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Inequality of Opportunity and Income Redistribution*

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Abstract

We examine how people redistribute income when there is uncertainty about the role luck plays in determining opportunities and outcomes. We elicit redistribution decisions from a U.S.-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. Our findings have implications for models that seek to understand and predict redistribution attitudes, and help to explain the gap between lab evidence on support for redistribution and U.S. inequality trends.

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1 Introduction

Individuals' support for redistribution is a key input in the design and implementation of many social policies, including government subsidies and tax regimes. Several prominent models emphasize the central role that fairness attitudes play in driving individuals' redistribution decisions (e.g., Alesina and Angeletos, 2005; Bénabou and Tirole, 2006). A growing body of experimental work has found that most people hold meritocratic fairness ideals: they tolerate income disparities that are due to differences in effort but choose to redistribute when income differences are due to circumstances beyond individuals' control, such as luck (e.g., Cappelen et al., 2007, 2013; Almås et al., 2020). However, the prevalence of meritocratic principles documented in empirical work is difficult to reconcile with the recent trends in income inequality in the United States. The impact of circumstances beyond people's control has risen over the past decades (Chetty et al., 2014). Yet, contrary to meritocratic ideals, Americans' support for redistribution has not increased in recent decades (Ashok et al., 2015).

We propose that this disconnect between experimental findings and real-world redistribution trends is partly due to how the prior literature has implemented luck in lab settings. Previous work has mostly focused on redistribution behavior in situations in which the importance of luck is independent of individual effort. In reality, luck is often experienced through unequal opportunities that interact with effort, which makes it difficult for individuals to assess the source of inequality. For example, consider whether Microsoft founder Bill Gates' success was 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—one of many lucky breaks in Gates' career (Frank, 2016). However, he is also 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 assessing the exact impact of each factor poses a challenging inference problem.

This paper examines how individuals make redistribution decisions when luck creates income inequality through unequal opportunities that generate disparities in workers' returns to 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 are willing to tolerate. Individuals redistribute less, and their support for redistribution is less elastic to changes in the importance of luck when luck stems from unequal opportunities rather than affecting outcomes directly. We also document that individuals appear to hold biased beliefs about the impact of luck when it arises through lucky opportunities; specifically, they underestimate how small changes in opportunities can lead to large differences in outcomes. Overall, our findings suggest that meritocratic fairness ideals may be less prominent among Americans than the prior literature implies.

To motivate our experimental design and empirical approach, we present 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. The spectator observes workers' returns to effort and who won the competition, but does not observe their actual effort levels. 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 π, so that $(1-\pi)$ is the likelihood that the outcome is due to luck. In other words, π provides a direct measure of how important luck was in determining worker outcomes. This variable allows us to link the two experimental luck environments.

We recruited 2,400 Amazon Mechanical Turk (mTurk) workers to perform an encryption task and randomly paired them to compete for a fixed prize in a winner-takes-all environment. Then, we asked 1,170 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 are randomly assigned to one of two luck environments. In the *lucky outcomes* environment, we select the winner of each worker match by a coin flip with some probability q, and otherwise, based on the workers' performance. To vary the importance of luck as measured by π, we implement within-spectator variation of 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. To vary the importance of luck as measured by π, we implement within-spectator variation of the unequal opportunities between workers and exploit the fact that each ratio of multipliers maps to a unique value of π.

Our main result is that spectators' redistribution behavior differs substantially depending on whether luck is manifested as lucky outcomes or lucky opportunities. Redistribution is 15.3 percent lower when there are lucky opportunities. On average, spectators redistributed 27.6 percent of earnings from the winner to the loser when there are lucky outcomes and 23.3 percent when there are lucky opportunities. Redistribution is lower on average and almost for any degree of luck involved; that is, for any value of π. Moreover, spectators are significantly less responsive to changes in the importance of luck, as measured by the elasticity of redistribution with respect to π, when workers face unequal opportunities. A 10 percentage point increase in the likelihood that luck determined the winner causes a 3.7 percentage point increase in the share of earnings redistributed in the lucky outcomes environment but only a 1.9 percentage point increase in the lucky opportunities environment.

We implement two additional between-subjects treatments to test for potential mechanisms that drive the differences in redistribution across luck environments. 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 lucky opportunities environment, workers learn their multiplier before starting the encryption task. Hence, the difference in support for redistribution between the two types of luck could be due to spectators who believe that workers adjust their labor supply in response to a low or a high multiplier. To isolate the role of effort responses in driving our results, we introduce an "ex-post" lucky opportunities condition in which workers learn about their multiplier only *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 lucky opportunities conditions. Thus, different perceptions about how much effort workers exert do not explain the redistribution gap.

Second, we examine whether differences in redistribution persist when we provide information about the likelihood that the outcome is due to effort, π. Providing information about the importance of luck allows us to rule out the possibility of differential, inaccurate beliefs about π, and isolate the role of preferences in driving the differences in redistribution we observe. We find that informing spectators of π leads to a significant decrease in average redistribution in both luck environments. On average, spectators redistribute 16.3 percent less in the lucky outcomes environment and 13.0 percent less in the lucky opportunities environment. This decrease in redistribution is possibly due to our information intervention making the importance of effort salient, since π is defined as the probability that the winner completed more encryptions. More importantly, the *difference* in average redistribution across our luck environments remains unchanged in the information treatment.

We also find that redistribution is more elastic to changes in π in both luck environments when we provide information about π. On average, the elasticity of redistribution with respect to π increases by 41 percent in the lucky outcomes environment and by 60 percent in the lucky opportunities environment. However, the difference in this elasticity across luck environments does not significantly change when we provide information about π. Taken together, these results suggest that individuals hold different fairness views towards redistribution when there are lucky outcomes versus lucky opportunities. Moreover, the change in how responsive redistribution is with respect to changes in the importance of luck suggests that spectators have challenges inferring the importance of luck, even in relatively simple settings.

To further understand how biased beliefs may arise when making redistribution decisions, we examine how spectators incorporate unequal opportunities into their redistribution decisions. The impact of worker multipliers on π 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).[1] We present evidence that spectators rely on a simple heuristic of using linear multiplier differences when factoring the impact of opportunities into their redistribution decisions. This implies that spectators underappreciate the extent to which small differences in opportunities can greatly impact outcomes. When we provide information about π,

[1] The nonlinear relationship between luck and outcomes is not unique to our experiment and is a feature of many real-world situations (see Frank (2016)). Intuitively, if effort or skill is normally distributed in the population, most people's performance will be relatively similar. Thus, starting with only slightly advantageous opportunities can have a large impact on one's competitiveness, while increasing the advantage further has diminishing effects.

spectators reduce but do not eliminate their reliance on this linear approximation. That spectators put weight on multiplier differences beyond their impact on π is consistent with findings from psychology showing that people care about the process by which an outcome arrives (Lind and Tyler, 1988).[2]

We primarily contribute to the extensive 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 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 affects outcomes than when it emerges through unequal opportunities. More generally, our work relates to the literature on the determinants of support for redistribution, including other-regarding preferences (e.g., Charness and Rabin, 2002), fairness ideals (e.g., Konow, 2000; Cappelen et al., 2007), and context and perceptions (e.g., Fisman et al., 2015; Kuziemko et al., 2015). We also show that redistribution behavior in our lucky opportunities environment predicts real-world social and political views better than in the lucky outcomes environment.

We also engage more directly with an emerging literature that investigates how individuals make redistribution decisions where luck arises through unequal opportunities (Andre, 2022; Bhattacharya and Mollerstrom, 2022; Dong et al., 2022).[3] Our work is different in three main ways. First, we consider inequality of opportunity as differences in multipliers, which creates uncertainty about the source of income disparities. How individuals react to this uncertainty when making redistribution questions is the central question that we study. Second, by creating a common scale for the probabilistic impact of luck, we can directly compare varying levels of luck under the extensively studied lucky outcomes environment with our lucky opportunities environment. As such, our approach contributes to advancing the methodology of redistribution experiments by designing a portable definition of luck that can be mapped onto different tournament environments. In addition, our design allows us to assess redistribution behavior over a continuum of probabilistic-luck scenarios. This allows us to estimate the elasticity of redistribution with respect to changes in luck, moving beyond the pure luck or pure merit boundary cases that prior experimental settings have

[2]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 misperceptions leads to negligible changes in support for redistribution (Fehr et al., 2022, find similar evidence for Germany). 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.

[3]Andre (2022) finds that disparities in piece-rate wages produce large differences in worker effort and that spectators reward workers according to their effort irrespective of how differences in circumstances impacted workers' effort. Relatedly, Bhattacharya and Mollerstrom (2022) show that spectators accept significantly more inequality when chance determines who is allowed to work than when luck determines outcomes directly. Similarly, Dong et al. (2022) show that spectators tolerate greater income disparities when workers face differential opportunities to learn or to answer the full set of questions in an exam.

focused on.

We also replicate and extend several findings from the literature. First, our lucky outcomes results are consistent with the nonlinear relationship between redistribution and luck 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 this pattern of redistribution is partly due to inaccurate beliefs about the importance of luck. Second, we echo the null effect that the timing of luck has on redistribution found by Andre (2022). We extend this finding to a winner-takes-all setting in which there are no effort responses to unequal opportunities.

Finally, our results also speak 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), and we document the consequences of inappropriate inference in an important economic setting. Consistent with some spectators making errors in statistical reasoning, more numerate individuals in our panel are less likely to rely on heuristics when assessing the importance of unequal opportunities for outcomes.

2 Theoretical Framework

In this section, we present a stylized 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. Our goal 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 prize. 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 ($r_i = 0$) regardless of the importance of luck. We denote the share of spectators that never redistribute by θ. The setting below focuses on the remaining share of spectators who redistribute a positive amount. For these 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. 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:

$$U(r_i, f_i) = -(r_i - f_i)^2. \tag{1}$$

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

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

where π 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

$$r_i^* = \pi f_i + (1-\pi)(1-f_i). \tag{3}$$

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 (π). Provided $f_i < 1/2$, the optimal level of redistribution is decreasing in π; in other words, the more likely it is that the worker who solved more encryptions was the winner, the less the spectator redistributes. When $\pi = 1$ and thus effort solely determines the winner, spectators redistribute the fair share to the loser, $r_i^* = f_i$. When worker outcomes are due to pure luck (i.e., $\pi = 1/2$), spectators choose to equalize earnings and choose $r_i^* = 1/2$. The key inferential hurdle spectators face is forming beliefs about π. As is often the case in reality, spectators do not directly observe π. Instead, they must form an estimate of π based on noisy signals about the importance of luck. We investigate two environments that differ in how spectators must infer π.

In the lucky outcomes environment, there is a $q \in [0,1]$ 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 π from q, spectators must use Bayesian updating, which implies $\pi = 1 - 0.5q$. In the lucky opportunities 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 π 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

$$\pi = \Pr\Big(e_1 \geq e_2 \Big| m_1 e_1 > m_2 e_2, m_1, m_2\Big). \tag{4}$$

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

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

Expression (5) shows that π depends on the relative multiplier m_1/m_2. Notably, π is convex and decreasing in m_1/m_2 if worker 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 π may not be accurate for several reasons. When there are lucky outcomes, the spectator may fail to perform Bayesian updating. When there are lucky opportunities, they might not appreciate that a small multiplier advantage can correspond to a significant change in π. Instead, spectators may resort to simple heuristics, such as comparing multiplier differences rather than assessing how multiplier ratios translate to differences in π. Since a spectator's estimate of π may deviate from the truth, we use $\tilde{\pi}_i$ to denote spectator i's subjective estimate of π. Then, spectator i's redistribution decision becomes

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

If f_i and $\tilde{\pi}_i$ are independent, the average level of redistribution in the population is given by:

$$\bar{r}^* = (1 - \theta)\left(\tilde{\pi} f + (1 - \tilde{\pi})(1 - f)\right), \tag{7}$$

where $\tilde{\pi}$ is the average estimate of π, and f is the average share of earnings that spectators deem fair for the less productive worker among the $1 - \theta$ share of spectators who choose to redistribute some 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 $\tau \in \{\text{Opportunity}, \text{Outcome}\}$ to θ, $\tilde{\pi}$, and f as these terms may depend on whether luck arises through lucky opportunities or lucky outcomes.

First, we compare the average level of redistribution between the luck environments. Equation (7) highlights that average redistribution depends on three factors: the share of spectators who do not redistribute any earnings (θ_τ), the average fair share among those who do redistribute (f_τ), 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.

We refer to differences in the share of spectators that decide not to redistribute any earnings across luck environments as differences in the "extensive margin" of redistribution. For example, some spectators might always attribute success to worker effort as long as winning would not have been possible without exerting effort—a condition that always holds under lucky opportunities but not under lucky outcomes. Average redistribution may also differ due to changes in the average amount redistributed among spectators who are willing to redistribute sometimes; we refer to this as the "intensive margin" of redistribution. Intensive margin effects 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 underestimate the importance of luck when it interacts with effort, $\tilde{\pi}_{\text{Opportunity}} > \tilde{\pi}_{\text{Outcome}}$, which would decrease the amount of redistribution in lucky opportunities relative to lucky outcomes.

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 π:

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

Equation (8) shows that the average level of redistribution is decreasing in π as long as $\theta_\tau < 1$ and $\bar{f}_\tau < 1/2$. 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 π.

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 change, then redistribution will be less responsive to changes in π when there are lucky opportunities than when there are lucky outcomes.

Equations (7) and (8) form the basis of our primary empirical hypotheses. Both equations are determined by spectators' fairness views and their subjective beliefs. To isolate the role of fairness views (f_τ and θ_τ in our model), we consider an information intervention in which we tell spectators the value of π. This allows us to shut down the role of inaccurate beliefs in evaluating the differences in redistribution between the lucky opportunities and lucky outcomes environments.

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, the impact of a marginal increase in π on redistribution given by equation (8) in the information treatment becomes

$$\left.\frac{\partial \bar{r}^*}{\partial \pi}\right|_{\tilde{\pi}=\pi} = -2(1-\theta_\tau)\left(\frac{1}{2} - \bar{f}_\tau\right). \tag{9}$$

Therefore, the ratio of (8) to (9) recovers the elasticity of luck perceptions to changes in the actual importance of luck, $\partial \tilde{\pi}_\tau / \partial \pi$. Therefore, if the information treatment makes spectators more responsive to changes in luck, this implies that $\partial \tilde{\pi}_\tau / \partial \pi < 1$. In other words, by comparing the ratio of these two elasticities, we can test whether spectators underestimate the importance of increasing inequality of opportunity in the absence of precise information about π.

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.[4] 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), the timing of when luck is revealed to the workers (before vs. after), and the 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 π, the probability that the higher-effort worker won.

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 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 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 $\{\$0.50, \ldots, \$5.00\}$ redistribution choices are labeled as a "yes"-adjustment

[4] We designed all experimental programs in oTree (Chen et al., 2016).

choice and denote the final earnings for both the winner and the loser: that is, {(winner gets, loser gets)} = $\{(\$4.50, \$0.50)$, $(\$4.00, \$1.00)$, ..., $(\$0.50, \$4.50)$, $(\$0.00, \$5.00)\}$.[5]

To incentivize spectators to respond truthfully, we randomly select one of their 12 decisions and implement it. In other words, one of the spectator's decisions determines 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. We also assure spectators that workers do not know if they won and will only ever learn their final earnings. Moreover, while workers know a third party may influence their final earnings, the spectator's identity is entirely anonymous to the workers.

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 luck.

3.3.1 Lucky Outcomes vs. Lucky Opportunities

We randomly assign one-third of the spectators to redistribute earnings under lucky outcomes and two-thirds to redistribute earnings under lucky opportunities. In our lucky outcomes condition, we select the winner by a coin flip with probability q and by the number of correct encryptions with probability $1-q$. Thus, the impact of luck is independent of worker effort. In our lucky opportunities condition, we generate inequality of opportunity by randomly assigning effort multipliers to workers. For example, a worker with a multiplier of 1.2 who solved 20 encryptions would have a score of 24, while a worker with a multiplier of 3.0 who solved 10 encryptions would have a score of 30. The winner in each pair is the worker who has the higher score. Thus, effort and luck interact when there are lucky opportunities. 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 tenth.

We never inform spectators about the actual effort level of the workers, though we do provide some information about the role of luck. In the lucky outcomes 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 know that there is some unstated chance that a coin flip determines their outcomes. In the lucky opportunities condition, spectators know each worker's multiplier.[6] We inform spectators that workers only know of their own multiplier and do not know anything about the worker

[5] To combat the influence of anchoring effects in these redistribution choices, 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.

[6] Workers also know the distribution from which we draw multipliers.

they compete against. Appendix Figure C3 provides an example of a redistribution decision in our lucky outcomes condition and an example of a redistribution decision in our lucky opportunities condition.

3.3.2 Importance of Luck in Determining the Winner

We implement within-subject variation in the importance of luck across worker pairs. In the lucky outcomes environment, we implement variation in the importance of luck by varying q across matches. In the lucky opportunities environment, we implement variation in the importance of luck by varying the ratio between workers' multipliers across worker pairs. We 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 (π). In other words, π measures the likelihood that outcome differences are due to effort rather than luck. When $\pi = 0.50$, there was a 50 percent chance that the winner of the match was the one who exerted more effort; for example, when a coin flip determined the outcome ($q = 1$) in the lucky outcomes environment or when the ratio between worker multipliers is sufficiently large (so that the worker with the high multiplier always won the match) in the lucky opportunities environment. When $\pi = 1$, there was a 100 percent chance that the winner of the match was the one who exerted more effort; for example, when $q = 0$ or when both workers had the same effort multiplier.

Spectators make redistribution decisions for a total of 12 worker pairs. Each worker pair corresponds to a unique value of π drawn from one of the following 12 bins:

$$\pi \in \Big\{ \underbrace{\{0.50\}}_{\text{Bin 1}}, \underbrace{\{0.51, ..., 0.54\}}_{\text{Bin 2}}, \underbrace{\{0.55, 0.56, ..., 0.59\}}_{\text{Bin 3}}, ..., \underbrace{\{0.95, 0.96, ..., 0.99\}}_{\text{Bin 11}}, \underbrace{\{1\}}_{\text{Bin 12}} \Big\}. \tag{10}$$

For each spectator, we randomly draw one value of π from each of the 12 bins. This 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 π. We present the 12 trials in random order.

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 a coin flip q determined the winner. Therefore, it is necessary to map each π value to a corresponding (m_i, m_j) or a coin-flip probability q. The mapping from π to q is given by the formula $q = 2(1 - \pi)$. To map π to a multiplier pair, (m_i, m_j), it is sufficient to consider the relative multiplier $m \equiv \max\{m_i, m_j\}/\min\{m_i, m_j\}$. Given any relative multiplier m, 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 π 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 a one-to-one mapping from m to π (depicted in Panel B in Figure A1). For a given π, we then select a random worker pairing with a corresponding relative multiplier.

3.3.3 Timing of Opportunity Luck

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

3.3.4 Information Intervention

We randomly assign half of the spectators in each treatment to receive precise information about π. In the lucky opportunities condition, we present the following additional text on the redistribution decision screen: "Based on historical data for these multipliers, there is a $[\pi * 100]\%$ chance that the winner above completed more transcriptions than the loser." In the lucky outcomes condition, the equivalent text is: "There is a $[\pi * 100]\%$ chance that the winner above completed more encryptions than the loser." As noted above, the value of π varies from trial to trial. Appendix Figure C3 provides an example of the decision screens for the information treatments for both luck environments.

3.3.5 Workers' Awareness about Rules

Finally, we vary the timing of when workers learn about how luck plays a role in determining outcomes. In the rules-before condition, we inform workers that there will be effort multipliers or a coin flip that influences the outcome *before* they start the task. In the rules-after condition, we inform workers that there will be multipliers or a coin flip that influences the outcome *after* they complete the task. We randomly assign half of the spectators in the ex-post lucky opportunities and lucky outcomes conditions to the rules-before treatment and half to the rules-after treatment. By construction, we assign all participants in the baseline lucky opportunities condition to the rules-before treatment. Spectators have complete 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 and 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 workers' task.

After the 12 redistribution decisions, spectators 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 the spectators made and present the same information to them. We then ask spectators in the lucky outcomes condition how many encryptions they think workers solved on average. For spectators in the lucky opportunities condition, 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 had 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 completing 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 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.[7] 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

[7]See Appendix Table A1 for summary statistics on our sample of workers.

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.

Table 1: Average spectator characteristics by treatment condition

		Baseline condition			Information Treatment		
	All	Lucky Outcomes	Lucky Opportunities	Ex-Post Lucky Opportunities	Lucky Outcomes	Lucky Opportunities	Ex-Post Lucky Opportunities
	(1)	(2)	(3)	(4)	(5)	(6)	(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 composition of our spectator sample, comparing spectators treated with and without information about π (the likelihood that the winner completed more tasks than the loser), between lucky outcomes (columns (2) and (5)), lucky opportunities (columns (3) and (6)), and ex-post lucky opportunities (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 we observe stem from changes in the intensive or extensive margin of redistribution. Finally, we examine individual heterogeneity in redistribution behavior and whether spectators' redistribution decisions in our task predict their real-world social and political views.

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 (π). 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 the earnings. If $r_{ip} = 0.5$, both workers receive half of the total earnings.

4.1 Redistribution under Lucky Opportunities and Lucky Outcomes

Panel A of Table 2 reports the average level of redistribution across our luck treatments. When chance creates inequality by affecting outcomes directly (the lucky outcomes 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 lucky opportunities 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.

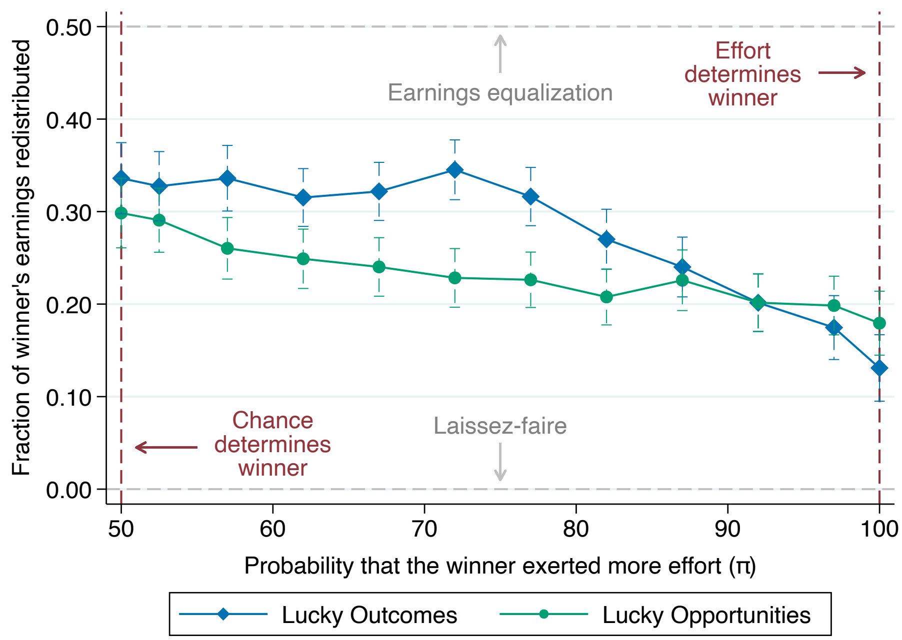
We also compare differences in the level of redistribution separately for the different likelihoods that luck determined the outcome. For this, we compute average redistribution for each experimental π bin, as defined in equation (10). Let $b \in \{1, ..., 12\}$ index the 12 experimental π bins. Recall that each spectator made a redistribution decision for a value of π from within each of these 12 bins. In Panel C of Table 2, we estimate regressions of the form:

$$r_{ib} = \sum_{b=1}^{12} \gamma_b \pi_b + \varepsilon_{ib}, \tag{11}$$

where π_b is an indicator that equals one if π_{ip} is in bin b. We estimate equation (11) separately for each treatment and interact the bins with treatment dummies to assess whether mean redistribution is the same across luck treatments at a given π bin. We cluster standard errors at the spectator level in all specifications.

Figure 1 plots the mean redistribution in the lucky outcomes and lucky opportunities conditions against π for each bin. Each point is our estimate of γ_b for a given bin and treatment. Figure 1 confirms that average redistribution is lower when there are lucky opportunities relative to lucky outcomes but also reveals two novel and striking patterns. First, the range over which redistribution is lower when there are lucky opportunities relative to lucky outcomes is given by $\pi \leq 0.85$, i.e., when the importance of effort is not too large. For $\pi \in (0.85, 1]$, in contrast, average redistribution is statistically equal in the two conditions. The second important difference is in the shape of the negative relationship between average redistribution and the likelihood that luck determined the winner. Consistent with our theoretical framework, redistribution tends to decline in π in both luck environments. In the lucky opportunities condition, redistribution is approximately linear and downward sloping from $\pi = 0.5$ to $\pi = 0.85$. However, spectators are unresponsive to incremental increases in π beyond that point: Redistribution is roughly flat from $\pi = 0.85$ to $\pi = 1$. In the lucky outcomes 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 π thereafter.

Figure 1: Redistribution and the probability that the winner completed more encryptions (π)



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: lucky outcomes and lucky opportunities.

To summarize the relationship between average redistribution and π 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, π_{ip}:

$$r_{ip} = \alpha + \beta \pi_{ip} + \varepsilon_{ip}, \tag{12}$$

where ε_{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 π_{ip}. The exogenous within-subject variation in π_{ip} allows us to identify β.

Panel B of Table 2 presents estimates of β 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 π leads to a 3.7 percentage point increase in the share of earnings redistributed in the lucky outcomes condition. However, redistribution is less elastic to changes in π in the lucky opportunities condition: A 10 percentage point decrease in π leads to a 2.0 percentage point increase in redistribution when luck emerges through unequal opportunities. To formally test for differences in how spectators react to changes in π, we estimate the following specification:

$$r_{ip} = \alpha_0 + \beta_0 \pi_{ip} + \alpha_1 \mathbb{1}_{\text{Opportunity},i} + \beta_1 \mathbb{1}_{\text{Opportunity},i} \pi_{ip} + \varepsilon_{ip}, \tag{13}$$

where $\mathbb{1}_{\text{Opportunity},i}$ is equal to one if spectator i was in the lucky opportunities condition. The coefficient β_1 measures the difference in the elasticity of redistribution with respect to π when there are lucky opportunities versus lucky outcomes. Column (3) of Table 2 shows that this coefficient is negative and economically and statistically significant ($p < 0.01$). In other words, spectators respond less to changes in the probability that the outcome is due to luck when luck stems from unequal opportunities versus affecting outcomes directly. This is despite the fact that changes in luck are observationally equivalent in terms of their impact on outcomes across the two conditions.

We observe redistribution for two important boundary cases that have been the focus of much of the prior literature (Cappelen et al., 2007, 2013; Almås et al., 2020).[8] 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 two extremes. We find that large differences in redistribution behavior between lucky outcomes and lucky opportunities 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 the two luck environments.

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, captured by the variable θ in our framework from Section 2. 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 our two luck environments. 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.[9] Column (1) shows that 9.6

[8] A notable exception is Cappelen et al. (2022), who examine how redistribution behavior responds to changes in q in the lucky outcomes environment. We replicate the concave relationship they find when luck emerges through exogenous coin-flip probabilities.

[9] In Table A2, we re-estimate these models under the assumption that someone who redistributed either once or

Table 2: Fraction redistributed as a function of π

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

Notes: This table shows estimates of redistribution under lucky outcomes (column 1), lucky opportunities (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 split into 12 bins. The 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.

percent of spectators never redistribute when there are lucky outcomes. However, this fraction is significantly higher when workers face unequal opportunities: On average, 15.9 percent of spectators do not redistribute when there are lucky opportunities. 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)
Lucky Opportunities	0.063***	0.063***	0.063*	0.064*
	(0.024)	(0.024)	(0.034)	(0.035)
Knows π		−0.011	−0.010	−0.014
		(0.024)	(0.030)	(0.031)
Lucky Opportunities × knows π			−0.002	0.001
			(0.048)	(0.049)
Constant	0.096***	0.102***	0.102***	0.121
	(0.015)	(0.019)	(0.022)	(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 π, the slope flattens if there are more of them (see θ_τ in equation (8)). Thus, the change in the extensive margin of redistribution partly explains the changes in aggregate redistribution levels across our luck environments.

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 lucky outcomes and lucky opportunities conditions for this sub-sample: Spectators redistribute 30.7 percent on average when luck emerges through coin flips (column 1) and 28.0 percent on average when luck arises through productivity multipliers (column 2). This difference is statistically significant at the 10 percent level (column 3).

twice made a mistake and never wanted to redistribute anything either. We find an even larger difference between luck environments under this assumption.

We also continue to find that spectators are less sensitive to changes in the importance of luck in the lucky opportunities condition. In Panel B, columns (1) and (2) show that a 10 percentage point increase in π reduces redistribution by 4.1 percentage points in the lucky outcomes condition and by 2.4 percentage points in the lucky opportunities condition. This difference in slope is statistically significant ($p < 0.01$, column 3). Importantly, the magnitude of this difference is similar to the baseline estimates in Table 2. Thus, the diminished overall sensitivity to luck that we observe when luck stems from unequal opportunities is not merely due to more spectators deciding to redistribute nothing. Instead, 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 π for spectators who redistribute something

	Outcome: Fraction of earnings redistributed		
	Lucky Outcomes (1)	Lucky Opportunities (2)	Difference (3)
Panel A. Average redistribution			
Constant	0.307^{***}	0.280^{***}	0.027^{*}
	(0.009)	(0.012)	(0.015)
N (Redistributive decisions)	2,124	1,944	4,068
Panel B. Linear slope			
π	-0.041^{***}	-0.024^{***}	-0.018^{***}
	(0.005)	(0.004)	(0.007)
Constant	0.410^{***}	0.339^{***}	0.071^{***}
	(0.015)	(0.016)	(0.022)
N (Redistributive decisions)	2,124	1,944	4,068

Notes: Panel A shows the mean share of earnings redistributed under lucky outcomes (column 1), lucky opportunities (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 (π) 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.

4.3 Heterogeneity and Predicting Political and Social Views

An advantage of the Survey of Consumer Expectations panel is that it recruits a non-convenience, nationally representative sample of U.S. households, with a particular focus on historically hard-to-reach demographic groups. This allows us to examine heterogeneity in our results along a rich set of dimensions. We present the results from a heterogeneity analysis in Appendix Table A3. Panel A shows that female respondents tend to redistribute more on average in both the lucky outcomes and lucky opportunities environments. This is consistent with prior work showing that female spectators tend to accept less inequality on average (Almås et al., 2020). Conversely, respondents in households with annual incomes above $100,000 tend to redistribute less on average across both luck environments. Some existing empirical evidence already suggests that income and support for redistribution are negatively correlated (Alesina and Giuliano, 2011). Thus, our findings suggest that higher-income households are more likely to oppose redistribution not only because it is in their own financial interest but also because they hold different fairness views. Panel B highlights a number of additional differences across spectators' political and societal views. Most notably, people who self-reportedly tend to side with republicans on most issues display less support for redistribution than those who do not. This is consistent with both survey and experimental evidence that finds republicans are less likely to support redistribution (Ashok et al., 2015; Alesina et al., 2018; Almås et al., 2020).

We can also compare whether redistribution behavior in our lucky opportunities environment is more aligned with real-world social and political attitudes than behavior in the lucky outcomes environment. To assess this, in Appendix Table A4, we estimate the correlation between the average earnings redistributed by spectators in each environment and their self-reported political and social views. Panel A reveals that redistribution behavior in both luck environments correlates with real-world attitudes; however, behavior in the lucky opportunities condition tends to be more predictive. For example, the correlation between siding with the Democratic Party and average redistribution behavior is 0.08 in the lucky outcomes environment (column 1) and 0.14 in the lucky opportunities environment (column 2). The lucky opportunities environment is more predictive in 13 out of the 14 social and political attitudes displayed in Panel A, although some of the differences have large standard errors (column 3).

Panel B compares two summary indices of political attitudes. The first one is a z-score that averages all the individual attitudes in Panel A. The second index is the first component of a principal component analysis (PCA). This component puts a large weight on siding with the republican party and opposing government intervention, and thus reflects conservative values. Consistent with the main results, the summary indices show that behavior in the lucky opportunities condition is 45 to 62 percent more predictive of attitudes than behavior in the lucky outcomes condition. This provides suggestive evidence that redistribution decisions better reflect real-world social and political views when luck interacts with effort to determine outcomes. Focusing on environments with lucky outcomes might therefore understate the political divide in support for redistribution if opportunity luck is the dominant driver of inequality in reality.

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 the importance of luck in determining workers' outcomes is the same in both environments. 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 mostly due to differences in the intensive margin. Finally, we show that redistribution behavior in our lucky opportunities environment is more predictive of real-world social and political views than redistribution behavior in our lucky outcomes environment. In the following section, we explore several potential mechanisms that might drive these differences in redistribution between the two luck environments.

5 Mechanisms

We test two key mechanisms that may drive the patterns of redistribution that we observe across the lucky opportunities and lucky outcomes 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 correct possibly inaccurate beliefs about the importance of luck. This allows us to isolate the role differential fairness views may play in driving our main results.

5.1 The Timing of Luck and Effort Responses

An important difference between our luck environments is that lucky outcomes occur after completing the task, while unequal opportunities are known before. This reflects how lucky opportunities are commonly realized in many 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.[10] For example, spectators may hold workers with lower multipliers accountable for not overcoming their circumstances (by working harder) and therefore regard a smaller income share for the less productive worker as fair, $f_{\text{Opportunity}} < f_{\text{Outcome}}$. Spectators could also express compassion for workers who put in effort despite a low multiplier so that $f_{\text{Opportunity}} > f_{\text{Outcome}}$. Alternatively, the timing of luck could influence how much effort spectators expect workers to exert, thereby impacting perceptions about how important luck was in determining the outcome, $\tilde{\pi}_{\text{Opportunity}}$.

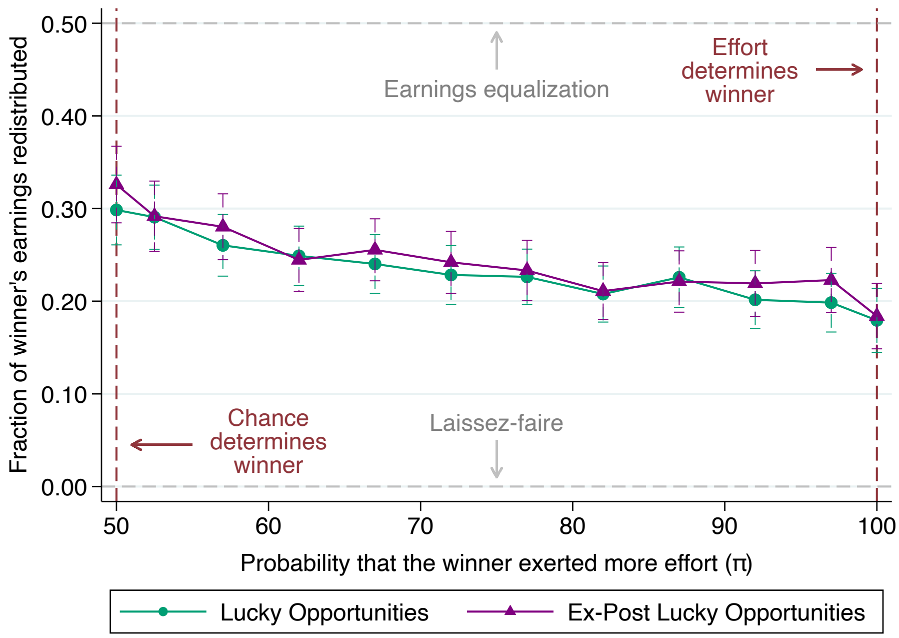
To test whether the timing of lucky opportunities affects redistribution, we compare spectators' redistribution decisions in the baseline lucky opportunities condition to those in the ex-post lucky opportunities condition. In both situations, workers in a pair face differential returns to their effort.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

In Appendix Table A6, we re-estimate the main specifications in Table 2 but compare redistribution between the baseline and ex-post lucky opportunities. Redistribution is neither economically nor statistically different across the two treatments. We find no significant differences in the average level of redistribution: The average amount of income redistributed was 23.4 percent in baseline lucky opportunities versus 24.4 percent in ex-post lucky opportunities ($p = 0.57$). We also find no

[10] In practice, we do not find any evidence that worker effort responds to receiving a high or low multiplier (see Appendix Table A5). 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 the distribution of worker effort in the lucky outcomes and lucky opportunities environments are equal ($p = 0.909$). However, what matters for redistribution behavior are spectators' beliefs about worker effort, which may not align with reality.

significant differences in the elasticity of redistribution to changes in luck using a linear specification ($p = 0.89$). Figure 2 plots our estimates of average redistribution for both lucky opportunities conditions across each π bin. Across the entire range of π bins, we find no differences in the level of redistribution.

Figure 2: Redistribution and π in the baseline and ex-post lucky opportunities conditions



Notes: This figure shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) as a function of the likelihood that the winner exerted more effort. It depicts two variations of the lucky opportunities condition: Workers in the baseline condition are aware of their multiplier prior to beginning the encryption task, and workers in the ex-post condition only learn their multiplier after completing the 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 lucky opportunities condition, 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 A7, 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 condition, workers knew exactly how we would determine the winner before working on the task. In the rules-after condition, workers were only told that solving more encryptions would increase their chance of winning before they began the task. Crucially, spectators in the rules-after treatments in both the lucky outcomes or ex-post lucky opportunities conditions knew that workers had identical information prior to beginning the task. Between these two conditions, there is thus no scope for differences in beliefs about the distribution of worker effort. Appendix Figure B2 compares average redistribution in the lucky outcomes and ex-post lucky opportunities conditions for only the rules-after scenarios. 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.[11]

Overall, we find no evidence that the timing of luck alters the redistribution behavior of spectators when there are lucky opportunities or lucky outcomes. This implies that the extent to which luck and effort are intertwined 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 a task.[12]

5.2 Information Provision Treatment

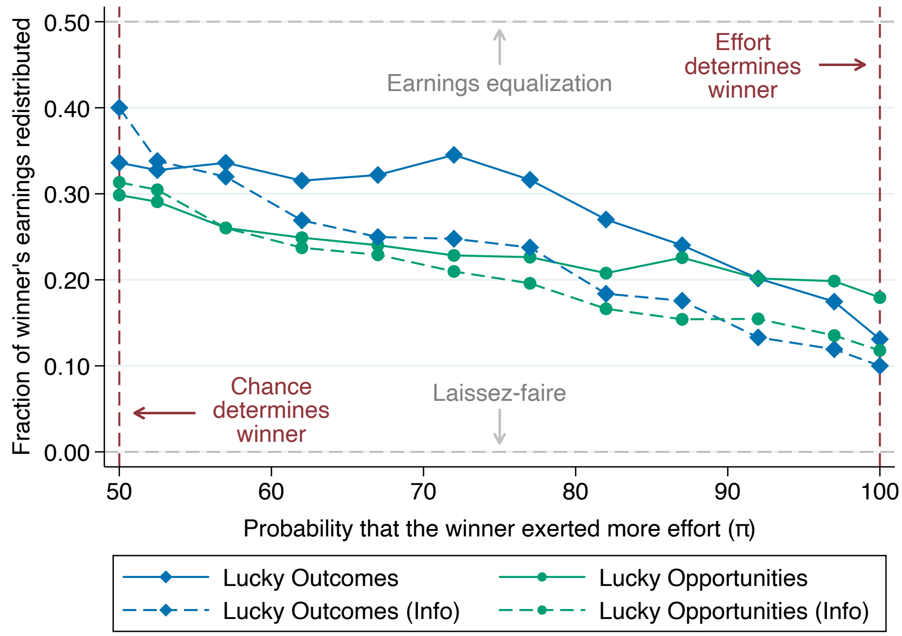
Spectators are less sensitive to changes in the importance of luck when it is experienced through unequal opportunities rather than directly by altering outcomes. This result persists even when workers face identical information prior to beginning the task. One possible mechanism is that spectators find 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 probability that an outcome was due to effort, π. We also examine whether the differences in redistribution across luck environments persist when we provide precise information about π.

We first compare redistribution in the baseline and information treatments to control for the role of inaccurate beliefs in driving differences in redistribution between lucky outcomes and lucky opportunities. 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 luck environments. Table A8, Panel A shows that average redistribution falls from 27.6 percent to 23.1 percent when there are lucky outcomes ($p < 0.01$) and from 23.9 percent to 20.8 percent when there are lucky opportunities ($p < 0.05$). This equates to a decrease in earnings for the worker who solved fewer encryptions of 16.3 and 13.0 percent in the lucky outcomes and lucky opportunities environments, respectively. Figure 3 plots the mean redistribution across each π bin for both luck environments split by our information intervention. This figure reveals that the decrease in redistribution occurs for nearly all π bins.

[11]We provide additional analysis of our rules-before and rules-after subtreatments in Appendix B.1.

[12]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.

Figure 3: The effect of providing information about π



Notes: This figure shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) as a function of the likelihood that the winner exerted more effort. Displayed are the two main experimental conditions—lucky outcomes and lucky opportunities—as well as whether spectators were provided with information provision about π.

One interpretation of the decreasing effect on redistribution is that our information treatment primed spectators to think more about the effort of the winner than the bad luck of the loser. Since π is expressed as the probability that the winner was the worker who solved more encryptions, it may have made the role of effort more salient and thus lead to a decline in redistribution. Since we are mostly interested in explaining the gap between the lucky opportunities and lucky outcomes environments, the potential salience effects of the information treatment under each environment are interesting but beyond the scope of this paper.

Second, we find that redistribution becomes more elastic to changes in the importance of luck when spectators are informed about π. Panel B of Table A8 shows that a 10 percentage point increase in π in the lucky outcomes environment causes spectators to redistribute 3.7 percent more of total income when there is no information about π compared to 5.2 percent more when there is full information. Similarly, a 10 percentage point increase in π in the lucky opportunities environment 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.

Crucially, we observe similar changes in redistribution in response to providing information across both luck environments. Panel A, column (3) of Table A8 shows that the change in the level of redistribution when spectators receive information about π is not significantly different across luck environments ($p = 0.74$). Moreover, Panel B shows that there is no significant difference in the change in slope when there is outcome luck relative to opportunity luck ($p = 0.43$). Therefore, the gap in both the level and slope of redistribution between lucky opportunities and lucky outcomes persists when we correct for potentially inaccurate beliefs.

Our information intervention allows us to quantify the extent to which spectators underact to changes in the importance of luck in determining workers' outcomes. In Section 2.1, we show that the ratio of redistribution elasticities (with respect to changes in π) in our baseline and information treatments provides a measure of this underreaction. Table 5 presents our empirical estimates of this ratio for both luck environments. In the lucky outcomes environment, we estimate a ratio of 0.71, which implies an underreaction of 29 percent. This muted response to changes in luck is even more pronounced in the lucky opportunities environment: we estimate a ratio of 0.54, which implies an underreaction of 46 percent. This is consistent with spectators finding it more difficult to assess the importance of luck when it arises through unequal opportunities rather than directly through outcomes. However, we caution that while our estimate of the difference in underreaction to π is large, it is also noisy and not significantly different from zero (see column (3)).

Table 5: Estimates of underreaction to importance of luck

	Lucky Outcomes (1)	Lucky Opportunities (2)	Difference (3)
$\partial\tilde{\pi}_\tau/\partial\pi$	0.711^{***}	0.541^{***}	0.171
	(0.101)	(0.113)	(0.151)
N	4,728	4,680	9,408

Notes: This Table presents estimates of the elasticity of luck perceptions to changes in the actual importance of luck, $\partial\tilde{\pi}_\tau/\partial\pi$. We calculate this elasticity by calculating the ratio of redistribution elasticities with respect to changes in π in our baseline and information treatments. See Section 2.1 for details. Standard errors estimated through the delta method in parentheses.***, ** and * denote significance at the 10%, 5%, and 1% level, respectively.

We also examine whether providing information about π alters the share of spectators who redistribute nothing (columns (2) to (4) of Table 3). We find no significant effect of the information intervention on whether spectators never redistribute. That is, even with complete information about the likelihood that luck determined the winner, spectators are more likely to never redistribute when workers face unequal opportunities than when they face lucky outcomes.

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 at least partly driven by spectators holding different fairness views.

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 simple heuristics.

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."[13] According to this heuristic, individuals 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 π 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 1.00 to 1.20 decreases the likelihood that the worker who solved more encryptions won from around 100 percent to 77 percent.

In Table 6, we test whether spectators base their redistribution decisions on the multiplier difference in the absence of full information about π. We first focus on spectators in the baseline lucky opportunities environment who observe workers' multipliers but not π directly. Column (1) reproduces the specification in Panel B of Table 2. Column (2) replaces true π 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 A9, we include higher-order polynomials and find no significant effects even though such polynomials provide a successively better fit to true π. Column (3) includes both the actual empirical π 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 the actual empirical π that falls short of conventional significance levels ($p = 0.065$). In other words, when spectators do not know π, they focus on linear multiplier differences when making their redistribution decisions. This can also be seen in Panel A of Figure 4, which shows that in the baseline lucky opportunities environment, mean redistribution is approximately linear in the multiplier difference.

Our theoretical framework predicts that meritocratic spectators will base their decisions on π when we provide full information about its value. In columns (4) through (6), we estimate the same specifications for spectators who receive our information intervention in the lucky opportunities condition. Column (5) again shows 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 π directly in column (6), though it continues to be significant. In other words, even

[13] 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).

Table 6: Testing for a linearization heuristic

	Dependent Variable: Fraction of earnings redistributed					
	No π provisions (Baseline)			π provisions (Information)		
	(1)	(2)	(3)	(4)	(5)	(6)
π	-0.020^{***}		-0.009^{*}	-0.037^{***}		-0.028^{***}
	(0.004)		(0.005)	(0.004)		(0.005)
Multiplier difference		0.040^{***}	0.024^{**}		0.068^{***}	0.019^{**}
		(0.008)	(0.010)		(0.007)	(0.008)
Constant	0.283^{***}	0.203^{***}	0.237^{***}	0.296^{***}	0.154^{***}	0.262^{***}
	(0.009)	(0.006)	(0.018)	(0.009)	(0.006)	(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 table shows the fraction of earnings redistributed under our lucky opportunities environment under three different regression specifications. 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.

when we provide information about π, spectators place some weight on the multiplier difference. The estimated effect of the empirical π is large and significant as well: A 10 percentage point increase in π leads to a 2.8 percentage point decrease in the share of the total earnings redistributed. This is evident visually in Panel A of Figure 4, which shows that spectators factor the nonlinear association between the multiplier difference into their redistribution decisions if they observe π.

A key question is whether relying on linear multiplier differences reflects spectator preferences or an error in statistical reasoning. Table 6 provides mixed evidence: Spectators appear to factor in π when they only observe multipliers, but the linear multiplier difference remains a significant predictor of when there is perfect information about π. To shed more light on this question, we compare the distribution choices of high- and low-numeracy spectators.[14] Intuitively, we expect that high- and low-numeracy spectators have the same preferences on average, but 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.

Panel B of Figure 4 presents our main results split by numeracy.[15] Consistent with the idea that linearization is a cognitive shortcut, high-numeracy spectators are more elastic to changes in π: A 10 percentage point increase in π leads high-numeracy spectators to redistribute 3.3 percent less of total income. Low-numeracy spectators are much less responsive to changes in π: A 10 percentage point increase in π leads low-numeracy spectators to redistribute 1.0 percent less of total income. For low-numeracy spectators, the effect of an increase in π on redistribution in the lucky opportunities condition is less than one-third of that for high-numeracy spectators. This

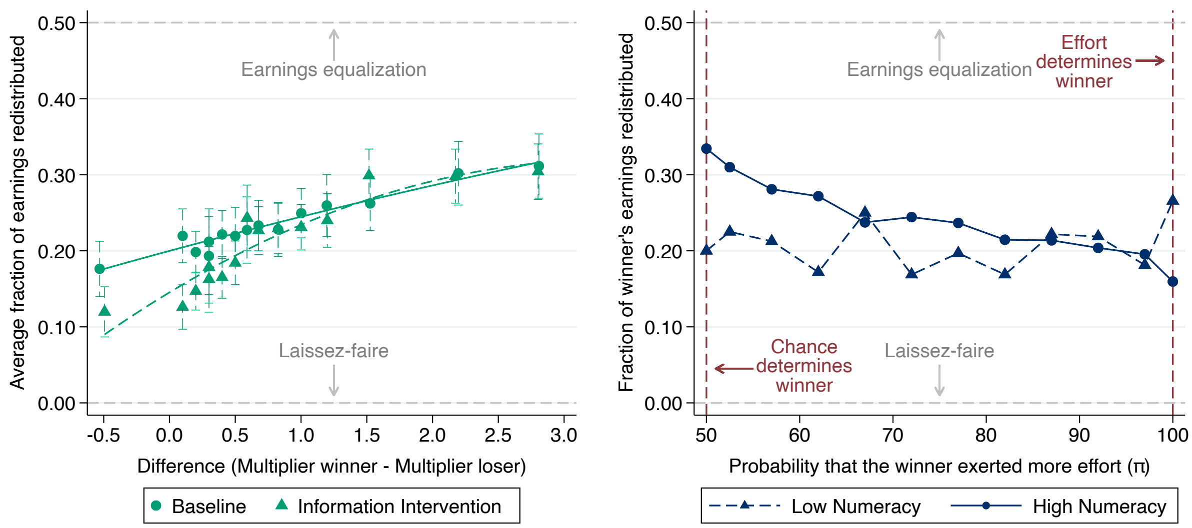
[14] We use the definition of high and low numeracy in the New York Fed's Survey of Consumer Expectations. It is based on five questions designed to assess financial literacy. We provide these questions in Appendix B.2. All respondents complete these questions when they first join the panel. The survey categorizes respondents as "high numeracy" if they answer four or more of these questions correctly and as "low numeracy" otherwise.

[15] Appendix Table A10 provides the underlying regression estimates.

result suggests that errors in statistical reasoning partly drive redistribution when spectators are not informed about the value of π.

Figure 4: Redistribution by linear multiplier difference and numerical literacy

Panel A. Linear Multiplier Difference **Panel B.** Numeracy



Notes: Panel A shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) as a function of the linear multiplier difference between the winner and the loser. Panel B shows the average share of earnings redistributed between workers as a function of the likelihood that the winner exerted more effort, split by our measure of numerical literacy. We exclude all spectators that failed our comprehension checks in panel B.

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 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 due to differences in effort but oppose those arising 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 people continue to hold such meritocratic fairness ideals when luck arises through unequal opportunities, and there is uncertainty about the role of luck in determining outcomes. 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 real-world inequality. Research that generates inequality through exogenous variation in outcomes has found that most Americans equalize incomes when income differences are due to luck (Almås et al., 2020). However, support for redistribution in the U.S. has remained stagnant over a period in which differences in opportunities became increasingly important (Chetty et al., 2014; Ashok et al., 2015). Consistent with these real-world trends, we show that redistribution is less sensitive to changes in luck when luck interacts with effort. Similarly, 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). Consistent with these cross-country comparisons, we show that Americans tolerate more inequality when it arises due to differential opportunities.

We also find that individuals appear to 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 a 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 mistakes. Models that seek to accommodate cognitive errors 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, popular media coverage (e.g., rags-to-riches stories) may substantially impact 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 lucky opportunities environment has a number of important features that affect redistribution, which are overlooked by a more simplistic lucky outcomes paradigm. We provide a portable, tractable, and rich environment to study income redistribution when there are unequal opportunities that can inform the development of inequality models and the design of optimal redistribution policies.

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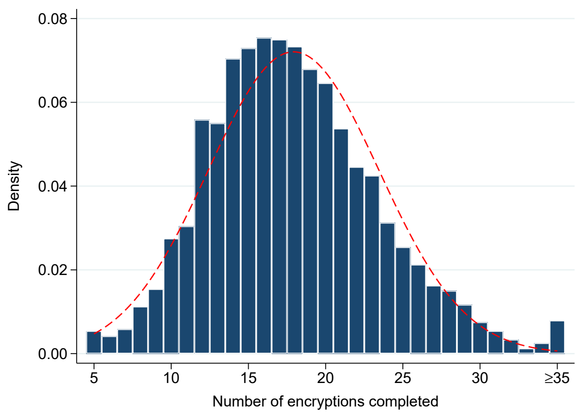
Appendix

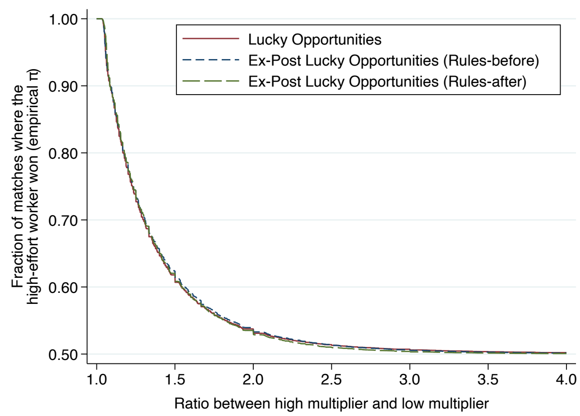
A Additional Figures and Tables

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

Panel A. Distribution of tasks completed in worker task

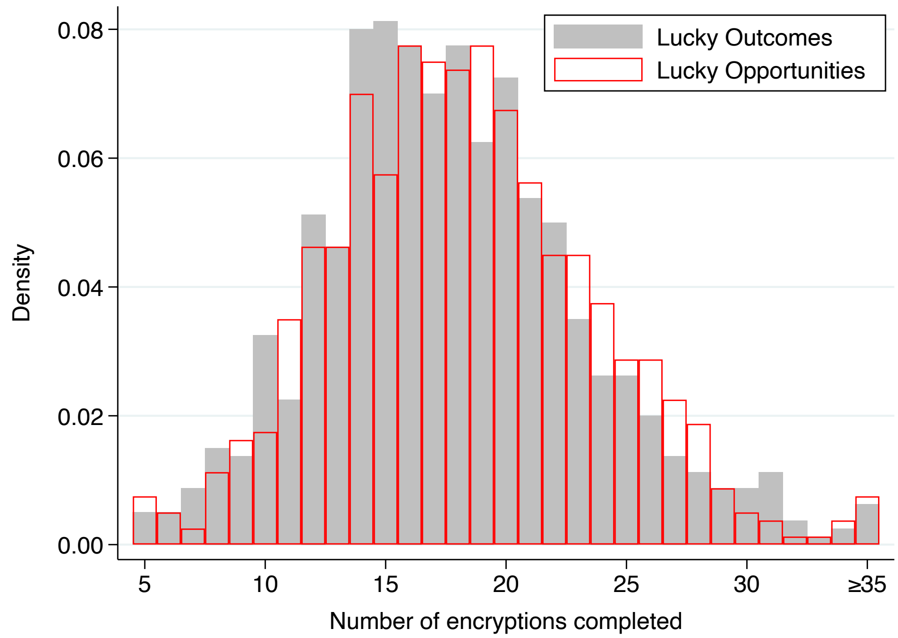


Panel B. Probability that the winner exerted more effort as a function of multiplier ratio



Notes: Panel A shows the distribution of the total number of correct three-word encryptions. The mean number of encryptions completed is 18 and the 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 shows the fraction of paired workers in which the worker who won the match completed more encryptions. Winners were determined based on a final score of correct encryptions times their score multiplier. Values near 0.5 are worker matches in which luck has a greater influence on the final outcome. Values 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 lucky outcomes and baseline lucky opportunities conditions. A Kolmogorov–Smirnov test for equality of distribution cannot reject the hypothesis that the distributions of worker effort in the two conditions are equal ($p = 0.909$).

Table A1: Average worker characteristics by treatment condition

Worker characteristics	Lucky Outcomes		Lucky Opportunities	Ex-Post Lucky Opportunities	
	Rules-Before	Rules-After		Rules-Before	Rules-After
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)
Panel A. Outcome: $= 1$ if does not redistribute in at least 10/12 rounds				
Lucky Opportunities	0.055**	0.055**	0.079**	0.075**
	(0.027)	(0.027)	(0.037)	(0.038)
Knows π		0.027	0.051	0.046
		(0.027)	(0.035)	(0.036)
Lucky Opportunities × knows π			−0.048	−0.042
			(0.053)	(0.054)
Constant	0.142***	0.129***	0.117***	0.082
	(0.018)	(0.021)	(0.023)	(0.125)
N	9,408	9,408	9,408	9,384
Panel B. Outcome: $= 1$ if does not redistribute in at least 11/12 rounds				
Lucky Opportunities	0.060**	0.060**	0.074**	0.069*
	(0.026)	(0.026)	(0.036)	(0.037)
Knows π		0.017	0.030	0.024
		(0.026)	(0.034)	(0.035)
Lucky Opportunities × knows π			−0.027	−0.021
			(0.052)	(0.052)
Constant	0.127***	0.118***	0.112***	0.057
	(0.017)	(0.020)	(0.022)	(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

	Lucky Outcomes		Lucky Opportunities	
	Mean Redist.	Elasticity w.r.t. π	Mean Redist.	Elasticity w.r.t. π
	(1)	(2)	(3)	(4)
Panel A. Demographic characteristics, education, and income				
Female	0.045^{**}	0.015^{*}	0.052^{**}	0.001
	(0.020)	(0.009)	(0.025)	(0.007)
35 or younger	−0.015	−0.011	−0.020	-0.025^{***}
	(0.025)	(0.012)	(0.026)	(0.008)
Married	-0.036^{*}	-0.016^{*}	−0.027	−0.005
	(0.021)	(0.009)	(0.025)	(0.008)
White	0.014	−0.010	0.028	0.020^{*}
	(0.025)	(0.011)	(0.040)	(0.011)
Completed college	−0.015	−0.014	0.023	−0.011
	(0.022)	(0.009)	(0.027)	(0.008)
HH income above 100k	-0.050^{**}	−0.013	-0.046^{*}	−0.004
	(0.024)	(0.009)	(0.026)	(0.007)
Panel B. Political and Social preferences				
Tend to side with republicans	-0.046^{*}	−0.007	-0.073^{***}	−0.009
	(0.025)	(0.011)	(0.027)	(0.008)
Oppose gov't interventions	-0.077^{***}	0.012	-0.067^{**}	0.002
	(0.027)	(0.012)	(0.029)	(0.008)
Conservative on social issues	−0.024	−0.013	-0.050^{*}	0.006
	(0.026)	(0.011)	(0.028)	(0.009)
Influece of hard work is fair	-0.063^{**}	-0.034^{**}	−0.011	-0.043^{***}
	(0.031)	(0.014)	(0.026)	(0.011)
Influece of talent is fair	−0.020	-0.061^{***}	−0.031	−0.009
	(0.045)	(0.015)	(0.035)	(0.013)
Influece of luck is fair	-0.046^{*}	−0.008	−0.036	−0.006
	(0.026)	(0.011)	(0.031)	(0.009)
Influece of connections is fair	−0.019	−0.011	-0.072^{**}	−0.003
	(0.029)	(0.012)	(0.034)	(0.010)
Key to success own hands	-0.069^{**}	0.013	-0.081^{***}	−0.005
	(0.026)	(0.011)	(0.025)	(0.009)
Gov't should never redistribute	-0.046^{*}	0.005	-0.070^{**}	0.008
	(0.024)	(0.011)	(0.028)	(0.008)
Gov't redistribute to correct luck	0.028	0.009	0.070^{**}	−0.018
	(0.031)	(0.014)	(0.032)	(0.011)
Income dist. in the US is fair	−0.011	0.011	-0.088^{***}	−0.006
	(0.029)	(0.015)	(0.027)	(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 to the difference between the 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 otherwise. ***, ** and * denote significance at the 10%, 5%, and 1% level, respectively.

Table A4: Correlation between redistribution behavior and political and social preferences

	Outcome: Fraction of earnings redistributed		
	Lucky Outcomes	Lucky Opportunities	Difference
Correlation with...	(1)	(2)	(3)
Panel A. Political and social preferences			
Tend to side with democrats	0.078	0.137	−0.059
	(0.029)	(0.039)	(0.048)
Tend to side with republicans (−)	0.093	0.140	−0.046
	(0.030)	(0.038)	(0.048)
Oppose gov't interventions (−)	0.119	0.159	−0.040
	(0.032)	(0.040)	(0.052)
Conservative on social issues (−)	0.073	0.118	−0.045
	(0.030)	(0.038)	(0.048)
Influece of hard work is fair (−)	0.074	0.123	−0.049
	(0.030)	(0.035)	(0.046)
Influece of talent is fair (−)	0.029	0.120	−0.091
	(0.031)	(0.037)	(0.049)
Influece of luck is fair (−)	0.073	0.122	−0.049
	(0.031)	(0.039)	(0.050)
Influece of connections is fair (−)	0.044	0.074	−0.030
	(0.030)	(0.039)	(0.049)
Hard work brings a better life (−)	0.110	0.098	0.012
	(0.030)	(0.039)	(0.049)
Key to success own hands (−)	0.122	0.172	−0.050
	(0.030)	(0.036)	(0.047)
Gov't should never redistribute (−)	0.110	0.176	−0.066
	(0.031)	(0.036)	(0.048)
Gov't redistribute to correct luck	0.077	0.123	−0.046
	(0.029)	(0.038)	(0.048)
Gov't eliminate income differences	0.089	0.098	−0.009
	(0.030)	(0.035)	(0.047)
Income dist. in the US is fair (−)	0.035	0.090	−0.055
	(0.029)	(0.037)	(0.047)
Panel B. Summary indices			
z−score (−)	0.068	0.110	−0.042
	(0.016)	(0.019)	(0.025)
PCA first component (−)	0.140	0.204	−0.064
	(0.031)	(0.037)	(0.048)
N	4,728	4,680	9,408

Notes: This table shows the correlation between redistributive behavior in each treatment condition and political and social preferences. (−) denotes reverse coded. Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. ***, ** and * denote significance at the 10%, 5%, and 1% level, respectively.

Table A5: Actual worker effort and worker multiplier

	Outcome: Number of tasks completed by workers	
	Linear function	Non-parametric
	(1)	(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^{***}	18.754^{***}
	(0.439)	(0.386)
N	800	800

Notes: This table shows the number of tasks completed by workers in the baseline lucky opportunities condition. Workers 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 A6: Fraction redistributed as a function of π in baseline and ex-post lucky opportunities

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

Notes: Column 1 includes only spectators in the baseline lucky opportunities condition and column 2 includes only spectators under the ex-post lucky opportunities condition. Column 3 is the difference in spectator responses between columns 1 and 2. Panel A shows 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 (π). Panel C shows the relationship between redistribution and the likelihood that the winning worker performed better (π) split into 11 bins. The omitted category is $\pi = 0.50$. ***, ** and * denote significance at the 10%, 5%, and 1% level, respectively.

Table A7: 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***	30.779***
	(4.008)	(3.002)
N	390	390

Notes: This table shows spectators' perceived effort of workers assigned to each spectator for the luck opportunities condition. Recall that workers are randomly assigned an effort 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 A8: Fraction redistributed as a function of π and information treatment

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

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

Table A9: Fraction redistributed on polynomials of the multiplier difference

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

Notes: This table shows the average redistribution (from the winner's earnings to the loser) as a function of polynomials of multiplier differences for spectators in the lucky opportunities condition. We only include spectators in our baseline condition, where information about π is not explicitly provided. ***, ** and * denote significance at the 10%, 5%, and 1% level, respectively.

Table A10: Fraction redistributed as a function of π and numeracy

	Lucky Outcomes			Lucky Opportunities		
	Low numeracy (1)	High numeracy (2)	Difference (3)	Low numeracy (4)	High numeracy (5)	Difference (6)
Panel A. Average redistribution						
Constant	0.285***	0.273***	−0.011	0.203***	0.243***	0.040
	(0.023)	(0.011)	(0.025)	(0.022)	(0.015)	(0.026)
N	660	1704	2364	516	1812	2328
Panel B. Linear slope						
π	−0.071	−0.488***	−0.416***	0.064	−0.274***	−0.338***
	(0.076)	(0.053)	(0.092)	(0.078)	(0.040)	(0.087)
Constant	0.338***	0.637***	0.299***	0.155**	0.447***	0.292***
	(0.063)	(0.043)	(0.076)	(0.064)	(0.034)	(0.072)
N	660	1704	2364	516	1812	2328

Notes: This table shows estimates of redistribution as a function of spectators' numeracy under lucky outcomes (columns 1–3) and lucky opportunities (columns 4–6). Columns 1 and 4 include only spectators with low numeracy scores, while columns 2 and 5 include only spectators with high numeracy. Columns 3 and 4 show the differences in spectator responses. Panel A shows the average redistribution. Panel B shows a linear approximation between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker (π). ***, ** and * denote significance at the 10%, 5%, and 1% level, respectively.

B Empirical Appendix

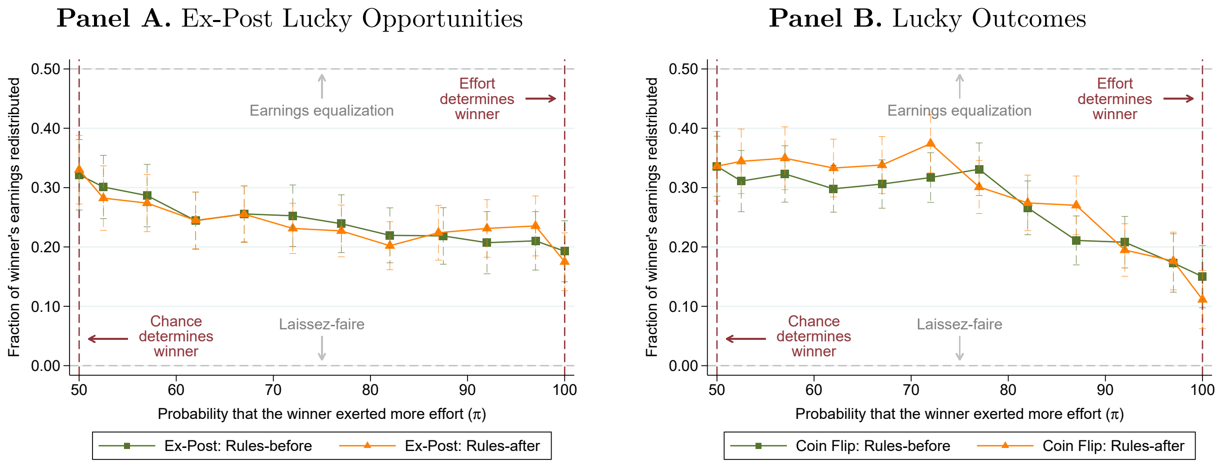
B.1 Anticipatory Effort Responses

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 the lucky outcomes and lucky opportunities environments that we observe are driven by the fact that luck manifests itself through productivity 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 ex-post lucky opportunities environment might work harder to insure against the possibility of drawing a bad multiplier, which, in turn, could shape redistribution preferences if spectators anticipate such behavior. Furthermore, our theoretical framework highlights that the perceived distribution of worker effort also affects beliefs about π. This provides a second channel through which perceptions of effort can drive a wedge between redistribution decisions across our ex-post lucky opportunities and lucky outcomes conditions.

To explore whether perceived differences in worker effort across environments can explain the differences in redistribution that we observe, 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 condition, workers were simply told that solving more encryptions would increase their chance of winning before they began the task. Crucially, workers in the lucky outcomes and ex-post lucky opportunities 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.

Appendix Figure B1 plots average redistribution for each π bin separately for our rules-before and rules-after subtreatments. Panel A shows that the redistribution decisions of spectators in the ex-post lucky opportunities condition are very similar and do not depend on workers learning 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 lucky outcomes environment. Appendix Tables B1 and B2 show that any differences in redistribution between the rules-before and rules-after subtreatments tend to be small and not statistically significant.

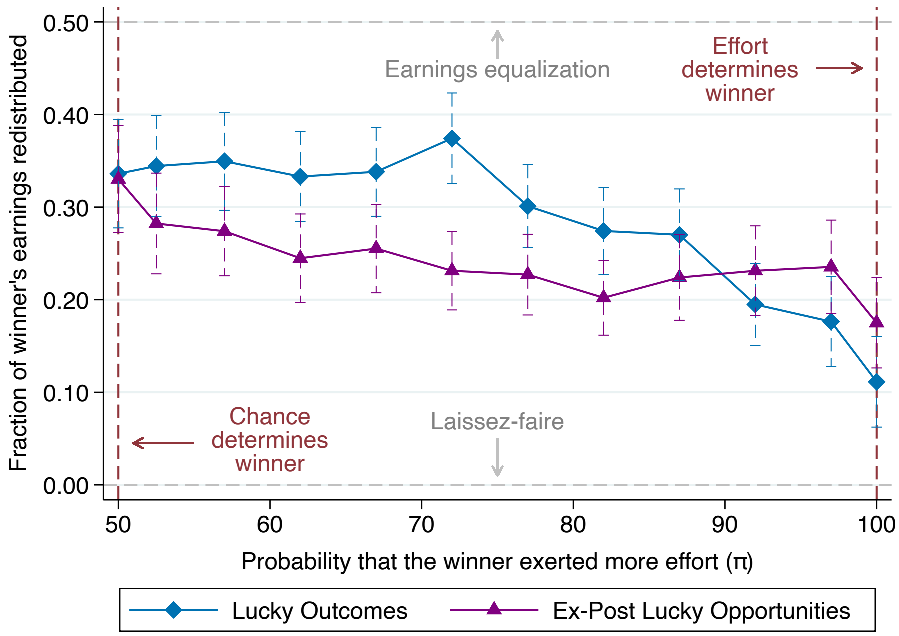
Figure B1: Redistribution and awareness of rules in the ex-post lucky opportunities and lucky outcomes conditions



Notes: This figure shows the average share of earnings redistributed between workers as a function of the likelihood that the winner exerted more effort, split by our rules-before and rules-after subtreatments. In rules-before, workers are aware of their multiplier prior to their encryption task, and in rules-after, workers are aware of their multiplier after completing their encryption task. Panel A depicts data from the ex-post lucky opportunities condition, and Panel B depicts data from the lucky outcomes condition.

Appendix Figure B2 compares average redistribution in the lucky outcomes and ex-post lucky opportunities environments for only the rules-after subtreatments. 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. Appendix Table B3 re-estimates our main specifications in Table 2 but only compares lucky outcomes and ex-post lucky opportunities for the rules-after scenario. We continue to find significant differences in the level and slope of redistribution. The estimated coefficients are similar in magnitude to the baseline results.

Figure B2: Redistribution and awareness of rules in lucky outcomes and ex-post lucky opportunities



Notes: This figure shows the average share of earnings redistributed between workers as a function of the likelihood that the winner exerted more effort for the rules-after subtreatments for lucky outcomes and ex-post lucky opportunity luck. 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 ex-post lucky opportunities and lucky outcomes 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 the lucky opportunities and lucky outcomes environment. 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 variant of lucky outcomes and ex-post lucky opportunities. 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 π and awareness of the rules in lucky outcomes condition

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

Notes: This table includes only spectators in the lucky outcomes 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 (π). Panel C: The relationship between redistribution and the likelihood that the winning worker performed better (π) 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 π and awareness of rules in ex-post lucky opportunities condition

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

Notes: This table includes only spectators under the ex-post lucky opportunities 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 (π). Panel C: The relationship between redistribution and the likelihood that the winning worker performed better (π) 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 π in ex-post lucky opportunities and lucky outcomes conditions (only rules-after)

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

Notes: This table includes only spectators in the rules-after condition. Column 1 includes only spectators in the lucky outcomes condition. Column 2 includes only spectators under the ex-post lucky opportunities condition. Column 3 shows the difference between columns 1 and 2. Panel A shows average redistribution. Panel B shows a linear approximation between the fraction of earnings redistributed and the likelihood that the winning worker performed better than the losing worker (π). Panel C shows the relationship between redistribution and the likelihood that the winning worker performed better (π) split into 11 bins. The omitted category is $\pi = 0.50$. ***, ** and * denote significance at the 10%, 5%, and 1% level, respectively.

B.2 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 percent 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?

C Experimental Design Appendix

Figure C1: Worker Encryption Task

Q	**X**	**D**	**A**	**C**	**V**	**U**	**R**	**P**	**W**	**L**	**Y**	**G**
754	579	860	708	344	725	950	314	532	595	654	838	327
Z	**F**	**M**	**N**	**T**	**B**	**K**	**O**	**H**	**S**	**E**	**I**	**J**
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 are randomized every round. Feedback on whether encryptions are correct or incorrect is 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:	○	○	○	○	○	○	○	○	○	○	○

Submit Decision

Notes: This figure shows the information and survey instruments common to all spectator redistribution decisions between two workers. Across all conditions, workers' 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 the loser earns $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 for Lucky Outcomes and Lucky Opportunities with Information

Worker ID:	sao9rqhr	qeha27vh
Coin-Flip Chance:	46%	
Result:	won	lost
Unadjusted Earnings:	$5.00	$0.00

There was a **46%** chance that the winner and the loser in this pair were 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.

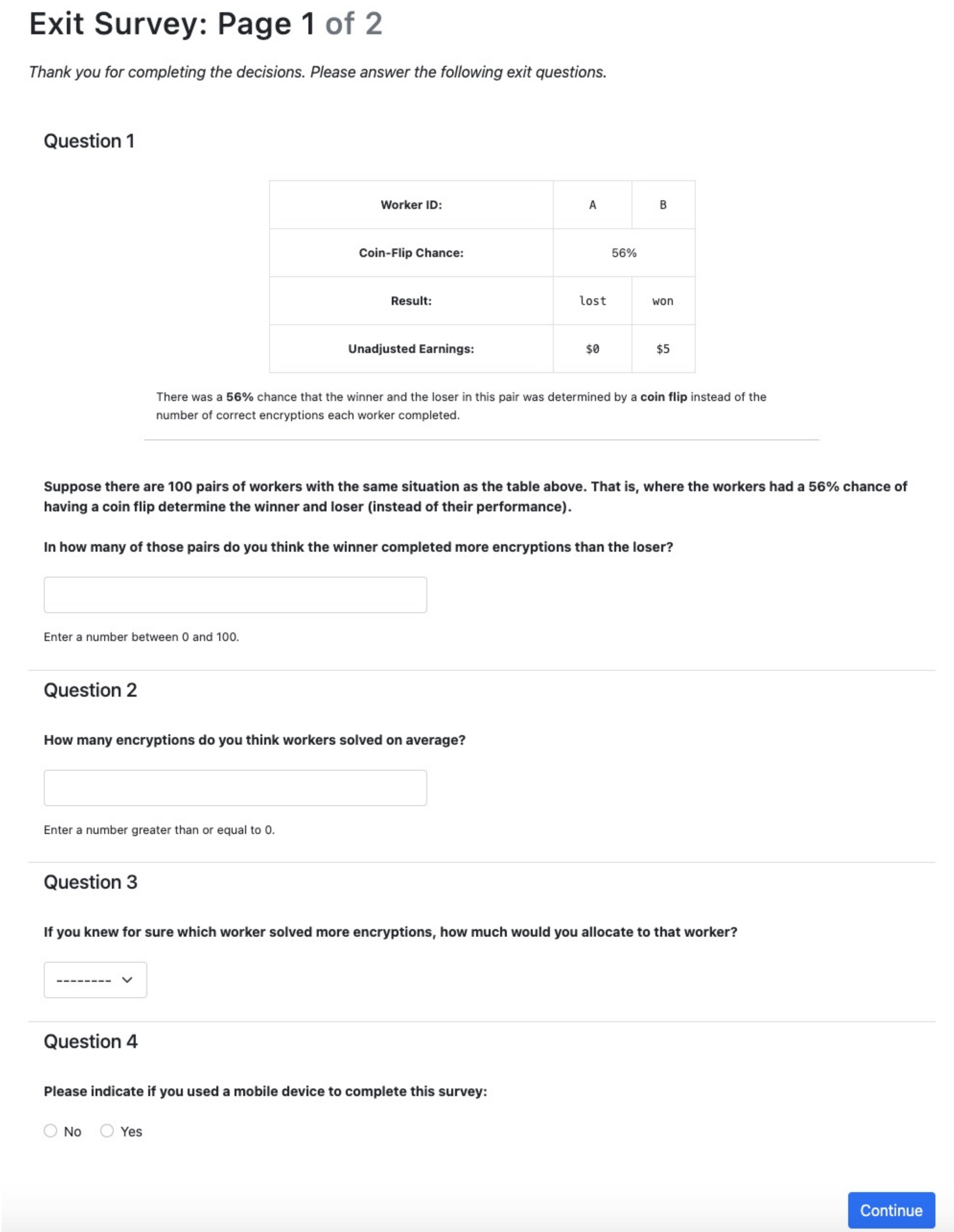
Worker ID:	ga2c8k8x	nkqqjd0n
Multiplier:	2.9	2.4
Result:	won	lost
Unadjusted Earnings:	$5.00	$0.00

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 lucky outcomes (top) and lucky opportunities (bottom) conditions. Included directly below the outcomes table is additional text to remind spectators 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 information condition spectators (see text next to ▷ symbol).

Figure C4: Part 1 of the Exit Survey (Lucky Outcomes)



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 (Lucky Opportunities)

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 or 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.	○	○	○	○	○
Hard work doesn't generally bring success—it's more a matter of luck and connections.	○	○	○	○	○
The government should redistribute income only to eliminate income differences that are due to differences in luck.	○	○	○	○	○
The government should never redistribute income, regardless of the source of income differences.	○	○	○	○	○
It is fair if luck influences a person's income.	○	○	○	○	○
It is fair if hard work influences a person's income.	○	○	○	○	○
When it comes to social issues, I am very conservative.	○	○	○	○	○
I oppose government interventions in matters concerning the economy	○	○	○	○	○
The income distribution in the US is fair.	○	○	○	○	○
It is fair if connections influence a person's income.	○	○	○	○	○
It is fair if talent influences a person's income.	○	○	○	○	○
I tend to side with Democrats on most issues.	○	○	○	○	○
Select disagree if you are reading this.	○	○	○	○	○
I tend to side with Republicans on most issues.	○	○	○	○	○
In the US, people hold the key to economic success in their own hands.	○	○	○	○	○
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.	○	○	○	○	○