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Inequality of Opportunity and Income Redistribution

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Abstract

We examine how redistribution decisions respond to the source of luck when there is uncertainty about its role in determining opportunities and outcomes. We elicit redistribution decisions from a representative U.S. sample who observe worker outcomes and whether luck could determine earnings directly ("lucky outcomes") or indirectly by providing one of the workers with a relative advantage ("lucky opportunities"). We find that participants redistribute less and are less responsive to changes in the importance of luck in environments with lucky opportunities. We show that individuals rely on a simple heuristic when assessing the impact of unequal opportunities, which leads them to underappreciate the extent to which small differences in opportunities can have a large impact on outcomes. These findings have implications for models of redistribution attitudes and help explain the gap between lab evidence on support for redistribution and inequality trends.

Keywords: Income inequality, demand for redistribution, fairness ideals.

JEL codes: C91, D63.

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1 Introduction

Individuals' support for redistribution is a crucial input into 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 remained the same 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 focused primarily on redistribution behavior in situations in which the impact of luck is independent of individual behavior. However, when we asked a representative sample of U.S. households what type of luck matters most for economic success in life, they mainly described unequal opportunities.[1] Unlike exogenous luck which is typically implemented in experimental studies, lucky opportunities only affect the chances of success in conjunction with individual efforts.

Opportunity luck could lead to differences in redistribution for two central reasons. First, it can be challenging for a neutral third party to determine accurately the role luck plays in an individual's outcomes when luck and effort are intertwined. For example, they might mistakenly attribute success to an individual's efforts instead of a lucky opportunity. Second, even with accurate beliefs about the role of luck, individuals may have a different tolerance for inequality when success depends on opportunities rather than external sources of luck. For example, proponents of the American Dream argue that hard work and determination can lead to success regardless of circumstances. They might, therefore, oppose redistribution when there is opportunity luck but support it when luck leads to success independently of effort.

[1]This finding is based on a survey we conducted with around 1,000 panelists from the New York Fed's *Survey of Consumer Expectations* in February 2023. We provide a detailed description and analysis of the survey in the Online Appendix B.1. The Online Appendix can be downloaded here.

We implement a novel experimental design to study how individuals make redistribution decisions when luck creates income inequality by altering the returns to individual 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 existing literature has focused. An important innovation of our design is that it enables us to control the importance of luck in determining outcomes regardless of its source. 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 substantial differences in outcomes. Our findings suggest that Americans are less meritocratic than the prior literature suggests.

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 conceptual 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 a signal about the importance of luck and who wins 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 directly measures how important luck was in determining worker outcomes. This variable allows us to link the two experimental luck environments by holding fixed π while varying the random process that generates it.

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 non-convenience U.S. nationally representative panel—to choose the final earnings allocation for pairs of workers. We randomly assigned spectators to one of two luck environments. In the *lucky outcomes* environment, we selected 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 implemented within-spectator variation in q. In the *lucky opportunities* environment, the winner of each match was the worker with the higher score, given by the number of encryptions completed times a randomly assigned effort multiplier. In other words, luck and effort interact to determine the winner in the *lucky opportunities* environment since they jointly affect the chances of winning. 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 any relative advantage for the winning worker maps to a unique value of π. In our baseline treatments, spectators do not observe π directly but do observe the multipliers of each worker in the lucky opportunities treatment and the probability that the winner was determined by a coin flip in the lucky outcomes treatment.

Our main result is that spectators' redistribution behavior differs substantially depending on whether luck arises through lucky outcomes or lucky opportunities. Average 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 were lucky outcomes and 23.3 percent when there were lucky opportunities. Redistribution is lower on average and for almost 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 ten 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. Importantly, we do not see any differences when π is at extreme values; that is, when luck or effort was the sole factor in determining the outcome. Consequently, redistribution differs because people respond differently to opportunity luck than to outcome luck when they face uncertainty about how consequential luck is.

We implement additional treatments to uncover the mechanisms that drive the differences in redistribution that we document 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 while informing spectators of π leads to changes in the level of redistribution in both environments, a difference in redistribution across our luck environments remains.

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, despite this heightened sensitivity to luck, the difference in this elasticity across environments is still significant 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.

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 relative opportunities 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).[2] We present evidence that spectators rely on a simple heuristic that linearly maps the winning worker's advantage into their redistribution decisions. These results imply that spectators underappreciate the extent to which small opportunity differences can greatly impact outcomes. When we provide information about π, spectators reduce but do not eliminate their reliance on this linear approximation. That spectators put weight on the relative advantage of workers beyond its 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).[3]

[2]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, since relative effort or skill levels are very concentrated in the population, people's performance will often be similar. Thus, starting with only slightly advantageous opportunities can greatly impact one's competitiveness, while increasing the advantage further has diminishing effects. We show in Online Appendix B.3 that the relationship between opportunities and winning is also convex if we randomly assign workers additive fixed score boosts (or headstarts) instead of using multipliers.

[3]Previous work has shown that Americans tend to be overly optimistic about social mobility, believing that individuals can overcome disadvantages early in life 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). These findings are consistent with our result that support for redistribution is relatively inelastic to changes in opportunity luck and with the conclusion that people's support for redistribution under unequal opportunities depends partially on nonstandard factors.

We primarily contribute to a broad 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 complements 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 redistribution behavior in the lucky outcomes environment.

We also engage more directly with emerging literature investigating how individuals make redistribution decisions where luck arises through unequal opportunities (Andre, 2022; Bhattacharya and Mollerstrom, 2022; Dong et al., 2022). Andre (2022) investigates whether spectators hold workers responsible for the unequal opportunities that they face. He finds that disparities in randomly assigned piece-rate wages produce large differences in worker effort. However, spectators reward workers solely according to their effort and irrespective of how differences in piece rates impact workers' performance. Dong et al. (2022) consider unequal opportunities in the form of either different employment opportunities or the quality of training. They find that spectators only partially account for these opportunity differences when making redistribution decisions relative to a pure-luck coin flip benchmark. Similarly, Bhattacharya and Mollerstrom (2022) consider an extreme form of unequal opportunities: whether individuals can work at all. They find that spectators accept significantly more inequality when chance determines who is allowed to work than when luck determines outcomes directly.

Our contribution is distinct in three fundamental ways. First and foremost, all the studies described in the prior paragraph focus on how spectators treat differences in actual performances between workers resulting from unequal opportunities. Therefore, redistribution decisions in these settings could reflect both fairness views about the source of inequality and a desire to reward workers for differential effort (Roemer and Trannoy, 2016). In contrast, we analyze redistribution preferences when workers face unequal opportunities but show similar performance levels otherwise. In other words, we consider situations in which two equally hard-working people end up with vastly different outcomes solely due to a disparity in the opportunities that they face. This allows us to identify the extent to which the *source* of luck impacts redistribution decisions.[4]

Second, we consider an environment in which the impact of unequal opportunities on worker income disparities is uncertain. How individuals react to this uncertainty when making redistribution decisions is an important policy question, given the opaque manner in which luck manifests in the real world. Third, 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 is broadly applicable to different tournament environments. In addition, our design allows us to assess redistribution behavior over a continuum of probabilistic luck scenarios. This innovation enables us to estimate the elasticity of redistribution with respect to incremental changes in luck, moving beyond the pure luck or pure merit boundary cases that prior experimental settings have focused on.

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 when there is 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 its source. We use this framework to clarify our main experimental hypotheses, define opportunity and outcome luck, and guide the interpretation of our results.

[4]Our experimental setting therefore connects to data showing that people in higher-paying occupations work roughly as many hours as people in lower-paying occupations. For example, Bick et al. (2018) estimate an elasticity of hours worked to total wages of just 0.1 for the U.S., and lower (sometimes even negative) elasticities for other OECD countries.

Consider an impartial spectator who observes initial earnings in a winner-takes-all environment in which two randomly paired workers compete 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 proportion of spectators who redistribute some positive amount. For these spectators, we can characterize r_i 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 is the worker who exerted more effort, then they implement the fair allocation, $r_i^* = f_i$. However, in reality and our experiment, spectators do not observe each worker's effort. 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 than the loser. Conversely, $1 - \pi$ is the probability that the worker who exerted less effort won, and thus that luck determined the winner.[5] In an interior solution to (2), 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 higher-effort worker was the winner, the less spectators redistribute. When $\pi = 1$ and thus effort

[5] In reality, spectators may have a more complex utility function that considers the difference in effort between the winning and losing worker. We do not model such preferences here for three reasons. First, our approach closely follows that of Cappelen et al. (2022), allowing us to benchmark our results to the prior literature. Second, if both π and f_i are functions of effort, then we cannot separately identify them without strong parametric assumptions. Finally, we analyze the actual effort data from our experiment in detail in Online Appendix B.5 and find that winners and losers have very similar effort levels across luck environments. Therefore, even if spectators had a more complex utility function, it would not affect our interpretation of the difference in redistribution between luck environments.

solely determines the winner, spectators redistribute the fair share to the loser, $r_i^* = f_i$. When outcomes are due to pure luck (i.e., $\pi = 1/2$), spectators equalize earnings and choose $r_i^* = 1/2$.

2.1 Opportunity Luck versus Outcome Luck

We examine two environments that differ in how luck influences worker outcomes. In environments with *opportunity luck*, a worker's chances of success are indirectly affected by altering how much effort they need to exert to be successful. More formally, a tournament exhibits opportunity luck if each worker's chance of winning increases in their effort level for any realizations of luck. Intuitively, opportunity luck implies that workers can always have some influence over their fate, even if opportunities are unequal. Our definition of opportunity luck is closely related to the concept of the American Dream: the idea that anyone, regardless of background or circumstances, can succeed through hard work and determination.

In contrast, we use the term *outcome luck* to describe environments in which luck directly determines the outcome, such as a coin toss, leaving an unlucky worker with no control over the outcome. Formally, we define outcome luck as any situation in which incremental effort has no impact on the likelihood of success in at least some states of the world. This captures situations in which exogenous factors, like winning a lottery, directly impact an individual's outcome. While our survey respondents rate such forms of luck as less prevalent than opportunity luck, it has been prominent in the prior literature due to its simplicity and theoretical traceability (e.g., Cappelen et al. (2010, 2013), Mollerstrom et al. (2015), Almås et al. (2020), Cappelen et al. (2020, 2022)).

Our experimental design considers two specific cases that are representative of our broader notions of opportunity luck and outcome luck. In our *lucky opportunities* treatment, 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. Conceptually, this approach is akin to assuming luck arises due to workers having different abilities or skills (e.g., Mirrlees (1971)), and therefore, their output is the product of their effort and luck. This encompasses a broad range of situations in which two workers face differential returns to effort, perhaps due to differences in education or training, time constraints, or family and social connections.[6] Without

[6]Alternatively, we could have considered situations in which workers face different "headstarts", for example, due to differential experience or starting points. Formally, we can model this type of opportunity luck as additive boosts to each individual worker's effort. While this type of opportunity luck might appear to be quite distinct from the multiplicative luck that we implement, we show in Online Appendix B.3 that both capture the key features of opportunity luck that we want to study: namely, that seemingly small differences in opportunities can have a big impact on the likelihood of success.

loss of generality, assume that worker 1 wins, which means $m_1e_1 > m_2e_2$. If the spectator observes the workers' multipliers and who won, the probability that the higher-effort worker is the winner is

$$\pi = \Pr\Big(e_1 \geq e_2 \Big| m_1e_1 > m_2e_2, m_1, m_2\Big). \tag{4}$$

Spectators must consider two cases when evaluating π. 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

$$\pi = \frac{\Pr\Big(e_1 \geq e_2\Big)}{\Pr\Big(m_1e_1 > m_2e_2\Big)} = \frac{1/2}{\Pr\left(e_2/e_1 < m_1/m_2\right)} \geq \frac{1}{2}. \tag{5}$$

Expression (5) shows that π depends on the relative multiplier m_1/m_2 or, equivalently, on the relative advantage conferred to worker 1. We show in Online Appendix B.2 that π is decreasing and convex in this relative advantage for any log-normal distribution of effort. Appendix Figure A1 (Panel B) also illustrates the convexity of π in m_1/m_2 graphically for the empirical distribution of worker effort that we observe in our experimental task. Intuitively, this convexity arises because the density of e_2/e_1, which measures the relative effort of the disadvantaged worker compared to the advantaged worker, is centered around one (equal effort) and decreases for larger values of e_2/e_1. Therefore, even small relative advantages can greatly impact who wins, whereas the incremental effect of increasing this relative advantage matters less.

Notably, the convexity of π in the relative advantage is not unique to the way we chose to model opportunity luck. We show in Online Appendix B.3 that a treatment based on additive headstarts also leads to a convex mapping from lucky headstarts to the likelihood that the winning worker exerted more effort (π) for the empirical distribution of worker effort that we observe. This is because $e_2 - e_1$, which is the relevant measure of relative effort in this case, has the most probability mass near zero (equal effort), and therefore the convexity intuition above still applies.[7]

In our *lucky outcomes* treatment, there is a $q \in [0, 1]$ probability that a coin flip determines the winner and a $1 - q$ probability that we select the winner based on the number of completed encryptions. To infer π from q, spectators must use Bayesian updating, which implies $\pi = 1-(1/2)q$. This corresponds to the form of luck implemented in Cappelen et al. (2022), and nests the pure-luck

[7]We also show in Online Appendix B.2 that the same intuition readily extends to other common effort distributions: for example, if worker effort is uniformly distributed.

($q = 1$) and no-luck ($q = 0$) corner cases that have been the focus of most of the prior experimental literature. Crucially, the extent of outcome luck, q, has a linear impact on the probability that the winner was determined by luck, π. This marks a key distinction between lucky outcomes and lucky opportunities and provides a rationale for why redistribution attitudes might differ across treatments.

2.2 Beliefs about Luck

The main 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, which 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 do not oppose to redistribution in general. In the next section, we use equation (7) to derive our main predictions.

2.3 Predictions and Comparative Statics

Our primary research question concerns how spectators' redistribution decisions depend on the source of luck. 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 these three factors.

We refer to differences in the share of spectators who decide not to redistribute 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 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 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 show that spectators' fairness views and subjective beliefs determine their redistribution decision. 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 approach allows us to shut down the role of inaccurate beliefs in evaluating the differences in redistribution between the two different luck 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, $\partial\tilde{\pi}_\tau/\partial\pi$. 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 without precise information about π.

3 Experimental Design

The experiment follows the impartial-spectator paradigm in Cappelen et al. (2013) and has three stages: a production stage, an earnings stage, and a redistribution stage.[8] 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 analysis will focus on the redistribution decisions of spectators, therefore, we limit our discussion of the production and earnings stage to the essential elements 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: variation in π, the probability that the higher-effort worker won.

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

3.1 Production and Earnings Stage

In the production stage, workers complete a real-effort task to 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). Panel A of Online 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. We initially allocate earnings of \$5 to the winner and \$0 to the losers. 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 12 redistribution decisions involving different real pairs of workers, with each decision varying in the importance of luck involved in determining the worker-pair outcome.

Spectators can choose to redistribute any amount from \$0 to \$5 in \$0.50 increments. We present each decision as an adjustment schedule (see Online Appendix Figure C1 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, which we label a "no"-adjustment choice. The remaining $\{\$0.50, \dots, \$5.00\}$ redistribution choices are labeled as a "yes"-adjustment choice and denote the final earnings for both the winner and the loser: that is, $\{(\text{winner gets, loser gets})\} = \{(\$4.50, \$0.50), (\$4.00, \$1.00), \dots, (\$0.50, \$4.50), (\$0.00, \$5.00)\}$.[9]

To incentivize spectators to respond truthfully, we randomly select and implement one of their 12 decisions. 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.

[9]To combat the influence of anchoring effects in these redistribution choices, we inform spectators that we did not tell workers whether they won or lost nor the exact amount they will earn in each case. Spectators know that we only informed workers that they could earn up to \$5 and that winning against their randomly assigned opponent increases their chances of earning more. This design removes any confounding issues relating to spectators' unwillingness to take earnings away from what workers might expect.

3.3 Spectator Treatments

Spectators always have some signal about the importance of chance in determining outcomes. However, we randomly vary between subjects whether luck interacts with effort, the timing of when it occurs, and the information available to spectators about the importance of luck. All spectators undergo detailed instructions and comprehension questions to learn the source and procedure of luck. The exogenous and random nature of luck is salient in all spectator conditions.[10]

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 with probability q. 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 ten 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.[11] 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.[12] We inform spectators that workers only know of their own multiplier and do not know anything about the worker they compete against. Online Appendix Figure C1 provides an example of a redistribution decision in our lucky outcomes condition and an example of a redistribution decision in our lucky opportunities condition.

[10] Screenshots of our experimental design and procedure are available in our Supplementary Materials.

[11] We chose the upper bound of $m = 4$ to ensure that it is possible to generate $\pi = 1/2$ (i.e., pure chance determines the winner) in our lucky opportunities treatment.

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

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 this variation by changing 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 portable common metric 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 match's winner 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 decisions in random order.

The key information we present on each decision 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 than the loser. This method 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 occurs. 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 decision to decision. Appendix Figure C1 shows 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 how luck plays a role in determining outcomes. In the rules-before condition, we inform workers that effort multipliers or a coin flip will influence the outcome *before* they start the task. In the rules-after condition, we inform workers that multipliers or a coin flip will influence 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 design details, we implement several 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 can only continue once they select the correct answer, and we briefly explain 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 that are central to our design.

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 selected one of the 12 decisions that the spectators made and presented 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 asked them how much they would allocate to the winner if they knew they had solved more encryptions.

The second part of the exit survey asks spectators to select their level of agreement with several 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."

3.5 Recruitment

3.5.1 Workers

We recruited 2,416 participants on Amazon Mechanical Turk to participate in the worker task. We restricted participation to workers that 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 consists of 1,170 panelists from the Federal Reserve Bank of New York's *Survey of Consumer Expectations* (SCE). This survey targets a non-convenience, 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: 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.

Table 1 reports descriptive statistics for the spectator sample.[13] The average spectator is 49 years old; 52 percent are female, 62 percent are married, and 14 percent are non-white. More than 62 percent of spectators attained a college degree, 58 percent work full-time, 15 percent work part-time, and 20 percent are retired. About a quarter (24 percent) of spectators have a household income below $40,000 per year and about a third (32 percent) more than $100,000 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.

4 Main Results

This section investigates how both the level and the elasticity of redistribution depend on whether luck stems from lucky outcomes or lucky opportunities. We also explore whether any differences we observe arise due to 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 luck altered outcomes independent of effort (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

[13] See Table A1 in the Online Appendix for summary statistics on our sample of workers.

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 losing worker.

Our main results hold even though the importance of luck was the same across the two luck environments on average. However, we can also compare differences in the level of redistribution for a given likelihood that luck determined the outcome. To implement 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:

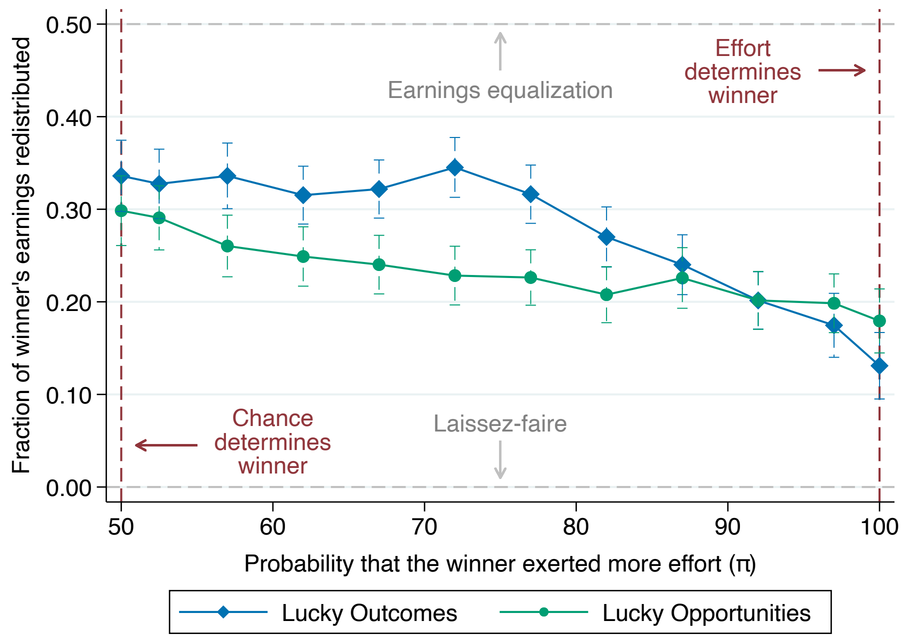
$$r_{ib} = \sum_{b=1}^{12} \gamma_b \pi_b + \varepsilon_{ib}, \tag{11}$$

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 formally 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, when the importance of effort is not too large (i.e., when $\pi \leq 0.85$), redistribution is lower when there are lucky opportunities relative to lucky outcomes. In contrast, average redistribution is statistically equal in the two conditions for $\pi \in (0.85, 1]$. The second notable difference is in the shape of the negative relationship between average redistribution and the likelihood that luck determines the winner. Consistent with our theoretical framework, redistribution tends to decline in π in both luck environments. In the lucky outcomes condition, 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 after that. In the lucky opportunities condition, we observe the opposite pattern: Redistribution is approximately linear and downward sloping from $\pi = 0.5$ to $\pi = 0.85$, but spectators are unresponsive to incremental increases in π beyond that point. We explore mechanisms that can give rise to this pattern in Section 5.2.2.

A similar pattern emerges when we instead plot redistribution as a function of differences in effort between the winner and loser. As Figure B6 in the Online Appendix illustrates, spectators redistribute significantly less in the lucky opportunities condition than in the lucky outcomes conditions holding fixed differences in effort levels between the winners and losers.

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 (blue) and lucky opportunities (green).

To summarize the relationship between average redistribution and π in each luck environment, 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 ten 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 ten 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 decreased sensitivity occurs even though changes in the importance of 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).[14] As shown in Figure 1, we find no significant differences in redistribution across the two environments in the cases where we chose the winner 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. Substantial differences in redistribution behavior between lucky outcomes and lucky opportunities emerge between the boundary cases, especially for $\pi \in [0.55, 0.85]$. Therefore, our results highlight that varying the degree to which luck matters is essential 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

To further understand why we observe a gap in both the level and slope of distribution across our luck environments, 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

[14] 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.

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.

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.[15] Column (1) shows that 9.6 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 chance directly influences outcomes.

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.

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

Next, we analyze differences in redistribution decisions among spectators that redistribute some amount in at least one of their 12 decisions. 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: On average, spectators redistribute 30.7 percent when luck emerges through coin flips (column 1) and 28.0 percent when luck arises through productivity multipliers (column 2). This difference is statistically significant at the ten percent level (column 3).

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 ten percentage point increase in π reduces redistribution by 4.1 percentage points in the lucky outcomes condition and 2.4 percentage points in the lucky opportunities condition. This difference in slope is statistically significant ($p < 0.01$, column 3). Notably, 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, changes in the responsiveness to the importance of luck in determining workers' outcomes among spectators who redistribute drive the result.

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 sample allows us to examine heterogeneity in our results along a rich set of dimensions. Furthermore, we can examine the external validity of our experimental measure of redistribution attitudes based on our lucky opportunities environment and compare it to measures based on the lucky outcomes environment used in prior work.

We present the results from a heterogeneity analysis in Table A3 in the Online Appendix. Panel A shows that female respondents tend to redistribute more on average in both the lucky outcomes and lucky opportunities environments. This result 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 finds 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 financial interest but also because they hold different fairness views. Panel B highlights some other 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 finding is consistent with survey and experimental evidence that Republicans are less likely to support redistribution (Ashok et al., 2015; Alesina et al., 2018; Almås et al., 2020).

We find that redistribution behavior in our lucky opportunities environment aligns more with real-world social and political attitudes than in the lucky outcomes environment. In Table A4 in the Online Appendix, 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). Behavior in the lucky opportunities environment is more predictive than in lucky outcomes in 13 of the 14 social and political attitudes displayed in Panel A, although some differences have large standard errors (column 3).

Panel B compares two summary indices of political attitudes. The first 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 in the lucky outcomes condition. This result suggests that redistribution decisions reflect real-world social and political views better when luck arises through unequal opportunities. Focusing on environments with lucky outcomes may therefore understate the political divide in support for redistribution if opportunity luck is the dominant driver of inequality in reality.

In summary, 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 even though the importance of luck in determining workers' outcomes is the same in both environments. Changes on both the intensive and extensive margin drive the overall differences in the average level of redistribution, while the different elasticity of redistribution to changes in luck is primarily due to differences in the intensive margin. Finally, we show that redistribution behavior in our lucky opportunities environment predicts real-world social and political views more than in our lucky outcomes environment.

5 Mechanisms

We explore two broad categories of mechanisms that may drive the patterns of redistribution that we observe across the lucky opportunities and lucky outcomes environments. First, we investigate whether actual or perceived differences in worker effort across luck environments can explain our main results. Specifically, we test whether spectators redistribute less because they believe learning about the extent of luck before working alters workers' willingness to exert effort. We also examine whether differences in the relative performance of winners and losers conditional on a given luck realization across treatments can explain our results. Second, since opportunities are a potentially more complex form of luck, we test whether spectators have inaccurate beliefs about the importance of luck in determining outcomes and whether they rely on heuristics when making redistribution decisions.

5.1 Beliefs about Worker Effort

5.1.1 Worker Responses to Opportunity Luck

A key difference between our luck environments is that lucky outcomes occur after completing the task, while unequal opportunities are known before. This aspect of the lucky opportunities condition reflects how luck typically arises 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.[16] 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, $\tilde{\pi}_{\text{Opportunity}} \neq \tilde{\pi}_{\text{Outcome}}$.

To examine whether the timing of lucky opportunities affects redistribution, we implemented an additional between-subjects treatment in which we align the timing of when workers learn about their luck across environments. In the "ex-post lucky opportunities" condition, workers learn their multipliers only *after* they complete the task. This is in contrast to our baseline lucky opportunities condition, in which we inform workers of their multipliers before they begin working on the encryption task. In both situations, workers in a pair face differential returns to their effort. However, our ex-post lucky opportunities condition aligns the timing of luck with lucky outcomes. To ensure this variation in the timing of when luck is realized "sinks in", we show spectators a visual timeline of the worker task sequence and require that they must pass a comprehension check about whether multipliers are revealed to workers before or after the task.[17]

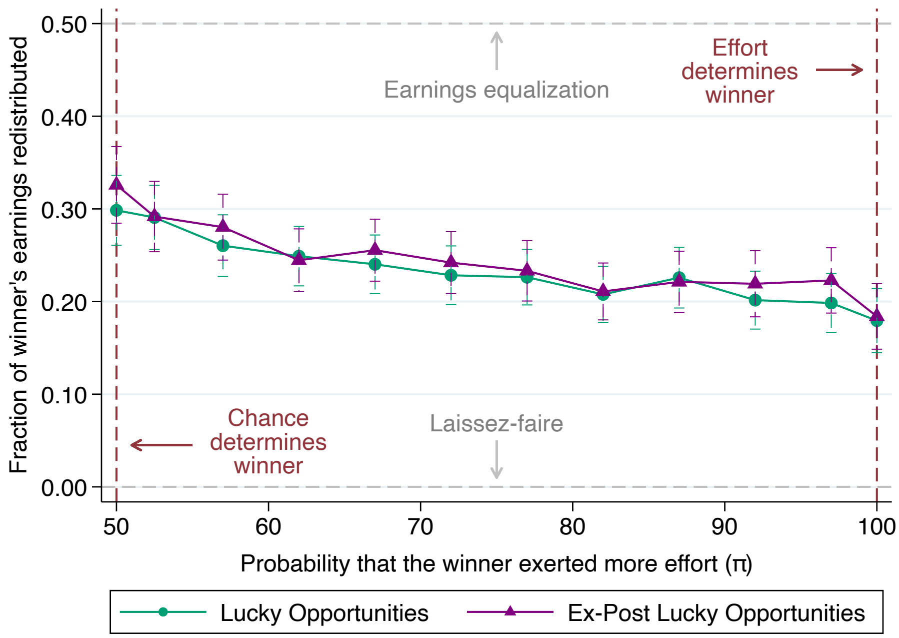
In Table A6 in the Online Appendix, we re-estimate the primary specifications in Table 2 but compare redistribution between the baseline and ex-post lucky opportunities. Redistribution is neither economically nor statistically different across the two treatments. We find no significant differences in the average level of redistribution: The average amount of income redistributed was

[16] Empirically, we do not find any evidence that worker effort responds to receiving a high or low multiplier (see Table A5 in the Online Appendix). We also observe no differences in the overall distribution of effort across luck environments (see Figure A2 in the Online Appendix). 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 we control for using our additional treatments.

[17] See Supplementary Materials, Figures 5 and 18.

23.4 percent in baseline lucky opportunities versus 24.4 percent in ex-post lucky opportunities ($p = 0.57$). We also find no significant differences in the elasticity of redistribution to changes in luck using a linear specification ($p = 0.89$). Figure 2 plots our estimates of the average 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.[18]

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 Table A7 in the Online Appendix, 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 from receiving a high or low multiplier.

[18]In Online Appendix B.5, we show that the effort gap between winners and losers is very similar in the two luck conditions across the entire range of π bins. As a consequence, potential differences in the winner-loser effort gap cannot explain the differences in redistributive behavior between the two luck environments.

Finally, it is possible that spectators believed that merely knowing there would be multipliers or coinflips would cause workers to put in differential effort across our luck environments. To fully eliminate any scope for differential beliefs about workers' effort responses, we implemented subtreatments in which workers did not receive any information about how the winner would be determined *prior to working on the task*. Crucially, spectators in the "rules-after" scenario in both the lucky outcomes and ex-post lucky opportunities conditions knew that workers had identical information before beginning the task. In Figure B4 in the Online Appendix, we show that whether workers find out that luck can determine the winner before or after working on the task has no impact on workers' performance levels or spectator's redistribution. In other words, even when workers face identical information prior to exerting effort, spectators redistribute less and are less sensitive to changes in luck when there are lucky opportunities relative to luck outcomes.

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 result suggests that whether luck alters outcomes in conjunction with an individual's effort is the primary driver of the differences in redistribution we observe across the two luck environments. Our results also complement Andre (2022), who finds that spectators base their decisions primarily on the workers' final effort while ignoring differential incentives to work hard.[19]

5.1.2 Effort Differences without Effort Responses

In our theoretical framework, we assume that the fair income share for the less-productive worker, f_i, is independent of the effort levels of the winner and loser. However, spectators might want to distribute more to winners if they expect a larger difference in effort between the winner and loser. If there are differences in the average effort gap between winners and losers across our luck environments, then the differences in redistribution that we observe might reflect a desire to reward winners for higher effort. For example, when a coin flip determines the winner independently of worker effort, a worker could have won with relatively low effort. Conversely, success always requires some effort in the lucky opportunities environment. Sophisticated spectators may be aware of this difference in the winner-loser effort gap, which could explain their greater propensity to redistribute

[19] Unlike in Andre (2022), worker effort is inelastic to the productivity multipliers in our experiment. This difference likely arises because our environment is a winner-takes-all tournament with a fixed working period, while Andre (2022) considers differential piece-rate wages and allows workers to choose how long they work. 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 there is a fixed working period.

in the lucky outcomes condition relative to the lucky opportunities condition.[20]

We provide several pieces of evidence against this explanation (see Online Appendix B.5 for details). First, the winner-loser effort gap is quantitatively similar in the two conditions across all values of π (Figure B5 in the Online Appendix). Depending on the value of π, the winner-loser effort gap ranges from 0.29 to 6.65 encryptions in the lucky outcomes condition and from 0.65 to 8.41 encryptions in the lucky opportunities condition. Across all values of π, the difference in the winner-loser effort gap between the two conditions is smaller than two encryptions, and it is only statistically significant at the one percent level for $\pi = 1$. Notably, for this value of π, redistribution is *higher* in the lucky opportunities condition than in the lucky outcomes, despite a higher winner-effort gap than in the lucky outcomes condition.

Next, we empirically show that the slight differences in the winner-loser effort gap across conditions cannot quantitatively account for the stark differences in redistribution observed across conditions. First, we measure the elasticity of redistribution with respect to the winner-loser effort gap. To do this, we estimate equation (12) replacing π_{ip} with the difference in tasks completed between the winner and the loser. We estimate that a one-task increase in the winner-loser effort gap decreases the share of earnings redistributed by 0.3 percentage points ($p < 0.01$). To assess how much of the observed differences in redistribution across conditions can be attributed to winner-loser gap differences, we multiply this elasticity by the observed winner-loser effort gap. We find that the winner-loser effort gap can account for only 0.2 percentage points of the difference in redistribution between the conditions on average across all values of π (see Figure B6 in the Online Appendix). This figure is small relative to the overall redistribution difference across conditions, which is equal to 4.2 percentage points. We conclude that differences in the winner-loser effort gap across our luck environments cannot explain our results.

5.2 Inaccurate Beliefs and Inference Challenges

5.2.1 Correcting Beliefs about π

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

[20]Observe that small differences in the winner-loser effort gap for certain values of π across luck environments are the result of the inherent features of outcome luck and opportunity luck, regardless of whether the latter is realized as additive boosters or multipliers. This is because the expected effort gap shrinks linearly in π under lucky outcomes. Under lucky opportunities, by contrast, the convex relationship between the winning worker's relative advantage and π leads to a convex relationship between π and the expected winner-loser effort gap.

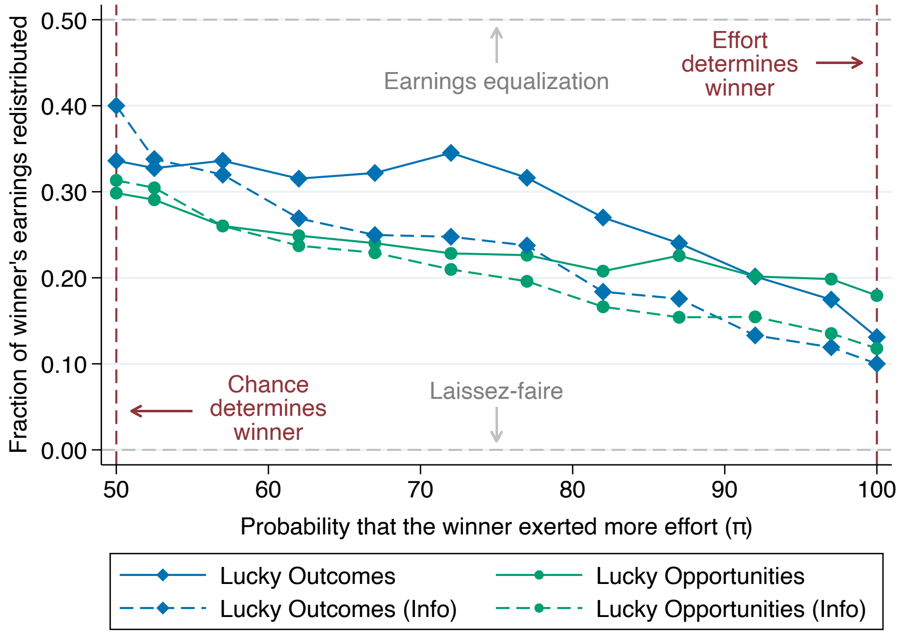
determining outcomes. In particular, inference with lucky opportunities might be more difficult given its interaction with effort. We leverage our information provision treatment to correct potentially inaccurate beliefs about the impact of luck. This information treatment allows us to explore whether inference challenges are the primary determinant of an observed redistribution gap between lucky opportunities and lucky outcomes. In other words, we can assess 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. In Table A8 in the Online Appendix, 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 change equates to a decrease in earnings for workers 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.

One possible explanation for the decrease in average redistribution in both luck environments is that our information treatment primed spectators to think more about the winner's effort than the loser's bad luck. Since we describe π 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 led to a decline in redistribution. Since we are primarily interested in explaining the gap between the lucky opportunities and lucky outcomes environments, the common framing effects from 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 ten 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 complete information about π. Similarly, a ten 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 about π compared to 3.2 percent more when there is complete information. This result is consistent with work showing that drawing attention to an attribute

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.

increases individuals' sensitivity to that attribute (Conlon, 2023).

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 no statistically significant difference in the change in slope when there is outcome luck relative to opportunity luck ($p = 0.43$). In other words, even with full information about the importance of luck, we continue to find that spectators redistribute less and are less sensitive to changes in luck's importance when it occurs through unequal opportunities rather than directly by altering outcomes.

Our information intervention allows us to quantify the extent to which spectators underreact to changes in luck's importance. In Section 2.3, 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 finding is consistent with spectators finding it more challenging 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 2.3 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 never to redistribute when workers face unequal opportunities than when they face lucky outcomes.

Overall, we find that the differences in redistribution choices across luck environments persist when spectators receive accurate information about the importance of luck (π). This suggests that the differences in redistribution across environments are at least partly driven by spectators holding different fairness views when luck arises through opportunities rather than exogenous sources.

5.2.2 A Linearization Heuristic

A large body of literature demonstrates that individuals often rely on heuristics or rules-of-thumb to make decisions in environments with uncertainty (Benjamin, 2019). Prior research has documented a particular heuristic in decision environments with nonlinearities: the "linearization heuristic."[21] According to this heuristic, individuals use linear approximations to simplify the decision process. Environments in which individuals face unequal opportunities can be rife with nonlinear outcomes,

[21] 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).

which may trigger such an inaccurate approximation. The mapping from the relative multiplier m to π in Panel B of Figure A1 in the Online Appendix shows that small differences in the relative multiplier can greatly impact whether chance determines the winner. For example, increasing the relative multiplier from 1.0 to 1.2 decreases the likelihood that the worker who solved more encryptions won from 100 to 77 percent. In Section 2.1 and Online Appendix B.2 and B.3, we show that the non-linear impact of luck on worker outcomes is a more general feature of opportunity luck that prevails even if luck is realized as an additive booster (headstart) to one's effort.

In Table 6, we test whether spectators base their redistribution decisions on the multiplier difference without complete information about π. We first focus on spectators in the baseline lucky opportunities environment who directly observe workers' multipliers but not π. 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 Table A9 in the Online Appendix, 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 the 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 redistribution decisions. This result is also evident in Panel A of Figure 4, which shows that mean redistribution in the baseline lucky opportunities environment is approximately linear in the multiplier difference.

Our theoretical framework predicts that meritocratic spectators will base their decisions on π when we provide complete 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 an important predictor of redistribution decisions. 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 when we provide information about π, spectators place some weight on the multiplier difference. The estimated effect of the empirical π is large and statistically significant: A ten percentage point increase in π leads to a 2.8 percentage point decrease in the share of the total earnings redistributed. This result is evident visually in Panel A of Figure 4, which shows that spectators factor the nonlinear

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.

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 spectator behavior when there is perfect information about π. We compare the distribution choices of high- and low-numeracy spectators to shed more light on this question.[22] 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.

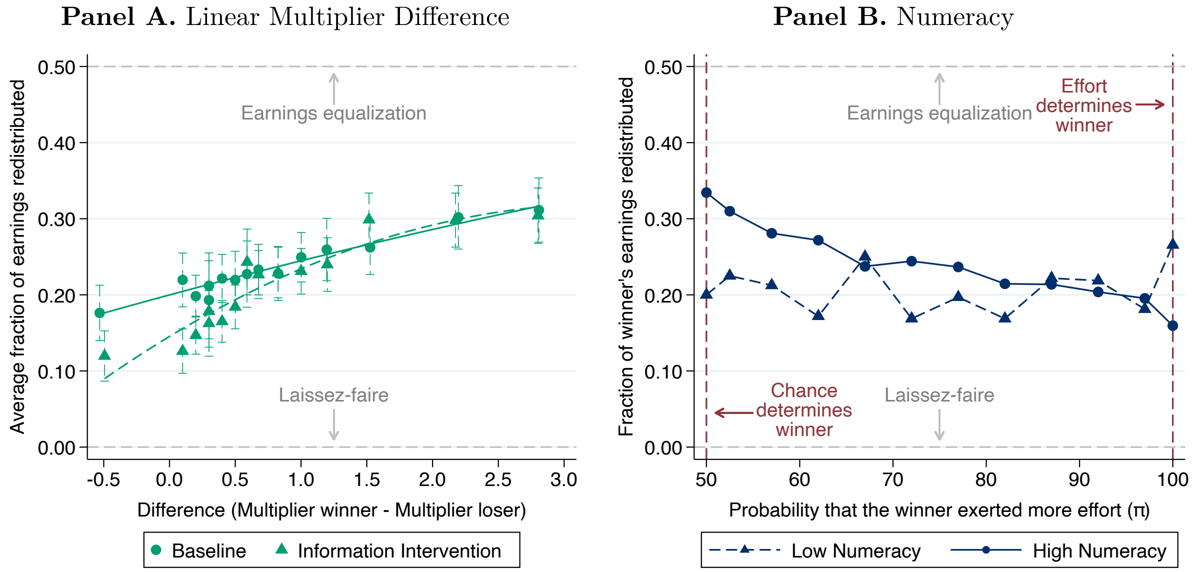
Panel B of Figure 4 presents our main results split by numeracy.[23] Consistent with the idea that linearization is a cognitive shortcut, high-numeracy spectators are more elastic to changes in π: A ten percentage point increase in π leads high-numeracy spectators to redistribute 3.3 percent less of total income. Low-numeracy spectators are much less responsive to changes in π: A ten 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 result suggests that errors in statistical reasoning partly drive redistribution when spectators are

[22]We use the definition of high and low numeracy in the New York Fed's Survey of Consumer Expectations, which is based on five questions designed to assess financial literacy. We provide these questions in Online Appendix B.6. 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.

[23]Table A10 in the Online Appendix provides the underlying regression estimates.

not informed about the value of π.

Figure 4: Redistribution by linear multiplier difference and numerical literacy



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 who failed our comprehension checks in panel B.

Overall, we find 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 greatly impact 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.

6 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. As a result, individuals may find it difficult to assess the source of inequality and may misattribute success to effort rather than luck. Alternatively, they might view inequality that stems from unequal opportunities as more acceptable than inequality that emerges from outcome luck, possibly because bad opportunity luck can, at least in principle, be overcome with sufficient effort whereas bad outcome luck cannot. This paper asks if meritocratic fairness ideals are as persistent 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 and effort are intertwined and are 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 U.S. 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. remained stagnant over a period when differences in opportunities became increasingly important (Chetty et al., 2014; Ashok et al., 2015). Consistent with these 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 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 stems from unequal opportunities rather than directly via outcomes. Even when spectators know the likelihood that luck determined the outcome, they are less likely ever to redistribute when there is inequality of opportunity and tend to redistribute less when they do. This result is consistent with the idea 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, individuals care about the process by which unequal outcomes arise, in addition to the overall importance of luck. This finding relates 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). An interesting avenue for future research is to explore environments in which the procedural fairness of opportunity luck is less clear, for example, by making the role of luck less transparent.

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 greatly impact outcomes. Providing information about the importance of luck reduces this reliance on heuristics, suggesting that they reflect simplified decision-making rules. Models that seek to accommodate cognitive errors hold some promise for predicting and explaining how beliefs shape redistribution attitudes.

Finally, our results show that readily available information greatly impacts 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 lead individuals to have a greater tolerance for inequality of opportunities, making them less willing to correct this source of unfairness through redistribution. Exploring how salient information shapes individuals' tolerance for inequality is a promising avenue for future research.

Taken together, our results highlight that redistribution preferences are not invariant to how luck combines with effort to determine outcomes. The lucky opportunities environment has several important features that affect redistribution, which the more simplistic lucky outcomes paradigm overlooks. 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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Online Appendix

Inequality of Opportunity and Income Redistribution

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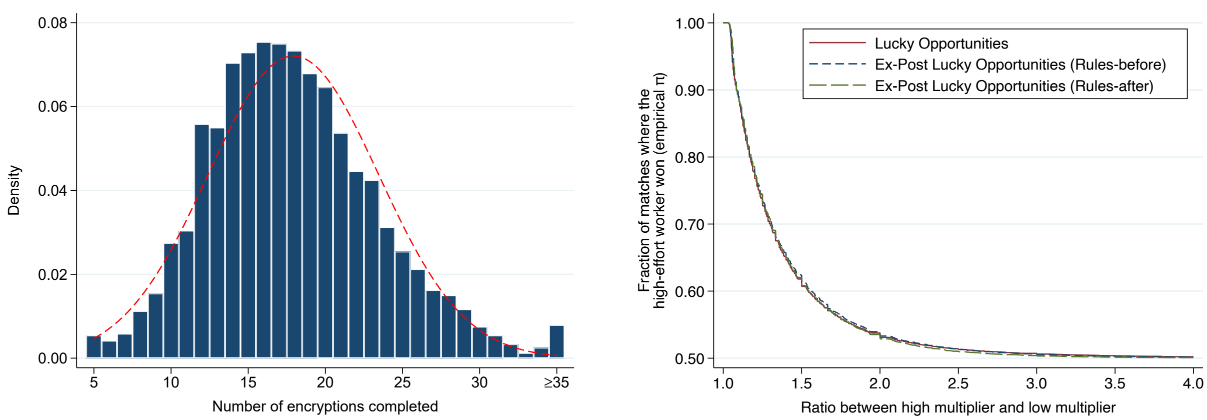
A Additional Figures and Tables

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

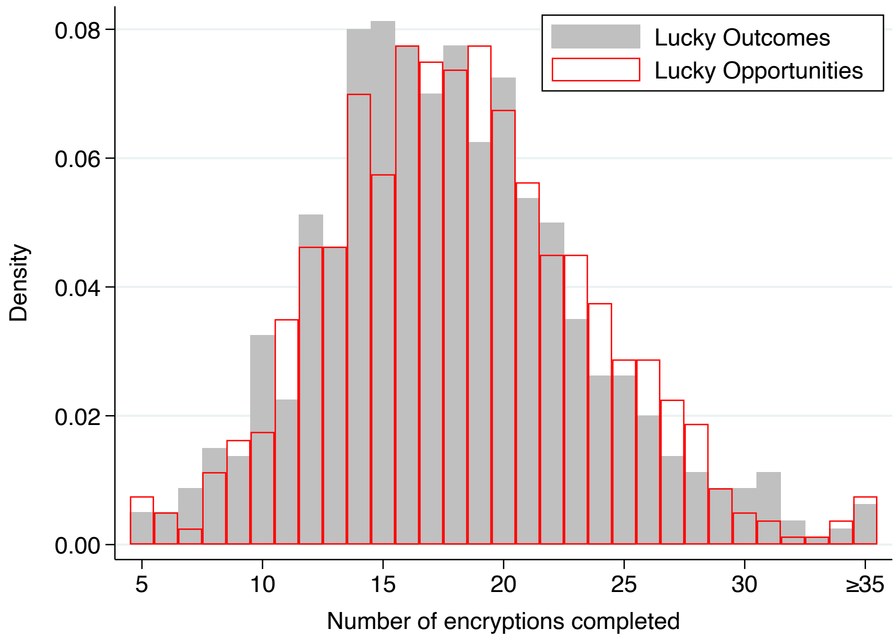
Panel A. Distribution of encryptions completed in worker task

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 Rules-Before	Lucky Outcomes Rules-After	Lucky Opportunities	Ex-Post Lucky Opportunities Rules-Before	Ex-Post Lucky Opportunities 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 $\times$ 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 $\times$ 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. (1)	Elasticity w.r.t. π (2)	Mean Redist. (3)	Elasticity w.r.t. π (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 relationship between redistribution behavior in each treatment condition and political and social preferences. Each cell shows the result from a bivariate OLS regression. We normalize variables by their standard deviation so that the coefficients of the regressions can be interpreted as the linear correlation coefficients. (−) 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 (1)	Non-parametric (2)
Multiplier	0.108	
	(0.106)	
Multiplier $\in [1.0, 1.5)$		-1.082^{*}
		(0.589)
Multiplier $\in [1.5, 2.0)$		0.256
		(0.704)
Multiplier $\in [2.0, 2.5)$		-0.506
		(0.613)
Multiplier $\in [2.5, 3.0)$		-1.162^{*}
		(0.647)
Multiplier $\in [3.0, 3.5)$		-0.526
		(0.634)
Constant	17.862^{***}	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	Non-parametric
	(1)	(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		
	Lucky Outcomes (1)	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.

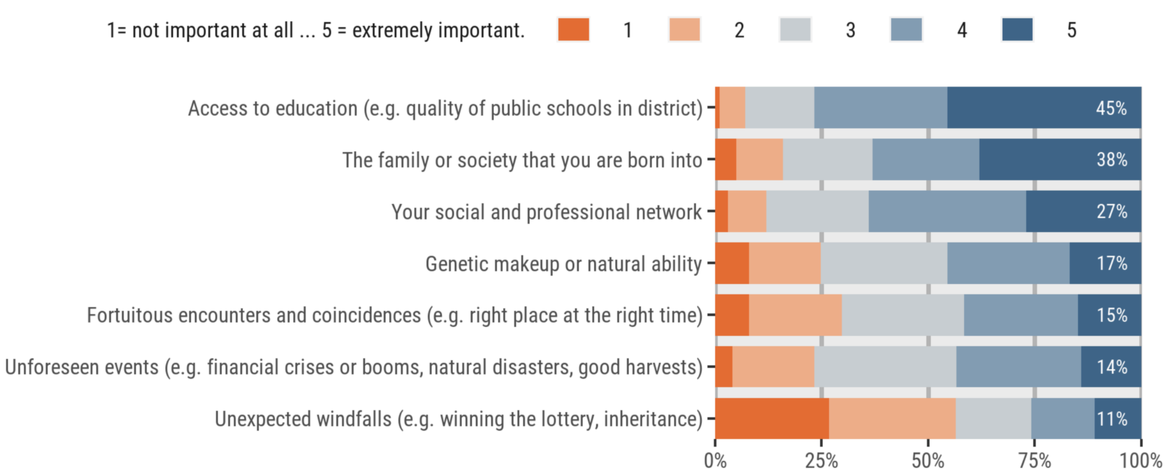
B Additional Results and Analysis

B.1 Luck Perceptions Survey

We surveyed over 1,000 panelists from the NY Fed's *Survey of Consumer Expectations* in February 2023 about the most important types of luck in determining people's life earnings. We conducted this survey by asking panelists to rank the importance of various luck events that occur in people's lives, including a balanced number of items exemplifying opportunity luck (e.g., access to education, the family or society someone is born into) and outcome luck (e.g., unforeseen events such as financial booms or busts, unexpected windfalls such as winning the lottery).

Most respondents agree that access to education, the family or society a person is born into, and their social or professional network are important in determining people's lifetime earnings.[24] These are all examples of luck as an opportunity, whereby luck confers an individual with a relative advantage. Around 50 percent of people state that unexpected windfalls are unimportant in determining life outcomes—an example of outcome luck, which is independent of effort. Other forms of outcome luck, such as fortuitous encounters and unforeseen events, are rated as less important.

Figure B1: Important Factors for Determining People's Life Earnings



Notes: Likert-type responses from the *Survey of Consumer Expecations* ($N = 1013$): "Circumstances beyond a person's control—or, their luck—can impact their life earnings. Please indicate on a scale from 1 to 5 how important you think the following factors are for determining people's life earnings . . . 1 = not important at all . . . 5 = extremely important." The order of factors displayed to the survey respondent is randomized. This question is revealed *before* the open-ended question eliciting important examples of luck in life.

[24] See Figure B1 for the panelists' Likert-type responses.

To support these survey responses, we also elicited open-text responses for the most important examples of luck in an individual's life.[25] Overall, 70.4% of respondents listed at least one example of lucky opportunities. In contrast, only 26.3% respondents mentioned at least one luck factor that is independent of an individual's effort, such as winning the lottery, being at the right place at the right time, or adverse weather events. A topic analysis of the text largely supports our main survey findings. Panelists indicated examples of opportunity luck in greater frequency. Using a Latent Dirichlet Allocation (LDA) analysis, we find that a majority of topics are related to luck that is non-separable from effort in determining life earnings (e.g., "family," "education," "birth," "health," "location," and "wealth").[26]

B.2 Formal Derivation of the Properties of π

In this section, we derive the properties of how opportunity luck maps to the likelihood that the winner was based on merit. Recall that $\pi = 1$ if the disadvantaged worker wins. Therefore, we restrict attention here to the more interesting case in which the advantaged (i.e., higher-multiplier) worker won. Without loss of generality, suppose the winner is worker 1 so that $m_1 \geq m_2$. As before, we write $m = m_1/m_2$ to denote the relative advantage of worker 1.

Let $x(e_1, e_2)$ denote a systematic measure of relative effort comparing the disadvantaged worker to the advantaged worker and denote the distribution of x by F. Let $\hat{x} = x(e, e)$ be the equal effort cutoff. Further, let $x^*(m)$ denote the relative effort threshold that $x(e_1, e_2)$ needs to exceed so that worker 2 wins. In our experiment, $x(e_1, e_2) = e_2/e_1$, $x^*(m) = m$ and $\hat{x} = 1$.

Using this notation, we can rewrite the expression for π given in the main text as follows:

$$\pi(m) = \Pr\left(x < \hat{x} | x \leq x^*(m)\right) = \frac{F\left(\hat{x}\right)}{F\left(x^*(m)\right)} = \frac{1/2}{F(m)}. \tag{B1}$$

Taking the derivative yields $d\pi(m)/dm = -f(m)/F(m)^2 < 0$, which shows that π decreases in m as stated in the main text. Next, consider the second derivative:

$$\frac{d^2\pi(m)}{dm^2} = \frac{-f'(m)F(m)^2 - 2F(m)f(m)(-f(m))}{F(m)^4}. \tag{B2}$$

[25] The exact question text was as follows: "It is often said that luck is important for success in life. In your view, what are the three most important examples of luck in an individual's life?". We asked this question before presenting panelists with the Likert-scale question to avoid priming them about certain factors.

[26] Other topics related to discussions of hard work and effort or whether luck is purely random.

Thus, convexity of π follows if

$$-f'(m)F(m) + 2f(m)^2 \geq 0 \qquad \Leftrightarrow \qquad 2f(m)^2 \geq f'(m)F(m). \tag{B3}$$

The second inequality is implied by log-concavity of F. Thus, to prove that π is convex in m, it is sufficient to show that F is log-concave. Notably, F is log-concave if $x = e_2/e_1$ is log-normally distributed (see Table 3 in Bagnoli and Bergstrom, 2006, for example). Since both e_1 and e_2 are log-normal, it follows that $\log(e_2/e_1) = \log(e_2) - \log(e_1)$ is the difference of two normally distributed variables ($\log(e_2)$ and $\log(e_1)$), which is itself normally distributed. That is, $x = e_2/e_1$ is log-normally distributed and as a result, π is convex.

Expression (B3) permits a straightforward assessment of the properties of $\pi(m)$ for other effort distributions. For example, for a uniform distribution over $[0, 1]$, notice that the CDF F for $x = e_2/e_1 \geq 1$ is given by $1/2 + 1/2(1 - 1/x)$. Based on that expression, it is easy to verify that (B3) holds, implying convexity of π. In fact, the result readily extends to any uniform distribution over $[0, c]$. To see this, simply multiply any relative advantage m by c so that the effective relative advantage $c \cdot m$ is uniformly distributed over $[0, c]$. To replicate the analysis above, note that f does not change since the c term cancels out when taking the ratio. The only change is that $x^*(m) = cm$ now. However, the constant c does not alter the necessary condition (B3) for π to be convex. Therefore, even in situations in which effort is uniformly dispersed in the population, there is a convex mapping from relative opportunities to the likelihood of success.

Similar conclusions emerge if we instead consider additive lucky headstarts instead of multipliers. Suppose the advantaged worker 1 receives a relative headstart $b > 0$. To analyze this case, we can simply redefine $x(e_1, e_2) = e_2 - e_1$, and therefore the equal-effort threshold becomes $\hat{x} = 0$. Since the effort threshold required to win is still a linear function of the relative advantage, i.e., $x^*(b) = b$, we can simply substitute m with b in the analysis above. If worker effort is normally distributed, then $x(e_1, e_2)$ is also normally distributed, and therefore log-concavity holds via equation B2.[27] As in the case above, we obtain the same prediction when effort is uniformly distributed over any interval $[0, c]$. To see why, notice that $e_2 - e_1$ follows a triangular distribution in this case, whose density is concave and thus log-concave. By Bagnoli and Bergstrom (2006), log-concavity of the density implies log-concavity of the distribution function F, which is sufficient for π being convex by the above arguments. Hence, convexity is also an inherent feature of lucky headstarts under

[27] While assuming a log-normal distribution of effort may be preferred to assuming normal, the distribution of $e_2 - e_1$ is analytically intractable if e_1 and e_2 are log-normally distributed.

reasonable assumptions about the effort distribution. While the exact properties of π will depend on the exact distribution of worker effort, we confirm in the following section that convexity holds for both additive and multiplicative opportunities for the empirical distribution of effort we observe.

B.3 Alternative Experiment with Additive Opportunities or "Headstarts"

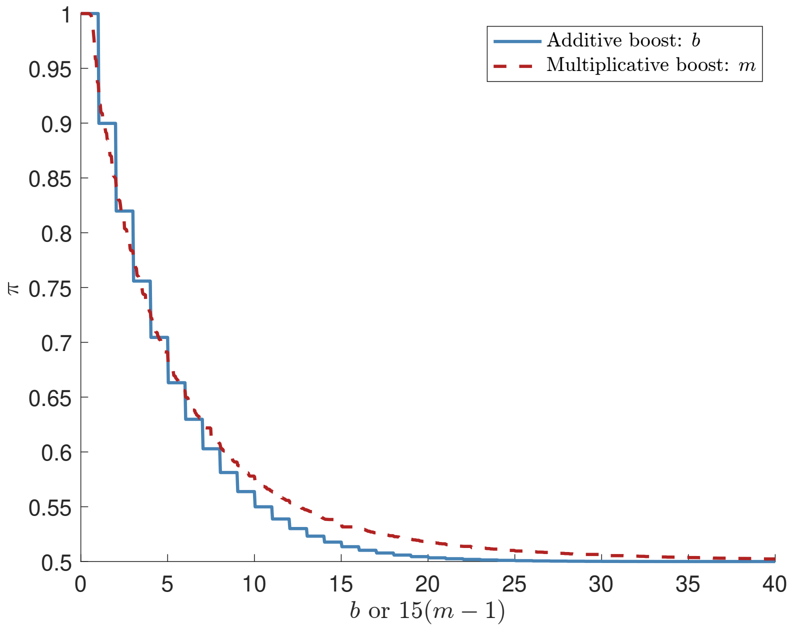
The critical feature of opportunity luck that we emphasize is that it induces a convex relationship between opportunities and how impactful luck is for individual outcomes. Intuitively, we study situations where relatively small differences in opportunities can substantially impact outcomes. Our theoretical framework and experimental design consider the case of productivity multipliers that amplify or dampen the returns to exerting effort. Panel B of Figure A1 shows that this type of opportunity luck indeed generates a convex association between the relative opportunities (the ratio of multipliers, m) and the likelihood that the winner was due to effort rather than luck, π.

Alternative forms of opportunity luck are similarly convex in terms of their impact on the outcome. In Section B.2, we described a hypothetical "lucky headstarts" treatment in which opportunity luck instead takes an additive form. Formally, suppose that workers i and j receive additive boosts, $b_1,\ b_2 \in [0, 1, ...B]$. The final score for each worker is simply the sum of their headstart and the number of solved encryptions: $b_j + e_j$ for $j \in \{1, 2\}$. Without loss of generality, suppose that worker 1 is the winner of the pair and define relative boost as $b \equiv b_1 - b_2$.

We can map the relative headstart, b, to the likelihood that the winner solved more encryptions, π, using the same procedure that we used for the relative multiplier ratio m in the main text. Specifically, for a given b, we can take the empirical effort distribution from our worker task and consider all possible pairings. For each pairing, we can assign a relative boost of b to either worker and then compute the empirical likelihood that the winner was the worker who solved more encryptions. The solid blue line in Figure B2 plots the empirical π as a function of the relative boost b. It depicts a highly convex relationship between the relative headstart and its impact on the outcome. A single-point headstart leads to a drop in π from 100 to 90 percent. A two-score advantage leads to an additional eight percentage point drop in π, while a three-score advantage leads to an additional six percentage point drop. In contrast, moving from a ten-score advantage to an 11-score advantage only leads to a one percentage point change in π.

The dashed red line in Figure B2 reproduces the relationship between the relative multiplier ratio m and π from our lucky opportunities treatment. The additive and multiplicative forms of opportunity luck are similar in their relationship with π. If anything, the additive headstart case

Figure B2: Additive vs. Multiplicative Opportunities



Notes: This figure shows the fraction of paired workers in which the worker who won the match completed more encryptions. We determine the winner by comparing the final scores and selecting the worker with the higher score. The solid blue line depicts the case with additive score boosts in which the final score is the number of correct encryptions plus an additive boost. The dashed red line depicts the case with multiplicative score boosts which the final score is the number of correct encryptions times a 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.

is slightly more convex in π than the multiplicative one. More broadly, this highlights that the convex relationship between opportunities and the importance of luck for the outcome is not due to the multiplicative nature of our lucky opportunities environment.

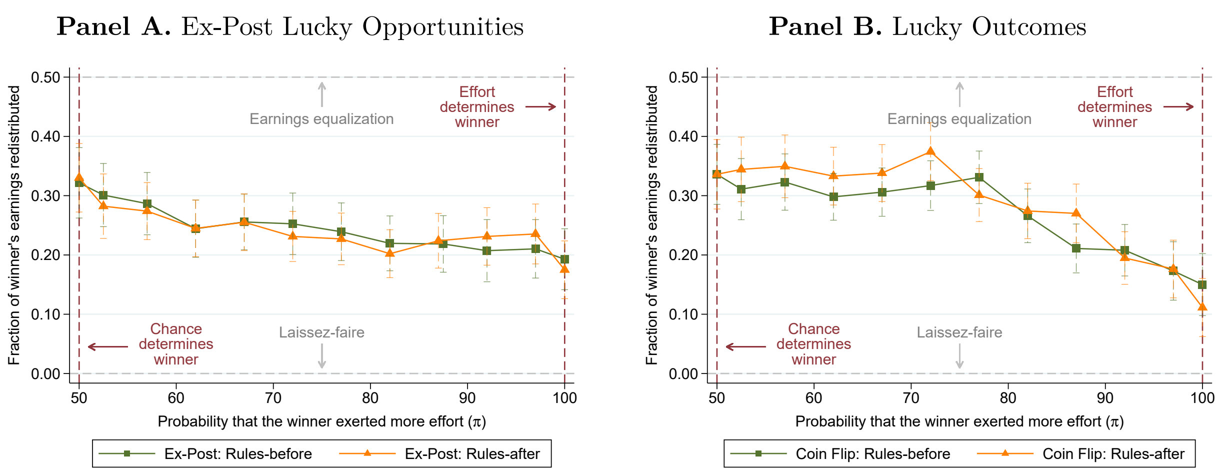
B.4 Anticipatory Effort Responses

In the main text, we show that whether workers learn their multipliers before or after working on the task has no impact on spectators' redistribution decisions. While this removes much of the scope for different beliefs about workers' effort responses, spectators might still expect the distribution of effort levels under lucky opportunities to be meaningfully different from lucky outcomes environments. In particular, spectators may believe that a worker who learns the rules of how effort multipliers determine outcomes may be motivated to exert different levels of effort independent of their knowledge about their assigned multiplier (i.e., under the ex-post opportunities condition) than a worker who learns how a coin flip impacts outcomes. 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. Alternatively, spectators might suspect that workers believe their efforts matter less and, thus, become less motivated to exert effort when there are lucky outcomes.

To control for and test this mechanism experimentally, we vary the timing of when workers learn how luck plays a role in determining outcomes in subtreatments. In the "rules-before" condition, we inform workers that effort multipliers or a coin flip will influence the outcome *before* they start the task. In the "rules-after" condition, we inform workers that multipliers or a coin flip will influence the outcome *after* they complete the task. Crucially, spectators in the rules-after treatments in both the lucky outcomes and ex-post lucky opportunities conditions knew that workers had identical information before beginning the task. Between these two conditions, there is thus no scope for differences in beliefs about the distribution of worker effort.

Figure B3 plots the 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. 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.

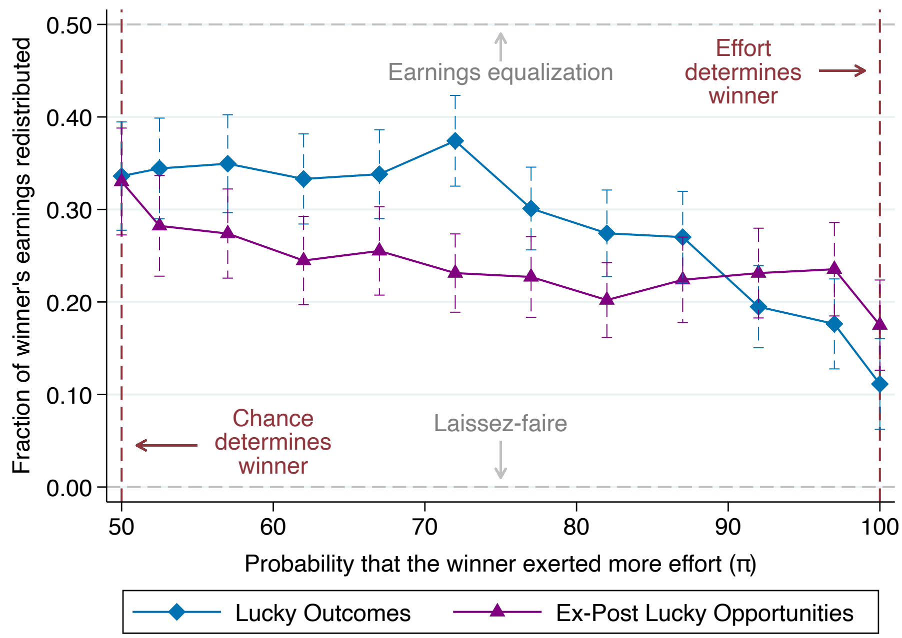
Figure B3: Redistribution and awareness of rules in the ex-post lucky opportunities and lucky outcomes conditions



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.

Figure B4 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. Table B3 re-estimates our main specifications in Table 2 from the main text 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 B4: 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 workers until after they perform their tasks.

Finally, we compare spectators' stated beliefs about average worker effort across the ex-post lucky opportunities and lucky outcomes conditions. We find no differences across these conditions: 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 tournament rules before or after completing the task: the median number of tasks spectators believe workers completed is 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	Ex-Post Lucky Opportunities	Difference
	(1)	(2)	(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.5 Effort Differences Across the π Distribution

The ex-post lucky opportunities treatment shows spectators' expectations about workers' potential effort responses do not drive our main treatment effect. Nonetheless, the effort levels of winners and losers conditional on π could differ across our luck treatments. This difference might arise because only worker pairs with certain effort levels can be selected for a particular π in the lucky opportunities condition. In contrast, workers with any effort level can be selected for a particular π in the lucky outcomes condition. If the effort difference between winners and losers differs between luck environments for fixed values of π, then sophisticated spectators that correctly anticipated these differences may support different levels of redistribution.

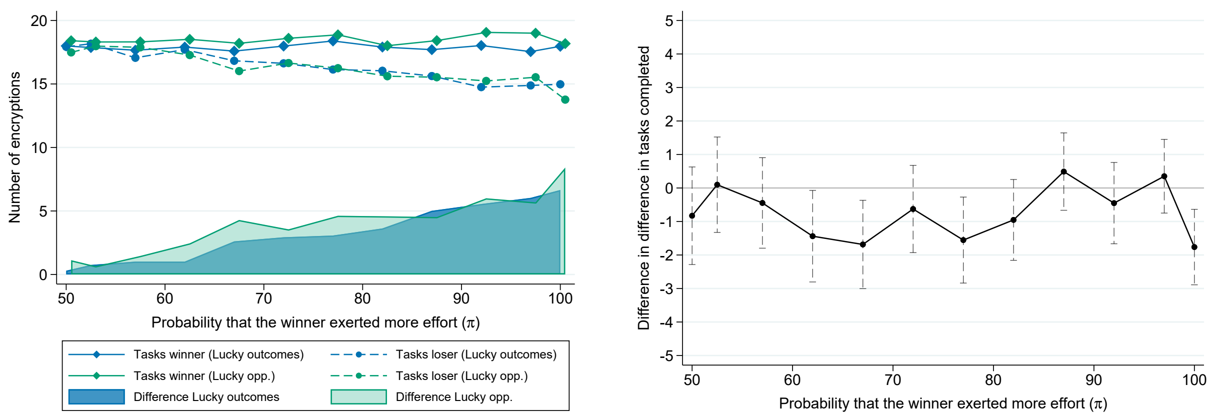
To assess this, Panel A of Figure B5 depicts the average number of encryptions completed by winners and losers in each luck treatment as a function of π, as well as the difference between the number of tasks completed by the winners and losers in each condition, or "winner-loser effort gap." Panel B of Figure B5 shows the difference between the winner-loser effort gap in the lucky opportunities condition relative to the lucky outcomes condition.

There are no meaningful differences in the number of encryptions completed by winners and losers across luck treatments. On average, winners in the lucky outcomes condition completed a similar number of encryptions as winners in the lucky opportunities condition across the entire range of π bins. For example, in the lucky outcomes condition, the average number of encryptions completed by winners ranges from 17.5 to 18.3 (depending on the value of π), whereas, in the lucky opportunities condition, the corresponding value ranges from 18.0 to 19.1. Similarly, losers in the two conditions completed a similar number of encryptions. As π increases, the winner-loser effort gap increases in both luck environments. Crucially, these effort differences are similar between our luck environments. For all values of π, the difference in the winner-loser effort gap between the two conditions is smaller than two encryptions.

Figure B5: Number of encryptions completed by workers across values of π

Panel A. Tasks completed by winners and losers and winner-loser effort gap

Panel B. Difference in winner-loser effort gap across conditions



Notes: Panel A shows the average number of encryptions completed across all worker pairs as a function of the luck treatment and the value of π. Shaded areas denote the average winner-loser effort gap, as measured by the difference between the number of encryptions completed by the winner and the loser. Panel B shows the difference between the winner-loser effort gap in the lucky outcomes condition and the lucky opportunities condition. Dashed lines denote 95 percent confidence intervals.

To determine how much of the difference in redistribution between lucky opportunities and lucky outcomes that we document in Section 4 can be attributed to differences in the winner-loser effort gap, we first estimate the relationship between redistribution and the winner-loser effort gap. Panel A of Figure B6 depicts the relationship between the fraction of earnings redistributed (y-axis) and the difference in tasks completed by the winner and loser (x-axis), separately by luck treatment. This figure shows a negative relationship between the two variables: on average, a higher winner-loser effort gap leads to less redistribution. A linear regression of the fraction of earnings redistributed on the winner-loser effort gap yields a coefficient of -0.003 ($p < 0.01$). This means that increasing the winner-loser effort gap by three encryptions decreases redistribution by approximately one percentage point.

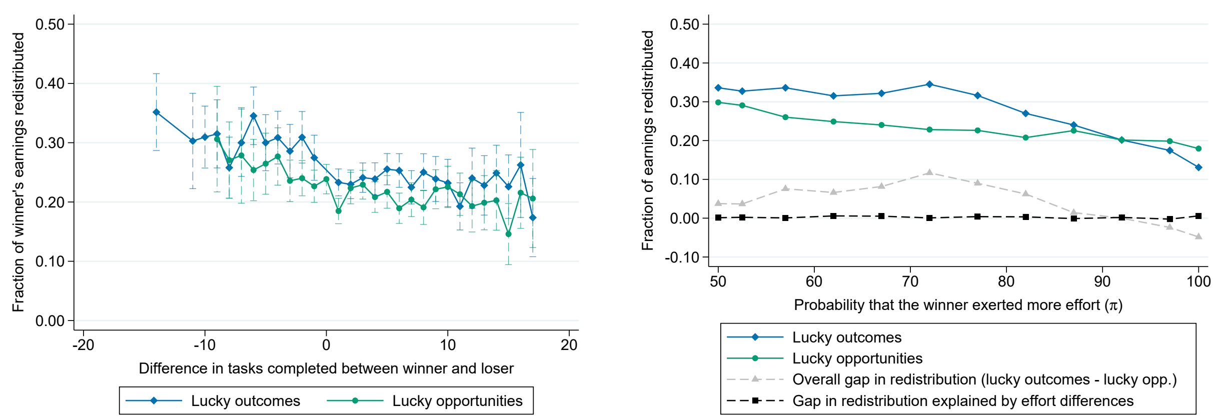
The difference in the winner-loser effort gap across conditions can account for only a small fraction of the difference in earnings redistributed across the luck treatments. We estimate using the elasticity of redistribution with respect to the winner-loser effort gap and the difference in the winner-loser effort gap across conditions and use it to calculate how much of the difference in redistribution across luck treatments we can attribute to differences in the winner-loser effort gap. Panel B of Figure B6 depicts this estimate along with the observed difference in redistribution.

When averaging over π, the effort gap between winners and losers contributes only 0.2 percentage points to the difference in redistribution between the conditions. This contribution is negligible compared to the average overall redistribution differences, which equals 4.2 percentage points across values of π. The small influence of the winner-loser effort gap primarily stems from the fact that empirically this gap is too small to impact redistributive behavior substantially.

Figure B6: Redistribution and differences in the winner-loser effort gap

Panel A. Earnings redistributed and differences in encryptions completed by winners and losers

Panel B. Redistributive gap predicted by differences in winner-loser effort gap



Notes: Panel A shows the average share of earnings redistributed between workers (from the higher-earning winner to the lower-earning loser) relative to the difference in encryptions completed between the winner and the loser. Panel B shows the average share of earnings redistributed between workers relative to the likelihood that the winner exerted more effort across the two luck conditions, as well as the difference between the fraction of earnings redistributed in the two conditions. This panel also shows estimates of how much of the difference in redistribution can be attributed to differences in the winner-loser effort gap across conditions.

B.6 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: Spectator Redistribution Screens for Lucky Outcomes and Lucky Opportunities
with Information about π

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).