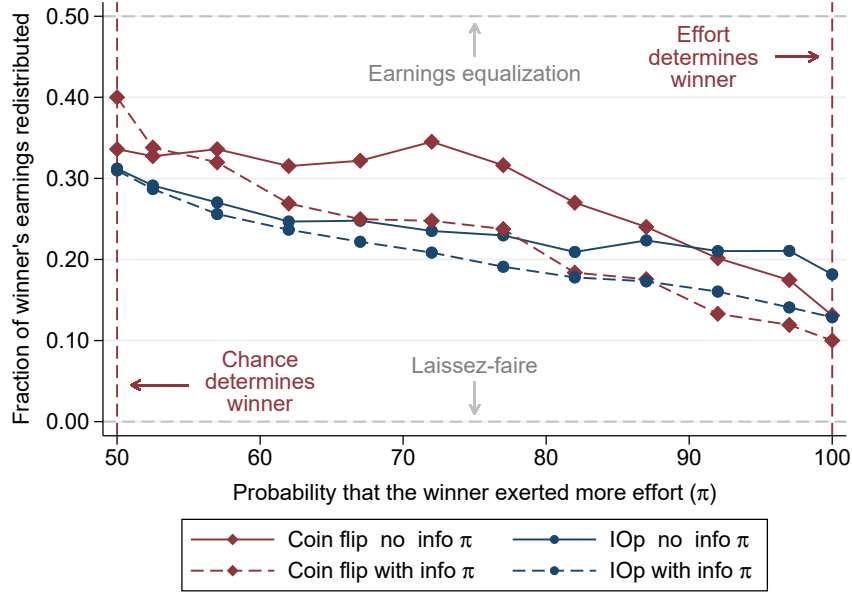
We first compare redistribution in the baseline and INFO treatments to test for the role of inaccurate beliefs in driving differences in redistribution between CF and IOp. Providing information about the importance of luck leads to substantial changes in spectators' redistribution behavior. First, it leads to a significant decrease in the amount redistributed in both the IOp and CF conditions. Table A7, Panel A shows that average redistribution falls from 27.6 percent to 23.1 percent in CF ( $p < 0.01$ ) and from 23.9 percent to 20.8 percent in IOp ( $p < 0.05$ ). Figure 3 plots the mean redistribution across each  $\pi$  bin for our CF and IOp treatments split by our information intervention. This figure reveals that the decrease in redistribution occurs for nearly all  $\pi$  bins.

Second, redistribution becomes more elastic to changes in the importance of luck when spectators are informed about  $\pi$ . Panel B of Table A7 shows that a 10 percentage point increase in  $\pi$  in the CF treatment causes spectators to redistribute 3.7 percent more of total income when there is no information about  $\pi$  compared to 5.2 percent more when there is full information. Similarly, a 10 percentage point increase in  $\pi$  in the IOp treatment causes spectators to redistribute an additional 2.0 percent of total income when there is no information compared to 3.2 percent more when there is full information.

We observe similar changes in redistribution in response to providing information across the CF and IOp conditions. Panel A, column (3) of Table A7 shows that the change in the level of redistribution when spectators receive information about  $\pi$  is not significantly different across luck conditions ( $p = 0.74$ ). Moreover, Panel B shows that there is no significant difference in the change in slope when there is outcome luck relative to opportunity luck ( $p = 0.43$ ). Overall, the gap in both the level and slope of redistribution between IOp and CF persists when we correct for potentially inaccurate beliefs.

We also examine whether providing information about  $\pi$  alters the share of spectators

Figure 3: The effect of providing information about  $\pi$



**Notes:** This figure shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) relative to the likelihood that the winner exerted more effort. Displayed are the two main experimental conditions—outcome luck (CF) and opportunity luck (IOp)—as well as whether spectators were provided with information provisions about  $\pi$  (INFO or Baseline).

who redistribute nothing (columns (2) to (4) of Table 3). We find no significant effect of the INFO intervention on whether spectators never redistribute. That is, even with complete information about the importance of luck, spectators are more likely to never redistribute when workers face unequal opportunities than when they face direct outcome luck.

Overall, we find that the differences in redistribution choices across luck environments are not driven by different perceptions of effort or differential beliefs about the role of luck. This suggests that the differences in redistribution across environments are mainly driven by spectators holding different fairness views. In other words, even when spectators are perfectly informed about the importance of luck in determining the outcome, they prefer to redistribute less when there is opportunity luck and are less sensitive to changes in its importance.

## 6 A Linearization Heuristic

Unequal opportunities present an inferential challenge for spectators: They observe limited information about individual opportunities and must use it to assess the overall importance

of luck in determining outcomes. In this section, we investigate how people incorporate information about unequal opportunities into their redistribution decisions. Specifically, we test whether, when faced with a complex mapping from unequal opportunities to the impact of luck on outcomes, spectators rely on a simple heuristic based on multiplier differences.

A large body of literature demonstrates that agents often rely on heuristics or rules-of-thumb to make decisions under uncertainty (Benjamin, 2019). A particular heuristic that has been documented in decision environments that feature nonlinearities is the “linearization heuristic.”<sup>13</sup> According to this heuristic, agents often use linear approximations as a way to simplify the decision process. Environments where individuals face unequal opportunities can be rife with nonlinear outcomes, which may trigger such an inaccurate approximation. The mapping from the relative multiplier  $m$  to  $\pi$  in Panel B of Appendix Figure A1 shows that small differences in the relative multiplier can have a large impact on whether chance determined the winner. For example, increasing the relative multiplier from 1.05 to 1.20 decreases the likelihood that the worker who solved more encryptions won from around 99 percent to 77 percent.

In Table 5, we test whether spectators base their redistribution decisions on the multiplier difference in the absence of full information about  $\pi$ . We first focus on spectators in our baseline IOp treatment who observe workers’ multipliers but not  $\pi$  directly. Column (1) reproduces the specification in Panel B of Table 2. Column (2) replaces true  $\pi$  with the linear multiplier difference. We estimate that a one percentage point increase in the difference in workers’ multipliers increases redistribution by four percentage points. In Appendix Table A8, we include higher-order polynomials and find no additional significant effects despite the fact that such polynomials provide a successively better fit than true  $\pi$ . Column (3) includes both the true empirical  $\pi$  and the linear multiplier difference. We continue to find that the linear multiplier difference significantly predicts redistribution behavior, albeit with a smaller magnitude. Conversely, we find a much smaller coefficient for true empirical  $\pi$  that falls short of conventional significance levels ( $p = 0.065$ ). In other words, when spectators do not know  $\pi$ , they focus on linear multiplier differences when making their redistribution decisions. This can also be seen in Appendix Figure A3, which shows that, in the baseline IOp condition,

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<sup>13</sup>For example, people systematically misperceive a linear relationship between fuel efficiency and miles per gallon when the true association is highly convex (Larrick and Soll, 2008). Other work has shown that taxpayers perceive the income tax schedule as linear (Rees-Jones and Taubinsky, 2020) and that individuals fail to account for compound interest (Stango and Zinman, 2009; Levy and Tasoff, 2016).



mean redistribution is approximately linear in the multiplier difference.

Table 5: Testing for a linearization heuristic

	Dependent Variable: Fraction of earnings redistributed					
	No $\pi$ provisions (Baseline)			$\pi$ provisions (INFO)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi$	-0.020*** (0.004)		-0.009* (0.005)	-0.037*** (0.004)		-0.028*** (0.005)
Multiplier difference		0.040*** (0.008)	0.024** (0.010)		0.068*** (0.007)	0.019** (0.008)
Constant	0.283*** (0.009)	0.203*** (0.006)	0.237*** (0.018)	0.296*** (0.009)	0.154*** (0.006)	0.262*** (0.016)
$N$	2,328	2,328	2,328	2,352	2,352	2,352
R-squared	0.57	0.57	0.57	0.58	0.57	0.58

**Notes:** This figure shows the fraction of earnings redistributed under IOp on three determining features of the decision environment. In columns 1 and 4, we control only for the empirical ex-ante probability that the high-earning worker is the one who exerted more effort. In columns 2 and 5, we control for only the linear multiplier difference. Finally, in columns 3 and 6, we control for both variables. \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Our theoretical framework predicts that meritocratic spectators will base their decisions on  $\pi$  when we provide full information about its value. In columns (4) through (6), we estimate the same specifications for spectators in the IOp-INFO condition. Column (5) again finds that the multiplier difference is a powerful predictor of redistribution decisions on its own. However, this coefficient drops by more than two-thirds when we control for the  $\pi$  directly in column (6). Moreover, we find a large, significant effect of the empirical  $\pi$  on redistribution decisions: A 10 percentage point increase in  $\pi$  leads to a 2.8 percentage point decrease in the share of the total earnings redistributed. However, we also continue to find a significant effect of the multiplier difference. In other words, even when we provide information about  $\pi$ , spectators place some weight on the multiplier difference.

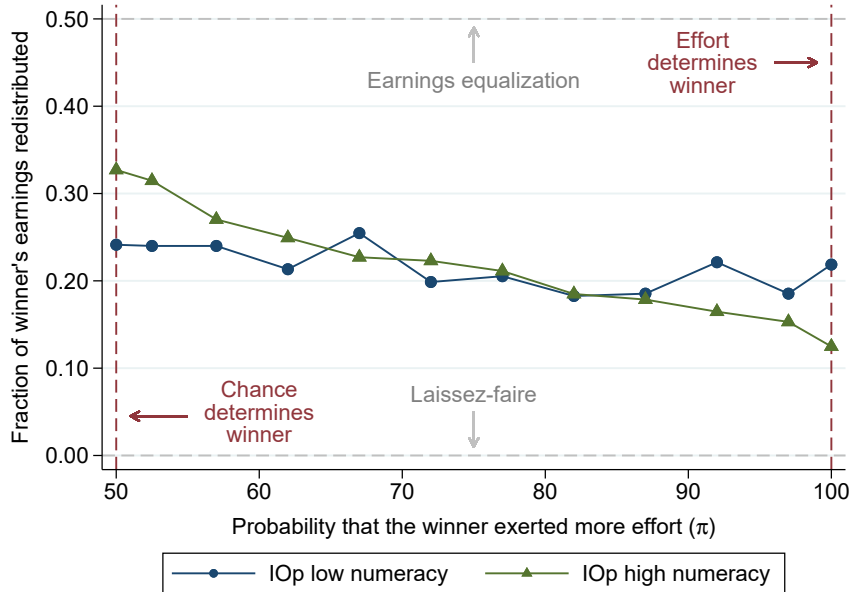
A key question is whether relying on linear multiplier differences reflects spectator preferences or an error in statistical reasoning. Table 5 provides mixed evidence: Spectators appear to factor in  $\pi$  when they only observe multipliers but the linear multiplier difference remains a significant predictor of when there is perfect information about  $\pi$ . To shed light on this question, we compare the distribution choices of high- and low-numeracy spectators.<sup>14</sup> Intuitively, we expect that high- and low-numeracy spectators have the same preferences on

<sup>14</sup>We use the definition of high and low numeracy in the New York Fed’s Survey of Consumer Expectations. It is based on five questions designed to assess financial literacy. We provide these questions in Appendix C.1. All respondents complete these questions when they first join the panel. The survey categorizes respondents as “high numeracy” if they answer four or more of these questions correctly and as “low numeracy” otherwise.

average but that high-numeracy spectators are less likely to rely on cognitive shortcuts, for example, due to a lower cognitive cost of estimating the importance of luck in a situation.

Figure 4 presents our main results split by numeracy.<sup>15</sup> Consistent with the idea that linearization is a cognitive shortcut, high-numeracy spectators are more elastic to changes in  $\pi$ : A 10 percentage point increase in  $\pi$  leads high-numeracy spectators to redistribute 3.3 percent less of total income. Low-numeracy spectators are much less responsive to changes in  $\pi$ : A 10 percentage point increase in  $\pi$  leads low-numeracy spectators to redistribute 1.0 percent less of total income. For low-numeracy spectators, the effect of an increase in  $\pi$  on redistribution in the IOp condition is less than one-third of that for high-numeracy spectators. This result suggests that errors in statistical reasoning partly drive redistribution when spectators are not informed about the value of  $\pi$ .

Figure 4: Redistribution and numerical literacy



**Notes:** This figure shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) relative to the likelihood that the winner exerted more effort. Displayed are the two main experimental conditions—outcome luck (CF) and opportunity luck (IOp)—as well as a measure of numerical literacy.

Overall, we find suggestive evidence that spectators deploy a simple heuristic when assessing the importance of unequal opportunities for worker outcomes. As a result, they underappreciate how small differences in opportunities can have a large impact on worker

<sup>15</sup>Appendix Table A9 provides the underlying regression estimates.

outcomes. Providing precise information about the importance of luck makes them more responsive to its role in determining outcomes and reduces their reliance on heuristics.

## 7 Discussion

Meritocratic fairness ideals contend that individuals are willing to tolerate inequalities that are due to differences in effort but oppose those that arise from chance. In a society characterized by inequality of opportunity, this distinction is obfuscated by the fact that luck and effort are intertwined, making it difficult for individuals to assess the source of inequality. This paper asks if in this more realistic setting, people view workers' outcomes as outside their control or if they hold them accountable for their fate. We find that individuals are more tolerant of inequality when luck interacts with effort, and less responsive to incremental changes in the importance of luck.

Our results offer a potential rationale for the apparent disconnect between the previous experimental literature and observed patterns of inequality in the U.S. Research that generates inequality through exogenous variation in outcomes has found that the majority of Americans equalize incomes when income differences are due to luck ([Almås et al., 2020](#)). However, the U.S. remains the most unequal country in the OECD while simultaneously ranking poorly on equality of opportunity ([Mitnik et al., 2020](#); [Corak, 2013](#)). Our results show that Americans tolerate more inequality when it is experienced through differential opportunities. In addition, mounting evidence suggests that as the role of luck increases, demand for redistribution increases. Yet, support for redistribution in the US has remained stagnant ([Ashok et al., 2015](#)), even though differences in opportunities have become increasingly important ([Chetty et al., 2014](#)). Our results indicate that redistribution is more inelastic to changes in luck when luck interacts with effort.

We also find that individuals hold different fairness views when luck is experienced through unequal opportunities rather than directly via outcomes. Even when spectators know the likelihood that luck determined the outcome, they are less likely to ever redistribute when there is inequality of opportunity and tend to redistribute less when they do. This result is reminiscent of the “American Dream,” namely, the belief that anyone, regardless of their initial circumstances or opportunities, can succeed if they work hard enough. In our experiment, this view is reflected by spectators holding workers accountable for their outcomes, even if

their low multiplier made it almost impossible for them to succeed.

We conclude by discussing several implications of our results for models that seek to understand and predict attitudes toward redistribution. First, spectators in our study factor in unequal opportunities in their decisions above and beyond its direct impact on outcomes. In other words, we find that individuals care about the process by which unequal outcomes arise, in addition to the overall importance of luck. This is related to research on procedural justice showing that individuals care about the legitimacy of the process by which an outcome is generated ([Lind and Tyler, 1988](#)). This nonstandard behavior is inconsistent with canonical models of redistribution, which assume that spectators only care about final outcomes and not about the process by which the outcome arrives. More broadly, this result implies that the consequentialist view taken by standard models of redistribution fails to capture important features of real-world attitudes.

Second, we document that in the absence of precise information about the role of luck, spectators rely on simple heuristics when factoring the impact of luck into their redistribution decisions. As a result, people fail to appreciate how small differences in initial circumstances can have a large impact on outcomes. Providing information about the importance of luck reduces this reliance on heuristics, suggesting that they are a mistake. Models that seek to accommodate cognitive errors might hold some promise for predicting and explaining how beliefs shape redistribution attitudes.

Finally, we find that readily available information can have a large impact on people’s redistribution decisions. This suggests that the information individuals frequently encounter might disproportionately impact their views on inequality and redistribution. For example, salient media information (e.g., rags-to-riches stories) may have a substantial impact on shaping individuals’ tolerance for inequality.

Taken together, our results highlight that redistribution preferences are not invariant to how luck interacts with effort to determine outcomes. The opportunity luck environment has a number of important features that affect redistribution that are overlooked by a more simplistic outcome luck paradigm. We deliver a portable, tractable, and rich environment to study income redistribution when there are unequal opportunities that can inform the development of models of inequality and optimal redistribution.

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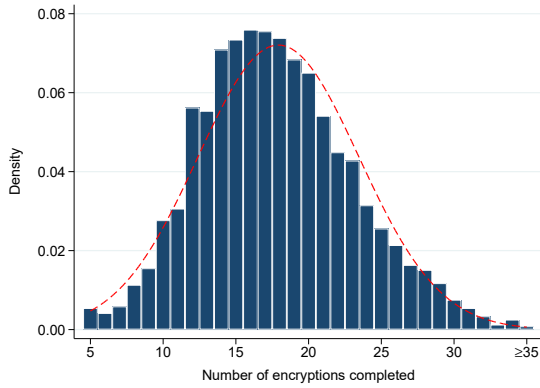
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# Appendix

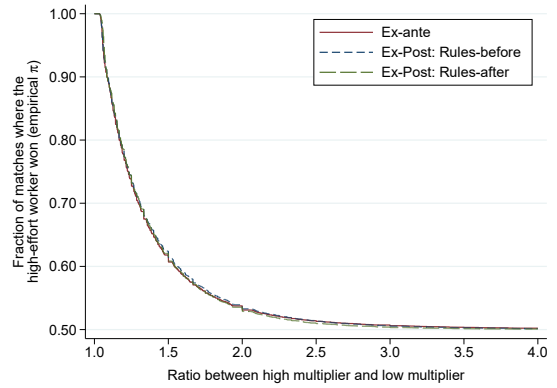
## A Additional Figures and Tables

Figure A1: Distribution of effort and probability of exerting more effort

Panel A. Distribution of tasks completed in worker task

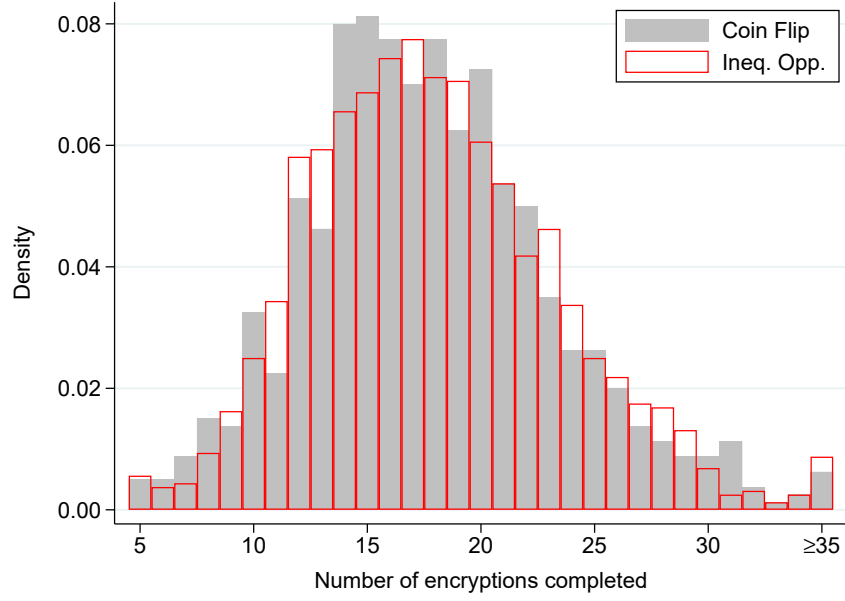


Panel B. Probability that the winner exerted more effort as a function of multiplier ratio



**Notes:** Panel A: This figure shows the distribution worker effort across all conditions, based on the number of correct three-word encryptions. The mean is 18 and standard deviation is 5.5. The red dashed line shows the density of a normal random variable that has the same mean and standardized deviation as the distribution of tasks completed. Panel B: This graph shows the fraction of paired workers in which the worker who won the tournament completed more encryptions. Winners were determined based on a final score of correct encryptions multiplied by their score multiplier. Likelihoods near 0.5 are worker matches in which luck has a greater influence on the final outcome. Likelihoods near 1.0 are worker matches in which luck has little influence on the final outcome.

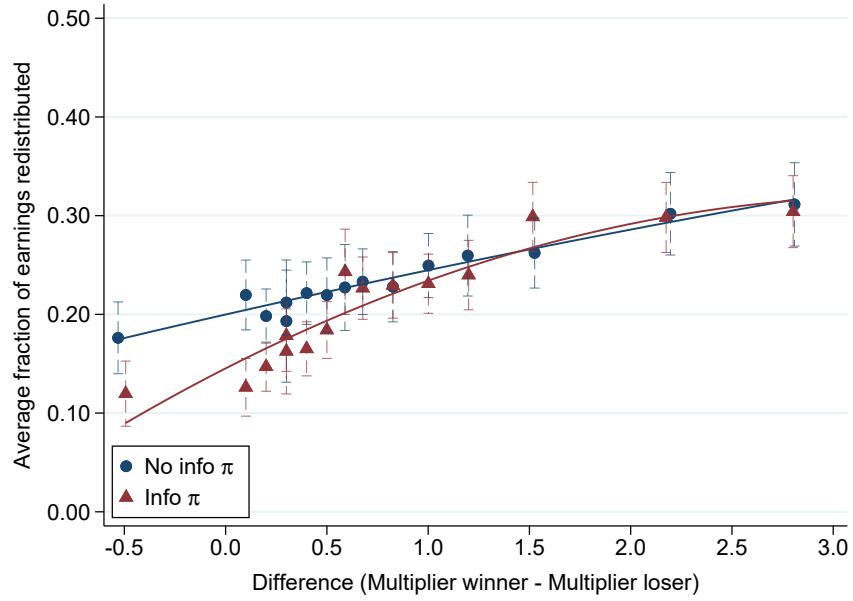
Figure A2: Histogram of tasks completed by condition



**Notes:** This figure shows the distribution of tasks completed by workers in the CF and baseline IOp condition. A Kolmogorov–Smirnov test for equality of distribution cannot not reject the hypothesis that distribution of worker effort in the CF and IOp conditions are equal ( $p = 0.909$ ). We also cannot reject equality of distributions using pairwise distribution comparisons of worker effort between CF and Baseline IOp ( $p = 0.359$ ) and between CF and IOp-EP ( $p = 0.393$ ).



Figure A3: Redistribution and worker multiplier difference



**Note:** This figure shows the average share of earnings that spectators redistribute on average from the winner to the loser as a function of the multipliers differences in the opportunity luck condition (IOp). The red line is the best-fitting quadratic estimate of the relationship between redistribution and multiplier difference.

Table A1: Average worker characteristics by treatment condition

Worker characteristics	CF		IOp-Baseline	IOp-EP	
	Baseline	INFO		Baseline	INFO
Age	39.08	37.87	38.18	37.95	38.53
Male	0.56	0.56	0.61	0.57	0.58
Married	0.62	0.70	0.67	0.58	0.73
White	0.76	0.76	0.79	0.70	0.76
Completed college	0.79	0.85	0.83	0.79	0.84
Income > 75,000	0.34	0.31	0.31	0.35	0.31
Has masters certification	0.33	0.42	0.34	0.28	0.40
Encryptions attempted	18.11	18.17	18.59	18.43	17.54
Encryptions completed	17.82	17.84	18.27	18.17	17.20
Average multiplier	–	–	2.58	2.56	2.53
Time spent in instructions	121.10	143.52	142.99	153.94	138.93
Time spent in comprehension screen	110.85	127.50	124.49	125.14	150.82
Average time spent in each round	17.43	17.29	17.03	17.10	17.76
Total time in experiment	817.84	841.46	875.63	913.38	879.16
Number of workers	400	400	800	400	400

**Notes:** This table shows summary statistics on our sample of workers. We exclude workers who completed fewer than five encryptions. The time spent in the experiment is measured in seconds.

Table A2: Fraction of spectators who do not redistribute across conditions

	(1)	(2)	(3)	(4)
<b>Panel A. Outcome: = 1 if does not redistribute in at least 10/12 rounds</b>				
IOp	0.055** (0.027)	0.055** (0.027)	0.079** (0.037)	0.075** (0.038)
Knows $\pi$		0.027 (0.027)	0.051 (0.035)	0.046 (0.036)
IOp $\times$ knows $\pi$			-0.048 (0.053)	-0.042 (0.054)
Constant	0.142*** (0.018)	0.129*** (0.021)	0.117*** (0.023)	0.082 (0.125)
$N$	9,408	9,408	9,408	9,384
<b>Panel B. Outcome: = 1 if does not redistribute in at least 11/12 rounds</b>				
IOp	0.060** (0.026)	0.060** (0.026)	0.074** (0.036)	0.069* (0.037)
Knows $\pi$		0.017 (0.026)	0.030 (0.034)	0.024 (0.035)
IOp $\times$ knows $\pi$			-0.027 (0.052)	-0.021 (0.052)
Constant	0.127*** (0.017)	0.118*** (0.020)	0.112*** (0.022)	0.057 (0.117)
$N$	9,408	9,408	9,408	9,384
Spectator-level controls	No	No	No	Yes

**Notes:** The dependent variable is the fraction of spectators who do not redistribute in at least 10/12 rounds (panel A) or at least 11/12 rounds (panel B). In column 4, we control for age, gender, marital status, number of children in the household, educational attainment, numerical literacy, race, indicators for working part-time and full-time, house ownership, income, region, the time spectators spent on the experiment, indicators for passing the comprehension and attention checks, an indicator that equals one if the spectator completed the survey in a mobile device, the probability that the winner exerted more effort on each worker-pair, round number fixed effects (to control for possible fatigue effects). Standard errors clustered at the spectator level. \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Table A3: Heterogeneity in redistribution  $\pi$ 

	Coin Flip Condition		IOp Condition	
	Mean Redist. (1)	Elasticity w.r.t. $\pi$ (2)	Mean Redist. (3)	Elasticity w.r.t. $\pi$ (4)
<b>Panel A. Demographic characteristics, education, and income</b>				
Female	0.045** (0.020)	0.015* (0.009)	0.052** (0.025)	0.001 (0.007)
35 or younger	-0.015 (0.025)	-0.011 (0.012)	-0.020 (0.026)	-0.025*** (0.008)
Married	-0.036* (0.021)	-0.016* (0.009)	-0.027 (0.025)	-0.005 (0.008)
White	0.014 (0.025)	-0.010 (0.011)	0.028 (0.040)	0.020* (0.011)
Completed college	-0.015 (0.022)	-0.014 (0.009)	0.023 (0.027)	-0.011 (0.008)
HH income above 100k	-0.050** (0.024)	-0.013 (0.009)	-0.046* (0.026)	-0.004 (0.007)
<b>Panel B. Political and Social preferences</b>				
Tend to side with republicans	-0.046* (0.025)	-0.007 (0.011)	-0.073*** (0.027)	-0.009 (0.008)
Oppose gov't interventions	-0.077*** (0.027)	0.012 (0.012)	-0.067** (0.029)	0.002 (0.008)
Conservative on social issues	-0.024 (0.026)	-0.013 (0.011)	-0.050* (0.028)	0.006 (0.009)
Influence of hard work is fair	-0.063** (0.031)	-0.034** (0.014)	-0.011 (0.026)	-0.043*** (0.011)
Influence of talent is fair	-0.020 (0.045)	-0.061*** (0.015)	-0.031 (0.035)	-0.009 (0.013)
Influence of luck is fair	-0.046* (0.026)	-0.008 (0.011)	-0.036 (0.031)	-0.006 (0.009)
Influence of connections is fair	-0.019 (0.029)	-0.011 (0.012)	-0.072** (0.034)	-0.003 (0.010)
Key to success own hands	-0.069** (0.026)	0.013 (0.011)	-0.081*** (0.025)	-0.005 (0.009)
Gov't should never redistribute	-0.046* (0.024)	0.005 (0.011)	-0.070** (0.028)	0.008 (0.008)
Gov't redistribute to correct luck	0.028 (0.031)	0.009 (0.014)	0.070** (0.032)	-0.018 (0.011)
Income dist. in the US is fair	-0.011 (0.029)	0.011 (0.015)	-0.088*** (0.027)	-0.006 (0.009)

**Notes:** This table shows the difference in mean redistribution and the slope of redistribution across various participant characteristics and stated preferences. Each row shows the result of an independent regression where the coefficient corresponds the difference between stated characteristic and the omitted category. All variables in Panel A are indicator variables. All variables in Panel B are indicators equal to one if the participant “agrees” or “strongly agrees” and zero if they “disagree” or “strongly disagree”. Those who “neither agree nor disagree” with the statement are excluded from the regression. \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Table A4: Actual worker effort and worker multiplier

	Outcome: Number of tasks completed by workers	
	Linear function (1)	Non-parametric (2)
Multiplier	0.108 (0.106)	
Multiplier $\in [1.0, 1.5)$		-1.082* (0.589)
Multiplier $\in [1.5, 2.0)$		0.256 (0.704)
Multiplier $\in [2.0, 2.5)$		-0.506 (0.613)
Multiplier $\in [2.5, 3.0)$		-1.162* (0.647)
Multiplier $\in [3.0, 3.5)$		-0.526 (0.634)
Constant	17.862*** (0.439)	18.754*** (0.386)
$N$	800	800

**Notes:** This table shows the number of tasks completed by workers in the Baseline condition. Workers in IOp are randomly assigned a score multiplier  $\in [1, 4]$  as a rate of return on the number of correct encryptions completed in 5 minutes. Omitted category in column (2) is multiplier  $\in [3.5, 4.0)$ . Negative coefficients indicate effort responses that are lower than those assigned to the highest multiplier bin; positive coefficients indicate effort responses that are higher than the highest multiplier bin. \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Table A5: Fraction redistributed as a function of  $\pi$  in baseline and Ex-Post IOp conditions

	Outcome: Fraction of earnings redistributed		
	baseline IOp condition	EP-IOp condition	Difference
	(1)	(2)	(3)
<b>Panel A. Average redistribution</b>			
Constant	0.234*** (0.013)	0.244*** (0.014)	-0.010 (0.019)
$N$	2328	2316	4644
<b>Panel B. Linear slope</b>			
$\pi$	-0.020*** (0.004)	-0.021*** (0.004)	0.001 (0.005)
Constant	0.283*** (0.016)	0.295*** (0.018)	-0.012 (0.024)
$N$	2328	2316	4644
<b>Panel C. Non-parametric estimation</b>			
$\pi \in (0.50, 0.55]$	-0.008 (0.008)	-0.036*** (0.011)	0.028* (0.014)
$\pi \in (0.55, 0.60]$	-0.046*** (0.010)	-0.050*** (0.011)	0.004 (0.015)
$\pi \in (0.60, 0.65]$	-0.063*** (0.010)	-0.076*** (0.012)	0.013 (0.016)
$\pi \in (0.65, 0.70]$	-0.071*** (0.012)	-0.081*** (0.012)	0.010 (0.017)
$\pi \in (0.70, 0.75]$	-0.087*** (0.011)	-0.091*** (0.013)	0.005 (0.017)
$\pi \in (0.75, 0.80]$	-0.095*** (0.012)	-0.106*** (0.013)	0.012 (0.018)
$\pi \in (0.80, 0.85]$	-0.119*** (0.013)	-0.116*** (0.014)	-0.003 (0.019)
$\pi \in (0.85, 0.90]$	-0.116*** (0.013)	-0.109*** (0.014)	-0.007 (0.019)
$\pi \in (0.90, 0.95]$	-0.128*** (0.015)	-0.123*** (0.015)	-0.005 (0.021)
$\pi \in (0.95, 1.00]$	-0.139*** (0.014)	-0.131*** (0.014)	-0.008 (0.020)
$\pi = 1.00$	-0.157*** (0.017)	-0.154*** (0.017)	-0.003 (0.024)
Constant	0.306*** (0.013)	0.316*** (0.014)	-0.010 (0.019)
$N$	4680	4632	9312

**Notes:** Column 1 includes only spectators under the baseline IOp condition and column 2 includes only spectators under the EP-IOp condition. Column 3 is the difference in spectator responses between columns 1 and 2. Panel A: Shows the average redistribution. Panel B: Shows the linear approximation between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker ( $\pi$ ). Panel C: The relationship between redistribution and the likelihood that the winning worker performed better ( $\pi$ ) is split into 11 bins. The omitted category is  $\pi = 0.50$ . \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Table A6: Perceived worker effort and worker multiplier

	Outcome: Spectator beliefs about encryptions completed	
	Linear function (1)	Non-parametric (2)
Multiplier	1.350 (1.495)	
Multiplier $\in [1.0, 1.5)$		-5.900 (4.550)
Multiplier $\in [1.5, 2.0)$		-1.496 (4.577)
Multiplier $\in [2.0, 2.5)$		-2.041 (4.286)
Multiplier $\in [2.5, 3.0)$		2.805 (4.432)
Multiplier $\in [3.0, 3.5)$		-4.496 (4.272)
Constant	25.634*** (4.008)	30.779*** (3.002)
$N$	390	390

**Notes:** This table shows spectators' perceived effort of workers assigned to each spectator for the Baseline only condition. Recall that workers in IOp are randomly assigned a score multiplier  $\in [1, 4]$  as a rate of return on the number of correct encryptions completed in 5 minutes. Omitted category in column (2) is multiplier  $\in [3.5, 4.0)$ . Negative coefficients indicate effort responses that are lower than those assigned to the highest multiplier bin; positive coefficients indicate effort responses that are higher than the highest multiplier bin. \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Table A7: Fraction redistributed as a function of  $\pi$  and info treatment

	Outcome: Fraction of earnings redistributed		
	Coin flip condition (1)	Inequality of opportunities (2)	Difference CF – IOp (3)
<b>Panel A. Average Redistribution</b>			
Knows $\pi$	−0.045*** (0.014)	−0.027 (0.017)	−0.018 (0.022)
Constant	0.276*** (0.010)	0.234*** (0.013)	0.042*** (0.016)
$N$	4728	4680	9408
<b>Panel B. Linear slope</b>			
$\pi$	−0.037*** (0.005)	−0.020*** (0.004)	−0.017*** (0.006)
Knows $\pi$	−0.008 (0.021)	0.014 (0.022)	−0.022 (0.030)
$\pi \times$ knows $\pi$	−0.015** (0.006)	−0.017*** (0.005)	0.002 (0.008)
Constant	0.368*** (0.016)	0.283*** (0.016)	0.085*** (0.023)
$N$	4728	4680	9408
<b>Panel C. Non-parametric estimation</b>			
Knows $\pi$	0.064** (0.025)	0.015 (0.025)	0.066** (0.031)
Knows $\pi \times \pi \in (0.50, 0.55]$	−0.053** (0.026)	−0.001 (0.017)	−0.051* (0.029)
Knows $\pi \times \pi \in (0.55, 0.60]$	−0.080*** (0.026)	−0.015 (0.020)	−0.068** (0.030)
Knows $\pi \times \pi \in (0.60, 0.65]$	−0.110*** (0.025)	−0.027 (0.020)	−0.103*** (0.030)
Knows $\pi \times \pi \in (0.65, 0.70]$	−0.136*** (0.027)	−0.026 (0.025)	−0.112*** (0.032)
Knows $\pi \times \pi \in (0.70, 0.75]$	−0.161*** (0.028)	−0.033 (0.022)	−0.137*** (0.033)
Knows $\pi \times \pi \in (0.75, 0.80]$	−0.143*** (0.030)	−0.045* (0.024)	−0.106*** (0.035)
Knows $\pi \times \pi \in (0.80, 0.85]$	−0.150*** (0.029)	−0.056** (0.026)	−0.121*** (0.035)
Knows $\pi \times \pi \in (0.85, 0.90]$	−0.128*** (0.031)	−0.087*** (0.026)	−0.080** (0.036)
Knows $\pi \times \pi \in (0.90, 0.95]$	−0.132*** (0.031)	−0.062** (0.029)	−0.085** (0.037)
Knows $\pi \times \pi \in (0.95, 1.00]$	−0.119*** (0.033)	−0.078*** (0.029)	−0.052 (0.039)
Knows $\pi \times \pi = 1.00$	−0.095*** (0.034)	−0.076** (0.034)	−0.044 (0.042)
Constant	0.336*** (0.020)	0.298*** (0.019)	0.024 (0.024)
$N$	4728	4680	14040

**Notes:** Column 1 includes only spectators under the CF condition and column 2 includes only spectators under the IOp condition. Column 3 is the difference in spectator responses between columns 1 and 2. Panel A: Shows the average redistribution. Included is a variable indicating whether the spectators were assigned to know  $\pi$  (INFO condition). Panel B: Shows the linear approximation between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker ( $\pi$ ). Included are variables indicating whether spectators were assigned to know  $\pi$  and the interaction of  $\pi$  and its provision to spectators. Panel C: The relationship between redistribution and the likelihood that the winning worker performed better ( $\pi$ ) is split into 11 bins. The omitted category is  $\pi = 0.50$ . \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.



Table A8: Fraction redistributed on polynomials of the multiplier difference

	Outcome: Fraction of earnings redistributed				
	(1)	(2)	(3)	(4)	(5)
(Multiplier difference)	0.040*** (0.008)	0.037*** (0.011)	0.042*** (0.011)	0.040*** (0.014)	0.039*** (0.014)
(Multiplier difference) <sup>2</sup>		0.001 (0.003)	0.014** (0.006)	0.016** (0.008)	0.013 (0.014)
(Multiplier difference) <sup>3</sup>			−0.006** (0.002)	−0.005 (0.003)	−0.003 (0.008)
(Multiplier difference) <sup>4</sup>				−0.000 (0.001)	0.000 (0.002)
(Multiplier difference) <sup>5</sup>					−0.000 (0.001)
<i>N</i>	2,328	2,328	2,328	2,328	2,328
R-squared	0.57	0.57	0.57	0.57	0.57

**Notes:** This figure shows the average redistribution (from the winner's earnings to the loser) as a function of polynomials of multiplier differences under opportunity luck (IOp) condition. Only Baseline spectators are included, where provisions about  $\pi$  are not explicitly provided. \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Table A9: Fraction redistributed as a function of  $\pi$  and numeracy

	Coin Flip			Inequality of opportunities		
	Low numeracy (1)	High numeracy (2)	Difference (3)	Low numeracy (4)	High numeracy (5)	Difference (6)
<b>Panel A. Average redistribution</b>						
Constant	0.285*** (0.023)	0.273*** (0.011)	-0.011 (0.025)	0.203*** (0.022)	0.243*** (0.015)	0.040 (0.026)
$N$	660	1704	2364	516	1812	2328
<b>Panel B. Linear slope</b>						
$\pi$	-0.071 (0.076)	-0.488*** (0.053)	-0.416*** (0.092)	0.064 (0.078)	-0.274*** (0.040)	-0.338*** (0.087)
Constant	0.338*** (0.063)	0.637*** (0.043)	0.299*** (0.076)	0.155** (0.064)	0.447*** (0.034)	0.292*** (0.072)
$N$	660	1704	2364	516	1812	2328

**Notes:** Columns 1 through 3 includes only spectators under the CF condition; columns 4 through 6 include only spectators under the IOp condition. Columns 1 and 4 include only spectators with low numeracy scores, columns 2 and 5 include only spectators with high numeracy. Columns 3 and 4 are the differences in spectator responses. Panel A: Shows the average redistribution. Panel B: Shows the linear approximation between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker ( $\pi$ ). \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

## B Additional Analysis

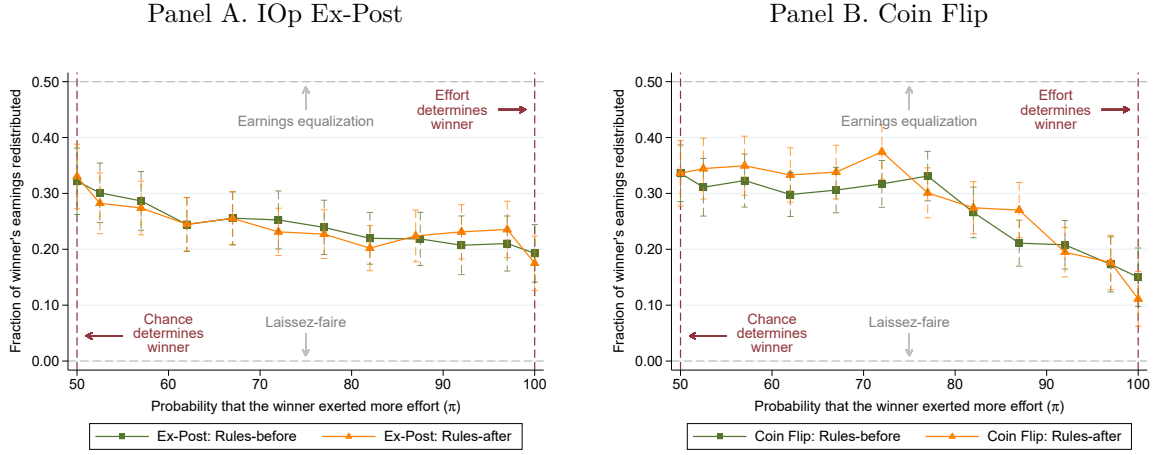
### B.1 Anticipatory Effort Responses

Whether workers learn their multiplier before or after completing the task has no impact on spectators' redistribution decisions. As a result, the differences in redistribution between outcome and opportunity luck that we observe are driven by fact that luck manifests itself through multipliers versus a coin flip. One potential reason for this difference is that spectators believe that the distribution of worker effort differs across these environments. For example, workers in the EP-IOP might work harder to insure against the possibility of drawing a bad multiplier, which could in turn shape redistribution preferences. Furthermore, our theoretical framework highlights that the perceived distribution of worker effort also affects beliefs about  $\pi$ . This provides a second channel through which perceptions of effort can drive a wedge between redistribution decisions across our EP-IOP and CF conditions.

To explore whether perceived differences in worker effort across environments can explain the differences in redistribution between IOP and CF, we compare redistribution in our *Rules-Before* and *Rules-After* subtreatments. In the Rules-Before condition, workers knew exactly how we would determine the winner before working on the task. In the Rules-After, workers were simply told that solving more encryptions would increase their chance of winning before they began the task. Crucially, workers in the CF and EP-IOP had identical information up until they had completed the task for the Rules-After subtreatments. This eliminated any scope for effort responses from workers across the two luck environments.

Figure B1 plots the average redistribution behavior of spectators for each  $\pi$  bin separately for our Rules-Before and Rules-After subtreatments. Panel A shows that the redistribution decisions of spectators in EP-IOP are very similar and do not depend on whether workers learn about how luck matters before or after working. Similarly, Panel B shows that whether the rules are revealed before or after working has no impact on the overall pattern of redistribution in the CF environment. Tables B2 and B1 show that the differences in redistribution between the Rules-Before and Rules-After subtreatments in the IOP-EP or CF environments tend to be small and not statistically significant.

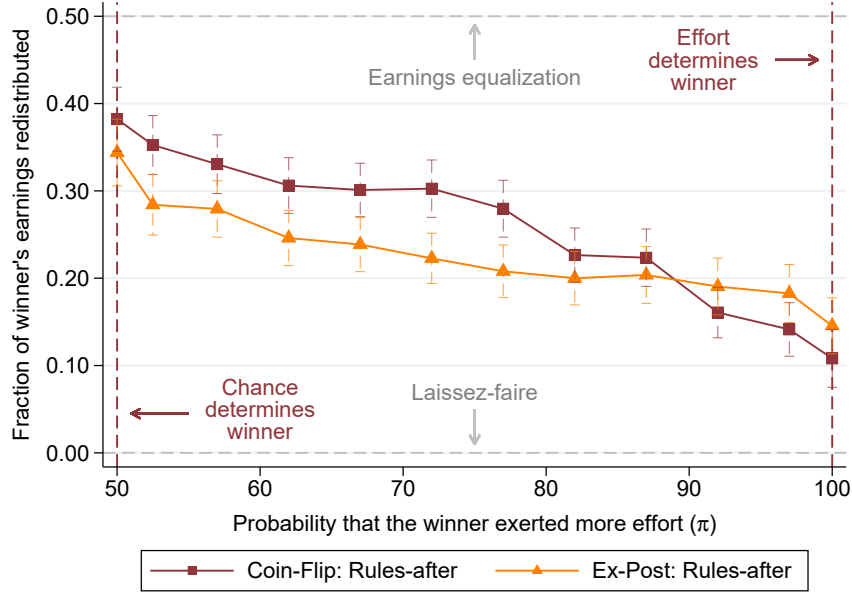
Figure B1: Redistribution and awareness of rules in the EP and CF conditions



**Notes:** This figure shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) relative to the difference in worker multipliers under the EP and CF conditions. Displayed are two variations of workers' awareness of rules: Rules-Before workers are aware of their multiplier prior to their encryption task and Rules-After workers are aware of their multiplier after completing their encryption task.

Figure B2 compares average redistribution in the CF and EP-IOP treatments for only the Rules-After subtrements. Even when workers faced identical information prior to exerting effort, spectators redistribute less when luck manifests itself through unequal opportunities than directly via a coin flip. Moreover, spectators continue to be less responsive to changes in the importance of luck. Table B3 re-estimates our main specifications in Table 2 but only compares CF and EP- IOP for the Rules-After scenario. We continue to find significant differences in the level and slope of redistribution, and the coefficient estimates that are similar in magnitude to the full-sample results.

Figure B2: Redistribution and awareness of rules in the CF and EP conditions



**Notes:** This figure shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) relative to the difference in worker multipliers under the Rules-After condition. Displayed are two conditions: outcome luck (CF) and opportunity luck (IOp). Note that these conditions are observationally identical to the worker until after they perform their tasks.

Finally, we can compare spectators' stated beliefs about average worker effort across the EP-IOp and CF conditions. We find no differences in the beliefs of spectators across these two environments: The median number of tasks spectators believe workers completed is 20 encryptions in both IOp and CF. We also find no differences based on whether workers learned about the rules of the tournament before or after completing the task: the median number of tasks spectators believe workers completed is also 20 in both Rules-Before and Rules-After in CF and EP-IOp. Overall, we find no evidence that differences in spectators' beliefs about the distribution of effort can explain the differences in redistribution across luck environments.

Table B1: Fraction redistributed as a function of  $\pi$  and Awareness of Rules in CF condition

	Outcome: Fraction of earnings redistributed		
	Rules before (1)	Rules after (2)	Difference Before - After (3)
<b>Panel A. Average redistribution</b>			
Constant	0.269*** (0.013)	0.284*** (0.016)	-0.014 (0.021)
$N$	1200	1164	2364
<b>Panel B. Linear slope</b>			
$\pi$	-0.034*** (0.007)	-0.041*** (0.006)	0.007 (0.009)
Constant	0.351*** (0.021)	0.385*** (0.024)	-0.033 (0.032)
$N$	1200	1164	2364
<b>Panel C. Non-parametric estimation</b>			
$\pi = 0.50$	0.336*** (0.026)	0.336*** (0.030)	-0.000 (0.040)
$\pi \in (0.50, 0.55]$	0.311*** (0.026)	0.344*** (0.028)	-0.033 (0.038)
$\pi \in (0.55, 0.60]$	0.323*** (0.024)	0.349*** (0.027)	-0.026 (0.036)
$\pi \in (0.60, 0.65]$	0.298*** (0.020)	0.333*** (0.025)	-0.035 (0.032)
$\pi \in (0.65, 0.70]$	0.306*** (0.021)	0.338*** (0.025)	-0.032 (0.032)
$\pi \in (0.70, 0.75]$	0.317*** (0.021)	0.374*** (0.025)	-0.057* (0.033)
$\pi \in (0.75, 0.80]$	0.331*** (0.023)	0.301*** (0.023)	0.030 (0.032)
$\pi \in (0.80, 0.85]$	0.266*** (0.023)	0.274*** (0.024)	-0.008 (0.033)
$\pi \in (0.85, 0.90]$	0.211*** (0.021)	0.270*** (0.025)	-0.059* (0.033)
$\pi \in (0.90, 0.95]$	0.208*** (0.022)	0.195*** (0.023)	0.013 (0.032)
$\pi \in (0.95, 1.00]$	0.173*** (0.025)	0.176*** (0.025)	-0.003 (0.035)
$\pi = 1.00$	0.150*** (0.027)	0.111*** (0.025)	0.039 (0.037)
$N$	1200	1164	2364

**Notes:** This table includes only spectators under the CF condition. Column 1 includes only spectators under the Rules-Before condition and column 2 includes only spectators under the Rules-After condition. Column 3 is the difference in spectator responses between columns 1 and 2. Panel A: Shows the average redistribution. Panel B: Shows the linear approximation between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker ( $\pi$ ). Panel C: The relationship between redistribution and the likelihood that the winning worker performed better ( $\pi$ ) is split into 11 bins. The omitted category is  $\pi = 0.50$ . \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Table B2: Fraction redistributed as a function of  $\pi$  and Awareness of Rules in EP-IOP condition

	Outcome: Fraction of earnings redistributed		
	Rules before (1)	Rules after (2)	Difference Before - After (3)
<b>Panel A. Average redistribution</b>			
Constant	0.246*** (0.020)	0.243*** (0.019)	0.003 (0.028)
$N$	1164	1152	2316
<b>Panel B. Linear slope</b>			
$\pi$	-0.022*** (0.005)	-0.019*** (0.005)	-0.003 (0.007)
Constant	0.300*** (0.026)	0.290*** (0.024)	0.010 (0.035)
$N$	1164	1152	2316
<b>Panel C. Non-parametric estimation</b>			
$\pi = 0.50$	0.322*** (0.030)	0.330*** (0.030)	-0.009 (0.042)
$\pi \in (0.50, 0.55]$	0.301*** (0.027)	0.282*** (0.028)	0.019 (0.039)
$\pi \in (0.55, 0.60]$	0.287*** (0.027)	0.274*** (0.025)	0.013 (0.036)
$\pi \in (0.60, 0.65]$	0.244*** (0.025)	0.245*** (0.024)	-0.000 (0.035)
$\pi \in (0.65, 0.70]$	0.256*** (0.024)	0.255*** (0.024)	0.000 (0.034)
$\pi \in (0.70, 0.75]$	0.253*** (0.027)	0.231*** (0.022)	0.021 (0.034)
$\pi \in (0.75, 0.80]$	0.239*** (0.025)	0.227*** (0.022)	0.012 (0.033)
$\pi \in (0.80, 0.85]$	0.220*** (0.024)	0.202*** (0.021)	0.018 (0.031)
$\pi \in (0.85, 0.90]$	0.219*** (0.024)	0.224*** (0.024)	-0.005 (0.034)
$\pi \in (0.90, 0.95]$	0.207*** (0.027)	0.231*** (0.025)	-0.024 (0.037)
$\pi \in (0.95, 1.00]$	0.210*** (0.025)	0.235*** (0.026)	-0.025 (0.036)
$\pi = 1.00$	0.193*** (0.026)	0.175*** (0.025)	0.018 (0.036)
$N$	1164	1152	2316

**Notes:** This table includes only spectators under the EP-IOP condition. Column 1 includes only spectators under the Rules-Before condition and column 2 includes only spectators under the Rules-After condition. Column 3 is the difference in spectator responses between columns 1 and 2. Panel A: Shows the average redistribution. Panel B: Shows the linear approximation between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker ( $\pi$ ). Panel C: The relationship between redistribution and the likelihood that the winning worker performed better ( $\pi$ ) is split into 11 bins. The omitted category is  $\pi = 0.50$ . \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.

Table B3: Fraction redistributed as a function of  $\pi$  in EP-IOpand CF conditions (only Rules-After)

	Outcome: Fraction of earnings redistributed		
	CF Rules-After (1)	IOP-EP Rules-After (2)	Difference CF-IOP-EP (3)
<b>Panel A. Average redistribution</b>			
Constant	0.284*** (0.016)	0.243*** (0.019)	0.041* (0.024)
$N$	1164	1152	2316
<b>Panel B. Linear slope</b>			
$\pi$	-0.041*** (0.006)	-0.019*** (0.005)	-0.022*** (0.008)
Constant	0.385*** (0.024)	0.290*** (0.024)	0.095*** (0.034)
$N$	1164	1152	2316
<b>Panel C. Non-parametric estimation</b>			
$\pi = 0.50$	0.336*** (0.030)	0.330*** (0.030)	0.006 (0.042)
$\pi \in (0.50, 0.55]$	0.344*** (0.028)	0.282*** (0.028)	0.062 (0.039)
$\pi \in (0.55, 0.60]$	0.349*** (0.027)	0.274*** (0.025)	0.076** (0.037)
$\pi \in (0.60, 0.65]$	0.333*** (0.025)	0.245*** (0.024)	0.088** (0.035)
$\pi \in (0.65, 0.70]$	0.338*** (0.025)	0.255*** (0.024)	0.083** (0.035)
$\pi \in (0.70, 0.75]$	0.374*** (0.025)	0.231*** (0.022)	0.143*** (0.033)
$\pi \in (0.75, 0.80]$	0.301*** (0.023)	0.227*** (0.022)	0.074** (0.032)
$\pi \in (0.80, 0.85]$	0.274*** (0.024)	0.202*** (0.021)	0.072** (0.032)
$\pi \in (0.85, 0.90]$	0.270*** (0.025)	0.224*** (0.024)	0.046 (0.035)
$\pi \in (0.90, 0.95]$	0.195*** (0.023)	0.231*** (0.025)	-0.036 (0.034)
$\pi \in (0.95, 1.00]$	0.176*** (0.025)	0.235*** (0.026)	-0.059 (0.036)
$\pi = 1.00$	0.111*** (0.025)	0.175*** (0.025)	-0.064* (0.035)
$N$	1164	1152	2316

**Notes:** This table includes only spectators under the Rules-After condition. Column 1 includes only spectators under the CF condition and column 2 includes only spectators under the EP-IOP condition. Column 3 is the difference in spectator responses between columns 1 and 2. Panel A: Shows the average redistribution. Panel B: Shows the linear approximation between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker ( $\pi$ ). Panel C: The relationship between redistribution and the likelihood that the winning worker performed better ( $\pi$ ) is split into 11 bins. The omitted category is  $\pi = 0.50$ . \*\*\*, \*\* and \* denote significance at the 10%, 5%, and 1% level, respectively.



## C Experimental Design Appendix

Figure C1: Worker Encryption Task

<b>Q</b>	<b>X</b>	<b>D</b>	<b>A</b>	<b>C</b>	<b>V</b>	<b>U</b>	<b>R</b>	<b>P</b>	<b>W</b>	<b>L</b>	<b>Y</b>	<b>G</b>
754	579	860	708	344	725	950	314	532	595	654	838	327
<b>Z</b>	<b>F</b>	<b>M</b>	<b>N</b>	<b>T</b>	<b>B</b>	<b>K</b>	<b>O</b>	<b>H</b>	<b>S</b>	<b>E</b>	<b>I</b>	<b>J</b>
190	776	627	980	830	803	603	673	536	490	545	445	925

Please translate the following word into code:

**RPZ:**

**Notes:** This figure shows an example encryption in the worker task. For each three-letter “word”, workers receive a codebook that maps letters to three-digit numbers. Once an encryption is submitted, a new word appears along with a new codebook. Words, codes, and the order in which the codebook letters appear is randomized every time. Feedback on whether encryptions are correct or incorrect are not provided. Workers have a total of 5 minutes to complete as many encryptions as possible.

Figure C2: Spectator Redistribution Choice

Decision  $p$  of 12

Worker ID:	1bx64fef	1uj72mti
Result:	won	lost
Unadjusted Earnings:	\$5.00	\$0.00

Do you want to change their earnings?  
Please choose the final, adjusted earnings for the above workers.

Change:	No	Yes									
Pay winner:	\$5.00	\$4.50	\$4.00	\$3.50	\$3.00	\$2.50	\$2.00	\$1.50	\$1.00	\$0.50	\$0.00
Pay loser:	\$0.00	\$0.50	\$1.00	\$1.50	\$2.00	\$2.50	\$3.00	\$3.50	\$4.00	\$4.50	\$5.00
Select one:	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Submit Decision

**Notes:** This figure shows the information and survey instruments common to all spectator redistribution decisions between two workers. Across all conditions, worker’s results and initial earnings are displayed. Spectators are asked whether they want to redistribute earnings. Where “No” indicates the winner maintains their \$5.00 earnings and loser earnings \$0.00. Redistribution options for “Yes” include \$0.50 increments up to redistributing all of the winner’s earnings to the loser. Including redistribution options beyond earnings equalization—i.e., pay winner \$2.50, pay loser \$2.50—was intended to minimize guiding spectator’s redistribution decisions towards earnings equalization.

Figure C3: Spectator Redistribution Choices Under CF, IOp, and INFO Conditions

<b>Worker ID:</b>	sao9rqhr	qeha27vh
<b>Coin-Flip Chance:</b>	46%	
<b>Result:</b>	won	lost
<b>Unadjusted Earnings:</b>	\$5.00	\$0.00

There was a **46%** chance that the winner and the loser in this pair was determined by a **coin flip** instead of the number of correct encryptions each worker completed.

▷ This means that there is a 77% chance that the winner above completed more transcriptions than the loser.

<b>Worker ID:</b>	ga2c8k8x	nkqqjd0n
<b>Multiplier:</b>	2.9	2.4
<b>Result:</b>	won	lost
<b>Unadjusted Earnings:</b>	\$5.00	\$0.00

The winner had a **higher score** than the loser in this pair. Each worker's score is the number of correct **encryptions** they completed *times* their **multiplier**.

▷ Based on historical data for these multipliers, there is a 77% chance that the winner above completed more transcriptions than the loser.

**Notes:** This figure shows the information for redistribution choices displayed to spectators under the CF (top) and IOp (bottom) conditions. Included directly below the outcomes table is additional text to remind spectators on how to interpret the form of luck involved in determining the winner and loser of the pair. The information provision converting the influence of luck as the likelihood that the winner performed better than the loser is only included for INFO condition spectators (see text next to ▷ symbol).

Figure C4: Part 1 of the Exit Survey (CF)

## Exit Survey: Page 1 of 2

Thank you for completing the decisions. Please answer the following exit questions.

### Question 1

Worker ID:	A	B
Coin-Flip Chance:	56%	
Result:	lost	won
Unadjusted Earnings:	\$0	\$5

There was a **56%** chance that the winner and the loser in this pair was determined by a **coin flip** instead of the number of correct encryptions each worker completed.

Suppose there are 100 pairs of workers with the same situation as the table above. That is, where the workers had a 56% chance of having a coin flip determine the winner and loser (instead of their performance).

In how many of those pairs do you think the winner completed more encryptions than the loser?

Enter a number between 0 and 100.

### Question 2

How many encryptions do you think workers solved on average?

Enter a number greater than or equal to 0.

### Question 3

If you knew for sure which worker solved more encryptions, how much would you allocate to that worker?

### Question 4

Please indicate if you used a mobile device to complete this survey:

☐ No ☐ Yes

Continue

Figure C5: Part 1 of the Exit Survey (IOp)

## Exit Survey: Page 1 of 2

Thank you for completing the decisions. Please answer the following exit questions.

### Question 1

Worker ID:	A	B
Multiplier:	1.2	4.0
Result:	lost	won
Unadjusted Earnings:	\$0	\$5

Remember: The winner had a **higher score** than the loser. Each worker's score is the number of correct **encryptions** they completed times their **multiplier**.

Suppose there are 100 pairs of workers with the same situation as the table above. That is, where the worker with a multiplier of **1.2** lost and the worker with a multiplier of **4.0** won.

In how many of those pairs do you think the winner completed more encryptions than the loser?

Enter a number between 0 and 100.

### Question 2

How many encryptions do you think a worker with a multiplier of **1.1** solved on average?

Enter a number greater than or equal to 0.

### Question 3

If you knew for sure which worker solved more encryptions, how much would you allocate to that worker?

Figure C6: Part 2 of the Exit Survey

## Exit Survey: Page 2 of 2

Please indicate your level of agreement or disagreement with the following statements:

	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
In the long run, hard work usually brings a better life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Hard work doesn't generally bring success—it's more a matter of luck and connections.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The government should redistribute income only to eliminate income differences that are due to differences in luck.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The government should never redistribute income, regardless of the source of income differences.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is fair if luck influences a person's income.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is fair if hard work influences a person's income.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
When it comes to social issues, I am very conservative.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I oppose government interventions in matters concerning the economy	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The income distribution in the US is fair.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is fair if connections influence a person's income.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is fair if talent influences a person's income.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I tend to side with Democrats on most issues.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Select disagree if you are reading this.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I tend to side with Republicans on most issues.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the US, people hold the key to economic success in their own hands.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The government should redistribute income to eliminate all income differences, regardless of whether they are mostly due to differences in luck, effort, or other factors.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## C.1 Numeracy Questions

1. In a sale, a shop is selling all items at half price. Before the sale, a sofa costs \$300. How much will it cost in the sale?
2. Let's say you have \$200 in a savings account. The account earns ten per cent interest per year. Interest accrues at each anniversary of the account. If you never withdraw money or interest payments, how much will you have in the account at the end of two years?
3. In the BIG BUCKS LOTTERY, the chances of winning a \$10.00 prize are 1%. What is your best guess about how many people would win a \$10.00 prize if 1,000 people each buy a single ticket from BIG BUCKS?
4. If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?
5. The chance of getting a viral infection is 0.0005. Out of 10,000 people, about how many of them are expected to get infected?