Excuses and Redistribution

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Abstract

This study explores how, when income inequality is perceived to arise from both effort and luck, excuses (self-serving belief distortions) can influence acceptance of inequality. In a controlled laboratory setting involving a real-effort task, participants make redistribution decisions between themselves and a partner. The study varied the degree of uncertainty about the role of effort and luck in determining initial earnings endowments. Belief elicitations indicate that increased uncertainty caused participants to be more likely to attribute their partner's success to luck. Furthermore, the use of excuses (attributing others' outcomes to luck) was found to reduce willingness to redistribute earnings to their partners. These findings highlight how excuses about the role of luck versus effort may contribute to the persistence of inequality even if many individuals have meritocratic principles, and how variation in the *degree of uncertainty* about the causes of inequality, across individuals or societies, may contribute to different degrees of biased beliefs and inequality. The paper also shows evidence of excuses in another sense: According to a structural model of fairness views, individuals tend to adopt a fairness view – egalitarian, meritocratic, or libertarian – to justify an allocation that benefits themselves.

Keywords: Experiment, Inequality, Fairness, Beliefs

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1 Introduction

Rising levels of income inequality have placed this subject at the center of public policy discussions (Atkinson, 2015; Piketty and Goldhammer, 2014, 2015; Stiglitz, 2012), with organizations such as the United Nations recognizing it as one of their 17 Sustainable Development Goals. Inequality in income distribution can arise from different factors, including differences in luck, preferences, and levels of effort, across individuals in society[1].

Research on fairness views has shown that acceptance of inequality depends crucially on whether it is attributed to effort or luck (Cappelen, Sørensen and Tungodden, 2010; Mollerstrom, Reme and Sørensen, 2015; Almås, Cappelen and Tungodden, 2020). Specifically, this research has documented three main views in societies: egalitarianism, libertarianism, and meritocracy (Almås, Cappelen and Tungodden, 2020). Egalitarianism implies that everyone should be rewarded equally, and therefore, no inequality is accepted, regardless of whether it is attributed to individuals' own choices or factors beyond their control. The libertarian fairness view holds that income inequalities arising from the market are fair, and as a result, redistribution is not necessary. Lastly, meritocracy, which has become central to public and political debates and has increasingly dominated discussions among U.S. presidential candidates over the past three decades (Sandel, 2020), legitimizes inequalities caused by individuals' own choices, like differences in effort, but not those resulting from luck or forces beyond an individual's control. Therefore, meritocracy is at the core of the American Dream, where everyone who works hard can get ahead, regardless of where they come from.

In a society with unequal opportunities, imperfect mobility, and other factors beyond people's control, however, it becomes difficult to distinguish how much of one's success (or failure) is due to personal responsibility versus luck, especially when both forces complement each other. As a result, the degree of inequality (and redistribution) people are willing to accept seemingly must depend importantly on their beliefs about the role luck plays in determining success. This crucial role for beliefs raises the possibility, however, that self-serving biases in beliefs (excuses) could influence attitudes towards inequality, particularly when individuals' own material well-being is at stake. It is also possible that excuses influence attitudes through non-belief channels, such as choosing a

[1] These are three broad categories where luck includes all factors beyond a person's controls, for example, inheritance, country of birth, ethnicity, genetics, opportunities, etc.

fairness view to justify keeping money for oneself.

This paper introduces uncertainty and excuse-seeking into the discussion on inequality acceptance when people's own utility is at stake, by examining two mechanisms by which people engage in self-serving behaviors. First, it explores how individuals' beliefs about the sources of income inequality–particularly the role of effort versus luck–shape their attitudes toward redistribution, focusing on whether excuse-seeking behavior enables individuals to justify retaining more resources for themselves while attributing others' success to luck. Second, it examines how individuals selectively "choose" what they consider fair in a self-serving way. Previous studies have shown that people use self-deception mechanisms to excuse selfish behaviors (Konow, 2000; Dana, Weber and Kuang, 2007; Di Tella et al., 2015; Exley, 2016). However, little is known about how excuse-seeking behavior, especially through belief distortion, affects inequality acceptance and redistribution.

It is crucial to understand the role of beliefs and excuse-seeking behavior in this environment, not only for economic reasons and for designing effective policies to reduce inequality, but also because these factors significantly impact political polarization and social stability. In a meritocratic society, success is seen as earned, but this also implies that those who fail have only themselves to blame, as discussed by Sandel (2020). When there is uncertainty about the roles of luck and effort, and people engage in excuse-seeking behaviors, those who succeed are more likely to believe that effort is the primary determinant of success, while those at the bottom of the income distribution tend to believe that luck plays a larger role. This divergence in beliefs fosters polarization and social unrest, as seen in the 2019 Chilean protests, where inequality was a central issue, ultimately leading to a lengthy and costly process to rewrite the constitution[2].

In summary, this paper takes up four main research questions. First, what is the role that uncertainty over the source of inequality plays in determining inequality acceptance? In the presence of uncertainty, do people exhibit excuse-seeking by believing that others' success is due to luck and others' failures due to a lack of effort? Does this distortion in beliefs affect preferences for redistribution and inequality acceptance? And do individuals exhibit excuse-seeking tendencies also in choosing their fairness ideals in ways that primarily benefit themselves?

These questions focus on the mechanisms that influence inequality acceptance and redistribu-

[2] After years of writing a new constitution and several rounds of elections, the constitution was not changed.

tion. Therefore, it is important to control for all other variables that affect redistribution in order to isolate the effects of uncertainty and beliefs. To achieve this, an experimental setting is necessary. In a laboratory experiment, participants make redistribution decisions under varying levels of uncertainty. The study consists of two main stages. First, participants complete a real-effort task where they are rewarded according to a piece rate. Luck is introduced by randomly assigning either a high or low piece rate (50% probability each), at the moment of performing the task, participants are not informed of their own piece rate, and feedback on their performance is not provided. In the second stage, participants are paired and decide how to redistribute the sum of their combined earnings, with one of the pair's decisions being randomly implemented.

The information available at the time of the redistribution decision varies by treatment. In the No Information treatment, participants are only informed of the individual earnings of the pair, while in the Partial Information treatment, they also receive information about the effort distribution of the participants. These treatments differ in the level of uncertainty, with the treatment that reveals effort distribution involving less uncertainty and offering less room for belief distortion. Before making the redistribution decision, participants' beliefs about the probability of receiving the high piece rate are elicited and incentivized.

To understand the role of uncertainty, beliefs between treatments are first compared, followed by an analysis of redistribution and inequality levels. As expected, in the No Information treatment, participants believe the probability that their partners received the high piece rate is higher at every earnings level compared to the Partial Information treatment. This suggests that greater uncertainty leads participants to attribute others' success more to luck. However, when comparing beliefs about their own luck, there is no significant difference between treatments. These results imply that, in the No Information treatment, participants perceive themselves as more deserving relative to their partners than in the Partial Information treatment.

These differences in beliefs lead to differences in redistribution, with participants in the No Information treatment being more likely to keep a larger share of earnings for themselves. Part of this difference can be explained by their beliefs: once controlling for their expected effort share conditional on their own beliefs, the difference between treatments decreases, highlighting excuse-seeking as a mechanism to justify self-interested behavior. This disparity in redistribution is also reflected in the levels of inequality implemented. In the No Information treatment, inequality (measured by the GINI coefficient) increases after redistribution, rising from levels similar to France to those comparable to Brazil. In contrast, in the Partial Information treatment, there is no significant change in overall inequality before and after redistribution.

Belief distortion about the role of luck versus effort is not the only potential mechanism for self-deception; individuals may also "choose" what they consider fair in a self-serving manner (Konow, 2000). This paper uses a structural model to estimate the prevalence of the three primary fairness views—egalitarian, libertarian, and meritocratic—in each treatment, as well as in subsamples of higher and lower earners. Consistent with the literature on fairness views (Cappelen et al., 2007, 2013*a*; Mollerstrom, Reme and Sørensen, 2015; Almås, Cappelen and Tungodden, 2020; Andre, 2024), the results confirm heterogeneity, with substantial shares across all three views. The estimates for participants in the bottom half of the earnings distribution from the production stage show strong support for redistribution, with over 70% holding either egalitarian or meritocratic views. In contrast, nearly 60% of participants in the upper half of the earnings distribution are libertarians. These findings suggest that participants selectively adopt fairness views in a self-serving way.

This study contributes to several strands of literature. First, it adds to the extensive experimental literature on preferences for redistribution and fairness views, which demonstrates that inequalities attributed to differences in effort are generally seen as more fair than those resulting from luck[3,4]. Closest to this study are several experimental papers that incorporate uncertainty about whether inequality arises from effort or luck, and study the decisions of spectators (third-parties) about how to redistribute between two other subjects (Cappelen et al., 2022; Preuss et al., 2023; Andre, 2024; Cappelen, de Haan and Tungodden, 2024). This paper differentiates itself by

[3] Much of the literature models luck as a coin flip that fully determines earnings. However, luck may also appear as differences in opportunities, influencing factors such as access to labor markets or education (Eisenkopf, Fischbacher and Föllmi-Heusi, 2013; Bhattacharya and Mollerstrom, 2022; Dong, Huang and Lien, 2022), or even the rewards for effort (Preuss et al., 2023; Andre, 2024). Effort and luck are not the only factors that influence preferences for redistribution. Differences in risk preferences – such as investment decisions or insurance coverage – also play a role(Cherry, 2001; Cappelen et al., 2007, 2011, 2013*a*; Mollerstrom, Reme and Sørensen, 2015; Akbaş, Ariely and Yuksel, 2019), as do efficiency concerns (Almås, Cappelen and Tungodden, 2020; Durante, Putterman and van der Weele, 2014).

[4] A non-exhaustive sample of this literature includes Ruffle (1998); Cherry, Frykblom and Shogren (2002); Cappelen, Sørensen and Tungodden (2010); Rodriguez-Lara and Moreno-Garrido (2012); Cappelen et al. (2013*b*); Ubeda (2014); Barr et al. (2015); Akbaş, Ariely and Yuksel (2019); Almås, Cappelen and Tungodden (2020); Andre (2024); Bartling et al. (2024)

taking a stakeholder perspective, where individuals' own incomes are redistributed and thus fairness preferences may conflict with material self-interest, creating the potential for self-serving attitudes to emerge.

Distinct from distortions in beliefs about the role of luck versus effort, previous work has discussed how individuals may choose views of what is fair in a self-serving way. Konow (2000) was among the first to examine the role of meritocracy (or the accountability principle) and self-deception in redistributive preferences, showing that people adopt self-serving fairness views when they are stakeholders, compared to when they are spectators. Rodriguez-Lara and Moreno-Garrido (2012), Durante, Putterman and van der Weele (2014), Ubeda (2014), and Amasino, Pace and van der Weele (2024) find similar results. This paper extends the understanding of how self-serving biases can influence choice of fairness views, by using a structural model that allows characterizing three main fairness views separately for individuals, and showing that the prevalence of these views varies in self-serving ways in the upper relative to the lower halves of the earnings distribution.

This paper also contributes to the literature on self-serving and excuse-seeking behaviors in other environments. It has been shown that people avoid information to act more selfishly (Dana, Weber and Kuang, 2007), adjust their risk preferences to justify self-interested behavior (Exley, 2016), and distort their beliefs in self-serving ways by assuming others behave corruptly (Di Tella et al., 2015), thus excusing their own selfish actions. This paper distinguishes itself from this literature, and specifically from Di Tella et al. (2015), by examining belief distortion in the context of inequality and redistribution, where beliefs about merit are subject to self-serving biases. Studying belief distortion in this environment is crucial, not only because of its economic implications but also because of its potential impacts on social stability and polarization.

Lastly, this paper connects with a broader literature on beliefs about social mobility and support for redistributive policies, which provides both theoretical results and evidence from observational data. A link between differences in support for redistribution between low and high income individuals, and differing beliefs about the role of luck in determining poverty, were initially studied empirically by Fong (2001) and theoretically by Alesina and Angeletos (2005). More recently, Alesina, Stantcheva and Teso (2018) and Fehr, Müller and Preuss (2022) examined how perceptions of social mobility influence these preferences. This body of research highlights that variations in beliefs about the impact of effort on success, within and across societies are fundamental in shaping redistributive preferences and support for redistributive policies. This study is complementary, by suggesting that the *degree of uncertainty* about the role of luck versus effort can be another important factor, with greater uncertainty leading to more self-serving beliefs. For example, uncertainty and resulting belief distortions may be greater in contexts where economic segregation, remote work, or lack of transparency about income sources obscure the true causes of inequality.

The remainder of the paper is structured as follows: Section 2 describes the experimental design, Section 3 introduces the theoretical framework, and Section 4 presents the main results. Section 5 classifies participants' decisions into the three predominant fairness views and provides a model of their distributive choices, and finally, Section 6 concludes.

2 Experimental Design

The experiment has two main stages: the production and redistribution stages. In the production stage, participants perform a real-effort task and earn a piece rate for each correctly completed task. In the redistribution stage, participants are randomly paired and they have to decide how to redistribute the combined earnings among themselves. The three between-subject design treatments differ in the amount of information provided to the participants during the redistribution stage: Full Information, Partial Information, and No Information.

Production Stage

In the production stage, participants work on the counting zero task (Abeler et al., 2011) for 25 minutes[5]. There are two equally likely piece rates; the high piece rate (P_H), where they earn 50 cents for each correctly counted table, and the low piece rate (P_L), where they earn 50 cents for every three correctly counted tables[6]. The number of correctly counted tables is considered the effort made by the participant (e_i)[7]. At the time of performing the real effort task, participants

[5]To allow participants to form beliefs about others not working during the 25 minutes, participants are allowed to use the browser if they want to stop working on the real-effort task, but they are not allowed to use their phones to avoid session effects.

[6]This payment scheme was chosen so participants could not infer the piece rate by looking at the earnings.

[7]The number of correctly counted tables is considered as effort instead of tables solved (correctly or incorrectly) because the counting zero task does not require ability beyond concentration, and participants could try to guess the

know there are two possible piece rates but they do not know which one they have. Participants do not receive any feedback. After the task is completed, participants only learn their earnings ($\$w_i$) but not the number of correctly counted tables. Participants are told that the earnings from this stage are provisional, but they do not know they will be paired and there will be a redistribution stage later[8].

Redistribution Stage

In the redistribution stage, participants are randomly paired and they have to redistribute the sum of their earnings ($X = w_i + w_j$). They have to choose how much money to keep for themselves and how much to give to their partner[9]. Both participants of the pair make the redistribution decisions, and one of the two decisions is randomly chosen to be implemented for payment.

The participants also make decisions in 10 additional hypothetical situations, which allows to determine participants' fairness views. Participants know that only one situation is the real one but do not know which one it is[10][11]. Each situation varies the partner's earnings, piece rate, and effort. For example, in situation 6, the partner's earnings are \$4, has the high piece rate, and counted 8 tables correctly, while in situation 5, the partner's earnings are \$3.50, has the low piece rate, and correctly counted 22 tables. Table B1 in the appendix summarizes each situation shown to participants for each treatment. Although in each treatment the information shown to participants in the hypothetical situations is the same, the total amount to redistribute is not the same, and therefore, the decisions are not the same, because it also depends on the earnings, piece rate, and effort of the participants themselves.

Treatments

The experiment consisted of three between-subject treatments that differed in the amount of information provided for the redistribution stage.

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number instead of count the zeros, and have a high number of tables solved, situations that are observed in the data.

[8] Before beginning the real-effort task, participants completed comprehension questions about how payments were determined and the instructions for this stage.

[9] They can choose any amount, in increments of 1 cent, between \$0 and \$X.

[10] This was confirmed with an unincentivized survey question at the end of the experiment, where 18.18% chose the option "Do not know", and only 3.41% correctly chose the real situation.

[11] The real situation was always the last decision they saw.

- Full Information: There is no uncertainty - participants know their own earnings, piece rate, and effort. They also know their partner's earnings, piece rate, and effort.

- Partial Information: Participants know their own earnings but do not know their own piece rate or effort. Their partner's earnings are also given but not their piece rate or effort. At the beginning of the redistribution stage, their beliefs about the probability of them having the high and low piece rate are elicited using BSR and following the same procedures as in Danz, Vesterlund and Wilson (2022). The distribution of correctly counted tables from the Full Information treatment is also given[12] (figure A1 in the appendix shows the distribution seen by participants). Before each redistribution decision, participants' beliefs about the probability that their partner got the high and low piece rate are elicited [13].

- No Information: The effort distribution is not given. Participants also see different hypothetical situations, where there is more uncertainty about their partner's earnings[14]. Since participants cannot update using Bayes, an additional stage is added before the redistribution stage to have a benchmark to compare beliefs to.

  – Spectator Stage: Participants are shown the earnings of a different participant from previous sessions, and their beliefs about the probability that this participant got the high and low piece rate are elicited. No additional information is provided. Participants are shown the earnings of five different participants. Columns 6 and 7 in table B1 show the situations used in this treatment in each stage. Three out of the five situations in the spectator stage are also shown in the redistribution stage of the No Information treatment[15]. In this stage, participants do not know there is going to be a redistribution stage later, so their spectator beliefs work as a benchmark, and conditional on the partner's earnings, any difference between their spectator beliefs and their partners'

[12] This allows having a clear Bayesian benchmark to compare the beliefs to.

[13] Participants see the same situations as in the Full Information treatment.

[14] The situations for the previous treatments were determined such that the Bayesian beliefs about the partner's piece rate covered the whole range. To do this, data from the counting zero tasks in Abeler et al. (2011) and Zimmermann (2020) was used, but the effort on those papers was much higher than in this sample, and the Bayesian posteriors ended up being extreme in the majority of the initial situations.

[15] The earnings for the situations of this stage were chosen by the experimenter. To determine the level of effort and piece rate, conditional on the earnings, one participant from the Full or Partial Information treatment was randomly chosen.

beliefs could be explained by motivated beliefs to excuse selfishness.

Table 1 summarizes the treatments.

Table 1: Overview of Treatments

Treatment	Information Known: About Self	Information Known: About Partner	Belief Elicitation	# Sessions	# Participants
Full Information	Piece Rate Effort Earnings	Piece Rate Effort Earnings	None	3	52
Partial Information	Earnings Effort Distribution	Earnings Effort Distribution	Self Partner	8	108
No Information	Earnings	Earnings	Spectator Self Partner	7	104

Implementation

Students were recruited to participate in the experiment at the Pittsburgh Experimental Economics Laboratory (PEEL) during April and September 2023. In total, 264 students participated in the experiment, with 52 students in the Full Information treatment, 108 in the Partial Information, and 104 in the No Information treatment[16][17].

The belief elicitations were incentivized using the BSR. For the spectator's belief elicitation, one out of the five decisions was chosen for payment, and participants could win \$1[18]. For the beliefs elicitation in the redistribution stage, one of the beliefs about their own piece rate or about their partner's in the real situation was randomly selected for payment[19][20]. The sessions lasted ap-

[16] The Partial and No Information treatments are separately preregistered in the AEA RCT Registry under the ID AEARCTR-0011312 and ID AEARCTR-0012181, respectively.

[17] Sessions sizes range from 10 to 22 participants.

[18] The probability of winning the \$1 depends on the accuracy of their guess for the actual piece rate. Let $k \in \{Low, High\}$ be the actual piece rate, and P_k the probability they think was the piece rate. The probability of winning is given by:

$$Pr(\text{winning}) = 1 - \left(1 - \frac{P_k}{100}\right)^2$$

[19] The payment for this belief elicitation varied across treatments. In the Partial Information treatment, participants could win \$4 and in the No Information treatment \$1.

[20] Since the incentive for the belief elicitation comes from the real situation, the situations for the No Information treatment only require the earnings, but not the piece rate or effort level.

proximately 45 minutes for the Full Information treatment, 60 minutes for the Partial Information, and 70 minutes for the No Information, with participants earning an average of \$13.83, \$16.93, and \$18.68, respectively.

The experiment was programmed using oTree (Chen, Schonger and Wickens, 2016). At the beginning, instructions about the real-effort task and piece rates were read aloud in addition to being provided on paper. After instructions were read, participants completed a set of comprehension questions. If they made a mistake, a short explanation was given, but they could not move to the next question until they answered correctly. After they have answered every question correctly, the production stage begins. In the Full and Partial Information treatments, the instructions for the following stage were shown on the screen, while in the No Information treatment, a new set of instructions was handed out and read aloud between the spectator and the redistribution stage. This was done to distract participants so they would not remember the spectator's earnings they had just seen. At the end of the experiment, participants answered demographic questions, including a free-response question about how they made their decisions, and a question asking which of the 11 situations they thought was the real one. In the No Information treatment, participants were also asked to state how much they agreed or disagreed (on a 5-point Likert scale) with a series of statements about the importance of income inequality and the role of luck. Instructions from the experiment are available in the Appendix.

3 Theoretical Framework

Following (Cappelen et al., 2013*a*) decision makers (participants) are assumed to be motivated by both their own earnings and fairness, and they choose the earnings they will keep to themselves (y) out of the sum of earnings of them and their partners (X) to maximize the following utility function:

$$V(y;\cdot) = \gamma y - \beta_i \frac{(y - m^{k(i)})^2}{2X}$$

where $m^{k(i)}$ correspond to the decision maker fairness view, i.e. how much they think they deserve, γ the weight attached to their own income, and β_i the weight attached to fairness.

As mentioned above, the three fairness views are:

- Egalitarian: $m^E = \frac{1}{2}X$
- Libertarian: $m^L = w_i$
- Meritocrat: $m^M = \frac{e_i}{e_i+e_j}X$

where w_i and e_i are the earnings and effort of the decision maker in the effort task, respectively, and e_j is the effort of their partner.

Under full information, the optimal distribution to themselves is:

$$y^* = \begin{cases} m^{k(i)} + \frac{\gamma}{\beta_i}X & if \quad \frac{\gamma}{\beta_i} \leq 1 - \frac{m^{k(i)}}{X} \\ X & if \quad \frac{\gamma}{\beta_i} > 1 - \frac{m^{k(i)}}{X} \end{cases} \tag{1}$$

The optimal distribution depends on participants' fairness views and the importance they place on fairness relative to their own income. If fairness is very important to them ($\beta_i \rightarrow \infty$), they will redistribute to themselves what they consider fair. The less they care about fairness (smaller values of β_i), the more they redistribute to themselves above what they consider fair. If the weight of self-interest relative to fairness ($\frac{\gamma}{\beta_i}$) exceeds the share of total earnings they believe their partner deserves ($1 - \frac{m^{k(i)}}{X}$), they will take everything for themselves. In the extreme case where they do not care about fairness ($\beta \rightarrow 0$), they will always take everything, regardless of their fairness views. This highlights a crucial distinction between selfishness and fairness: while individuals may hold varying opinions about what is fair if they prioritize their own income above others, their fairness views will not influence their decisions, and they will act solely in their own best interest.

Under incomplete information, decision makers only observe their own earnings (w_i) and their partner (w_j), but they do not know the effort levels done by either of them or their respective piece rates. This information is only relevant for individuals with meritocratic fairness views, as egalitarians and libertarians are unaffected by effort levels in their fairness assessments. Hence, under incomplete information, the optimal distribution for meritocrats is given by:

$$y^*_M = \begin{cases} \left(\mathbb{E}\left[\frac{e_i}{e_i+e_j}\middle|(w_i, w_j)\right] + \frac{\gamma}{\beta_i}\right)X & \text{if} \quad \frac{\gamma}{\beta_i} \leq 1 - \mathbb{E}\left[\frac{e_i}{e_i+e_j}|(w_i, w_j)\right] \\ X & \text{if} \quad \frac{\gamma}{\beta_i} > 1 - \mathbb{E}\left[\frac{e_i}{e_i+e_j}|(w_i, w_j)\right] \end{cases}$$

Therefore, the effect of limited information on redistribution will depend on the proportion of participants with meritocratic fairness views and the expected effort share, which relies on their beliefs about having the high piece rate for both themselves and their partners, given the earnings they observe. In the presence of motivated beliefs, participants may perceive the probability that their partner received the high piece rate as weakly higher than it actually was while believing the probability that they themselves received the high piece rate as weakly lower. This bias would lead participants to overestimate their own effort share, increasing both the redistribution to themselves and the frequency of purely selfish decisions ($y^* = X$).

4 Main Results

4.1 Beliefs

This section compares the differences in beliefs between the No Information and Partial Information treatments for both the partner and self. It also examines the differences in beliefs between the partner and spectator in the No Information treatment. A detailed analysis of the partners' beliefs and the Bayesian benchmark is provided in Appendix C. The main analysis focuses on the hypothetical situations, comparing the Partial Information and No Information treatments, as well as the partner and spectator in the No Information treatment, excluding the final decision made by participants, which corresponds to the real scenario.

4.1.1 Beliefs About Own Piece Rate

Figure 1 displays the average beliefs about participants' own piece rate by treatment, separated into those who received the high piece rate and those who received the low piece rate. On average, participants who received the low piece rate believed they had a 24.6% chance of having the high piece rate in the Partial Information treatment and a 22.9% chance in the No Information treatment. Those who received the high piece rate believed they had it with a probability of 84% in the Partial Information treatment and 82.3% in the No Information treatment. The difference between treatments is not statistically significant for either group ($p = 0.7294$ and $p = 0.747$ respectively).

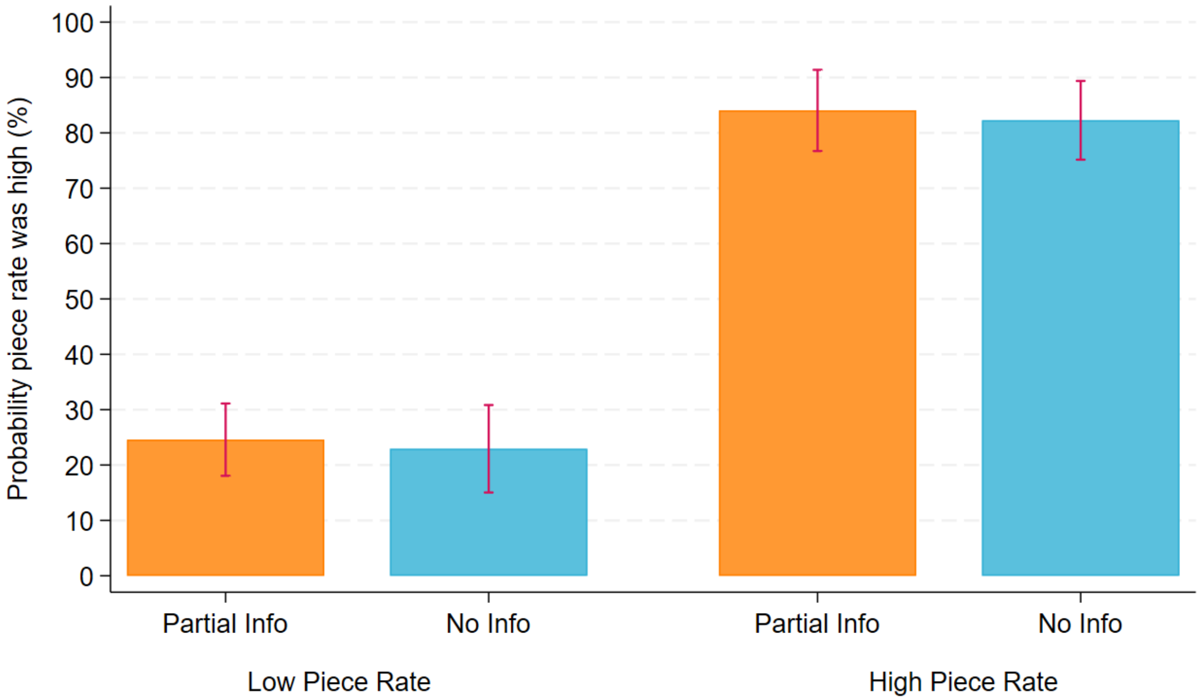

Figure 1: Probability of having the high piece rate by actual piece rate

This suggests that having more information does not affect participants' beliefs about the role of luck in determining their own earnings. Table 2 presents the corresponding regressions, with the Partial Information treatment as the reference category and the probability of having the high piece rate as the dependent variable. The estimate for being in the No Information treatment is not significant ($p = 0.723$). As expected, both earnings and the actual piece rate significantly and positively affect beliefs: each additional dollar of earnings increases the probability of believing they had the high piece rate by 2.92 percentage points, while actually receiving the high piece rate raises this probability by 44.35 percentage points. Columns 3 and 4 show the effect of information and earnings on beliefs, separated by the actual piece rate received. As in the pooled regression, having more information does not influence beliefs ($p = 0.904$ for those with the low piece rate and $p = 0.623$ for those with the high piece rate). For participants with the low piece rate, their earnings did not have a significant effect on their beliefs about themselves ($p = 0.143$), which could be explained by the fact that for lower earnings, the Bayesian posterior is not linear with respect to earnings, as demonstrated in Appendix C figure D1.

Table 2: Probability Own Piece Rate was High

	Main		Low Piece Rate	High Piece Rate
	(1)	(2)	(3)	(4)
No Info	1.205	1.385	-0.684	2.640
	(3.520)	(3.898)	(5.654)	(5.352)
Own Earnings	3.186***	2.928***	3.323	2.856***
	(0.722)	(0.771)	(2.251)	(0.777)
Own Piece Rate	41.63***	44.35***		
	(5.319)	(5.615)		
Constant	14.44***	0.0767		71.87***
	(3.610)	(21.77)		(23.15)
Observations	212	212	117	95
Controls	No	Yes	Yes	Yes

Note: The table reports OLS estimates for participants in the Partial and No Information treatments, where the dependent variable is participants' belief about the probability that their own piece rate was high (in %). The key independent variable is "No Info", indicating if the participant was in the No Information treatment. "Own Earnings" and "Own Piece Rate" refer to the earnings and piece rate the participant received during the Production Stage, though participants did not observe their own piece rate. Column 1 and Column 2 present results with and without controls, while Columns 3 and 4 show heterogeneous effects based on the piece rate received. Controls include age, number of incorrect answers in comprehension questions, and indicators for male gender, political affiliation, ethnicity, college year, high income, and liberal political views. Column 3 excludes the constant term because, for participants with the low piece rate, the probability of having the high piece rate is expected to be close to zero. Standard errors are in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

Result: Excuses do not increase the likelihood that my own success is attributed to effort.

4.1.2 Beliefs About Partner's Piece Rate

Figure 2 shows the average belief for each partner's earnings by treatment. In both the Partial and No Information treatments, partner earnings are identical in three situations: \$5, \$5.5, and \$6. In these three cases, participants in the No Information treatment, on average, believe that the probability their partner got the high piece rate is 12.8, 11.1, and 10.3 percentage points higher, respectively, compared to the Partial Information treatment. These differences are highly significant ($p < 0.001$ for \$5 and \$5.5, and $p = 0.002$ for \$6). This pattern holds across all earnings levels, with an average difference of 13.5 percentage points between the Partial and No Information treatments ($p < 0.001$). These results suggest that in environments with greater uncertainty, participants are more likely to attribute their partner's earnings to luck rather than effort.

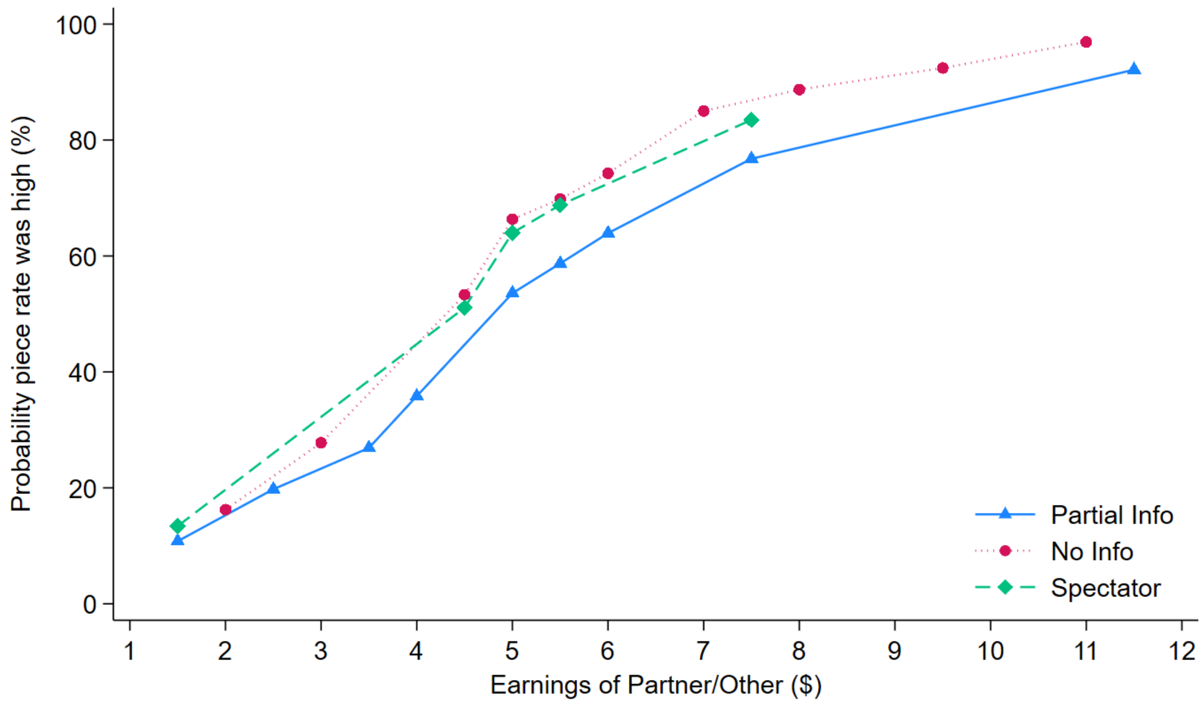

Figure 2: Belief that partner had the high piece rate

The regression analysis in Table 3 confirms these findings: being in environments with more uncertainty increases the belief that partners were lucky and, consequently, exerted less effort. Column 1 presents the effect of information for the same three situations, while Column 2 includes all hypothetical decisions made by participants. Columns 3 and 4 explore heterogeneous effects for participants with low and high piece rates, respectively. Across all specifications, the effect of information is highly significant, and as expected, the higher the partner's earnings, the higher the belief that they received the high piece rate.

The piece rate that participants themselves had influenced their beliefs about their partners. For those with the low piece rate, the constant is not significantly different from zero ($p = 0.431$), but for those with the high piece rate, it is 65.91 and highly significant ($p = 0.002$). The effect of increased uncertainty is larger for participants with the high piece rate than for those with the low piece rate. Interestingly, participants' political affiliations only played a role when they received the high piece rate, as shown in Table B5 in Appendix B. Democrats are 24.52 percentage points less likely to believe their partner had the high piece rate compared to Republicans ($p = 0.008$), and independents are 29.97 percentage points less likely ($p < 0.001$) to believe their partner had the high piece rate compared to Republicans. These political differences in beliefs are not observed for participants with the low piece rate, suggesting that political affiliations influence beliefs more when they had had luck.

Table 3: Probability Partner Piece Rate was High

	Same Situations (1)	All Decisions (2)	Low Piece Rate (3)	High Piece Rate (4)
No Info	11.45***	14.83***	10.21***	16.53***
	(2.919)	(1.803)	(3.598)	(4.576)
Partner Earnings	9.175***	7.029***	10.49***	7.558***
	(1.575)	(0.152)	(1.911)	(2.678)
Constant	34.11**	18.02*	-27.46	65.91***
	(16.37)	(9.285)	(34.73)	(20.72)
Observations	636	2120	351	285
Controls	Yes	Yes	Yes	Yes

Note: The table reports OLS estimates for participants in the Partial and No Information treatments, where the dependent variable is the belief about the probability that their partner's piece rate was high (in %). The independent variable of interest is "No Info", indicating if the participant was in the No Information treatment. "Partner Earnings" refers to the earnings their partner received during the Production Stage. Column 1 ("Same Situations") includes only decisions where the partner's earnings were the same across treatments - \$5, \$5.5, and \$6. Column 2 ("All Decisions") includes all hypothetical decisions made by participants. Column 3 ("Low Piece Rate") presents results for the same situations as in Column 1 but only for participants who received the low piece rate, while Column 4 ("High Piece Rate") presents results for those with the high piece rate. All regressions include controls for age, number of incorrect answers on comprehension questions, and indicators for male gender, political affiliation, ethnicity, college year, high income, and liberal political views. Standard errors are in parentheses and are clustered at the individual level (212 clusters for Columns 1 and 2, 117 clusters for Column 3, and 95 for Column 4). $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Result: Excuses increase the likelihood that partner success is attributed to luck

4.1.3 Spectators

Figure 2 also shows the average belief for each partner's earnings by type of decision - Spectator or Partner - in the No Information treatment. For both decision types, the other person's earnings are identical in three situations: \$4.5, \$5, and \$5.5. In these cases, participants believed their partner received the high piece rate 2.2, 2.3, and 1 percentage points higher, respectively, than for spectators, though these differences are not statistically significant ($p = 0.547$ for \$4.5, $p = 0.489$ for \$5, and $p = 0.763$ for \$5.5). This result suggests that participants are equally likely to attribute others' earnings to luck rather than effort, regardless of whether they need an excuse to justify selfish behavior. Table B2 in appendix B corroborates this result.

One possible explanation for this behavior is that redistribution and meritocracy are highly salient in people's minds (Sandel, 2020), and regardless of whether their earnings will be affected by redistribution, participants want to believe they deserve what they received. Another explanation is that the Partner and Spectator treatments in the No Information condition are within-subject, with both stages conducted consecutively. This could lead to the responses participants gave in the Spectator stage serving as an anchor for their beliefs about their partners.[21].

4.2 Redistribution and Inequality

As in the previous section, the analysis focuses on the hypothetical situations. Figure 3 shows the average share of pooled earnings (both their own and their partner's) that participants keep for themselves, broken down by their partner's earnings and treatment. In the three scenarios where partner earnings are the same across both treatments ($5, $5.5, and $6), participants in the No Information treatment, on average, keep 6.8 percentage points more of the earnings for themselves compared to those in the Partial Information treatment ($p < 0.001$). Across all earnings levels, participants in the No Information treatment tend to keep a larger share, with an overall average difference of 5.4 percentage points ($p < 0.001$), though this difference is not linear with respect to earnings. For earnings below $5, the difference between treatments is 2.8 percentage points ($p = 0.061$), while for earnings of $5 or more, the difference rises to 8 percentage points ($p < 0.001$).

Result:

- Excuses increase selfishness
- The effect of excuses increases with partner's earnings

Table 4 complements these results. After controlling for demographics, there is a weakly significant difference between treatments, with participants in the No Information treatment keeping 4.9 percentage points more of the earnings for themselves ($p = 0.098$). Expected effort share has

[21] Ideally, this would have been implemented as a between-subject treatment, where participants performed the real effort task and only answered the Spectator stage without the redistribution stage. However, due to funding and participant pool constraints at the time, this was not feasible.

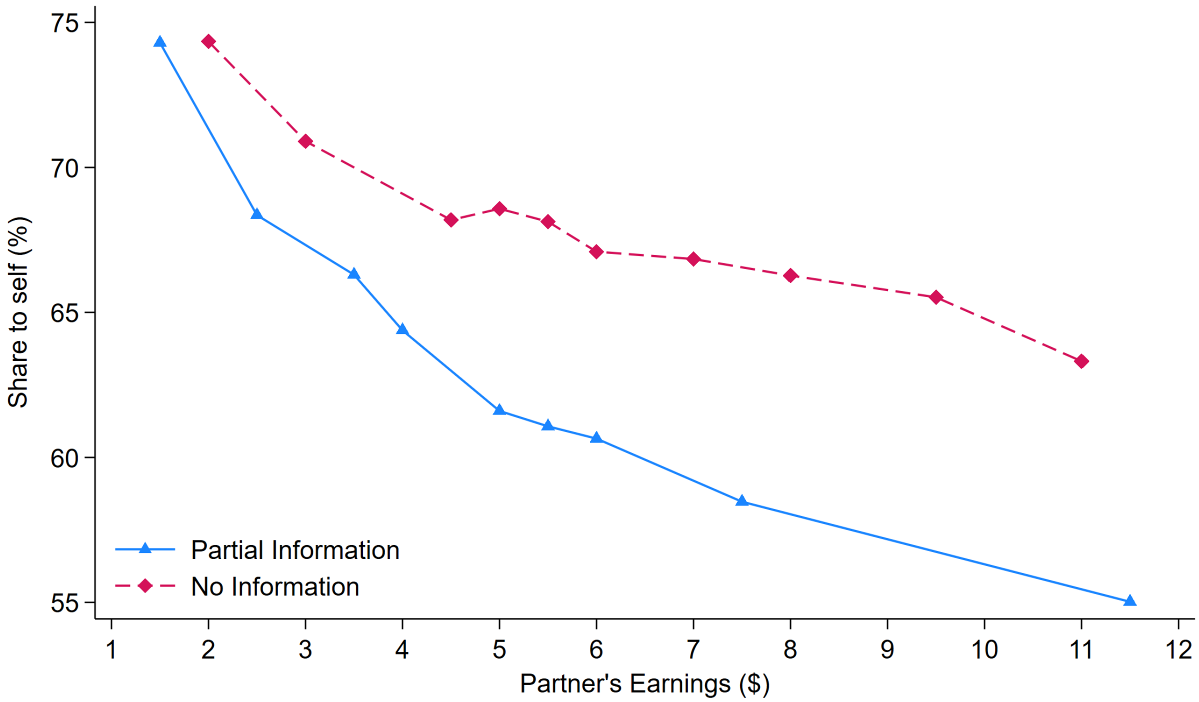

Figure 3: Share of joint earnings kept by decision maker

a significant and positive effect on redistribution to themselves ($p = 0.002$); the more participants believe they exerted more effort relative to their partner, the more they keep for themselves. As discussed in Section 3, beliefs should influence redistribution only for those holding a meritocratic fairness view; egalitarians and libertarians are expected to be unaffected by the information environment. Thus, one would expect the treatment effect on redistribution to disappear once the expected effort share is included. However, this is not observed in column (3), where the treatment effect remains nearly unchanged, even though it is not significant anymore ($p = 0.102$).

In column (4), it is assumed that the effect of effort share varies between treatments, potentially due to different proportions of meritocrats across treatments (unexplained by demographic characteristics). Once the interaction term is added, there is no significant difference between treatments either in the effect on redistribution or in the effect of effort share on redistribution ($p = 0.362$ and $p = 0.621$, respectively). Another possibility is that expected effort share has a different effect depending on the partner's earnings; column (5) in Table B6 confirms this relationship.

Inequality is measured by the GINI Coefficient between the pair for each decision:

Table 4: Redistribution to themselves

	(1)	(2)	(3)	(4)
No Info	6.825**	4.867*	4.732	9.746
	(2.820)	(2.930)	(2.880)	(10.68)
$\mathbb{E}$[Effort Share]			0.357***	0.410***
			(0.112)	(0.142)
No Info × $\mathbb{E}$[Effort Share]				-0.110
				(0.221)
Constant	61.11***	56.78***	38.61**	36.52**
	(1.857)	(19.27)	(17.95)	(17.92)
Observations	636	636	636	636
Controls	No	Yes	Yes	Yes

Note: Standard errors are in parentheses and clustered at the individual level.
$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

$$I_{is} = \left| \frac{y_i^s - (X^s - y_i^s)}{y_i^s + (X^s - y_i^s)} \right|$$

where s represents the situation. The inequality before and after redistribution is calculated. Inequality levels before and after redistribution were calculated, and Figure 4 illustrates the effect of redistribution on average inequality by treatment. In the Partial Information treatment, inequality does not significantly change after redistribution, whereas in the No Information treatment, inequality increases, rising from levels similar to France to those comparable to Brazil. These results suggest that inequality acceptance can be reduced without requiring complete information about effort and luck as sources of inequality. Instead, providing information about the distribution of effort within the population could help reduce inequality acceptance. This finding points to feasible policy interventions that target informational transparency as a means to mitigate inequality.

5 Fairness Views

The previous analysis focused on how uncertainty creates room for belief distortion, allowing individuals to accept higher levels of inequality and justify selfish behavior. A key assumption for uncertainty to provide excuses is that individuals hold a meritocratic fairness view, believing that redistribution should be based on effort. However, as Almås, Cappelen and Tungodden (2020)

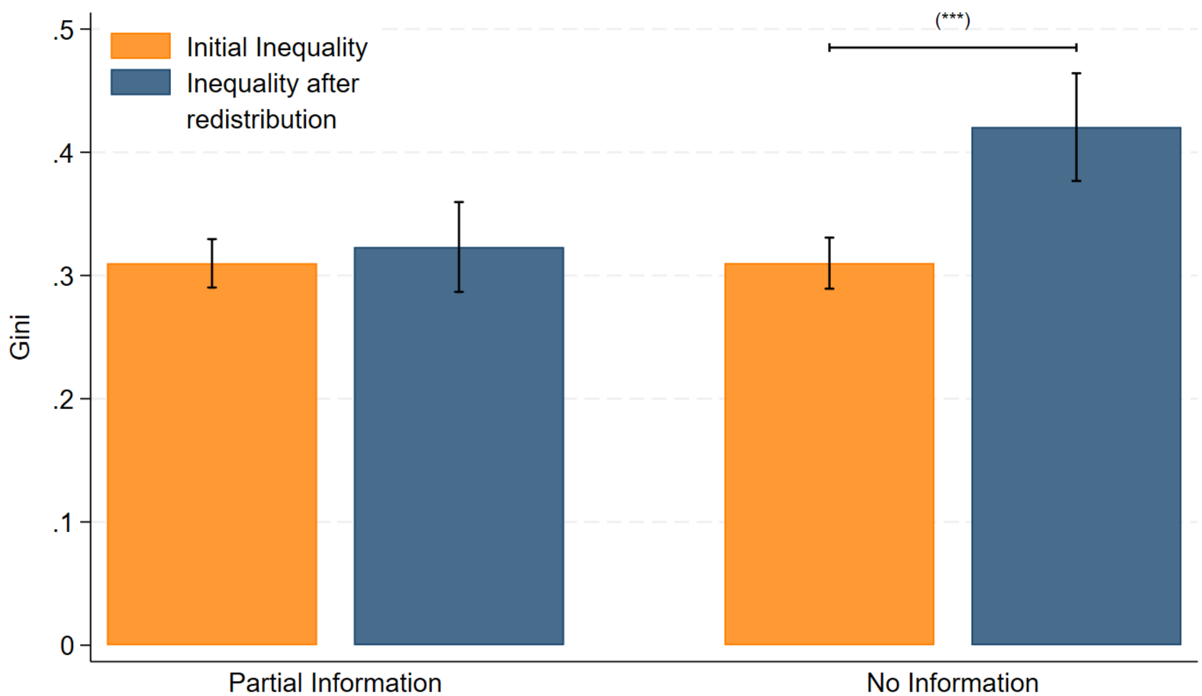

Figure 4: Inequality before and after redistribution

demonstrates, meritocracy is not the only fairness view; three main views—Egalitarian, Libertarian, and Meritocratic—are widely represented in society. Egalitarians reject inequality altogether, believing earnings should be split equally regardless of its source. At the opposite end, libertarians also disregard the source of inequality but oppose redistribution, considering initial inequalities to be fair.

For meritocrats, effort and luck influence the amount deemed fair but should not affect whether one holds a meritocratic view. In the absence of self-serving biases, fairness views may be expected to be independent of one's own earnings and effort. An alternative possibility, however, is that individuals may "choose" fairness views in self-serving ways (Konow, 2000). For example, those with higher earnings may adopt libertarian views, opposing redistribution irrespective of beliefs about luck and effort. Conversely, lower earners might lean towards egalitarianism, which calls for redistribution that aligns with their self-interest. Notably, this mechanism operates independently of any information available about effort.

5.1 Estimation of the Choice Model

Continuing following Cappelen et al. (2013*a*), it is assumed a discrete choice random utility model,

$$U(y;\cdot) = V(y;\cdot) + \epsilon_{iy} \text{ for } y \in \{0, 0.01, 0.02, ..., X\}$$

where each participant i is characterized by $(\beta_i, k(i))$, ϵ_{iy} is assumed to be i.i.d extreme value, and $\log \beta \sim N(\mu, \sigma^2)$. As in Cappelen et al. (2013*a*), the estimates of γ and β represent the weight of noise relative to own income and fairness, respectively.

The likelihood function of an individual is given by:

$$L_i(\boldsymbol{\theta}) = \sum_k \lambda_k \int_0^\infty \left(\prod_{j=1}^{J_i} \frac{e^{V(y_{ij};m^k,\beta)}}{\sum_{s\in Y_{ij}} e^{V(s;m^k,\beta)}} \right) f(\beta;\mu,\sigma) d\gamma$$

where λ_k is the population share following fairness view k, $j = 1, ..., J_i$ represents each decision made by each participant, $Y_{ij} \in \{0, ..., X_{ij}\}$ includes all possible distribution participant i can choose from in situation j, and $\boldsymbol{\theta} = (\lambda_E, \lambda_L, \lambda_M, \gamma, \mu, \sigma)$ is a vector with all parameters that are going to be estimated.

The model calculates the probability that participants follow each fairness view based on their decisions, and it estimates the population share for each view, the parameter γ, and the moments of the β distribution by maximizing the likelihood.

5.1.1 Results

Table 5 presents the estimation results for both the Partial Information and No Information treatments. The estimated population share of participants with egalitarian views is higher in the No Information treatment (0.469) than in the Partial Information treatment (0.278). For libertarian views, the population share is higher in the Partial Information treatment (0.398) compared to the No Information treatment (0.315). Similarly, the share of meritocratic views is higher in the Partial Information treatment (0.325) than in the No Information treatment (0.215).

The self-interest weight, γ, is higher in the No Information treatment (1.321) than in the Partial Information treatment (0.789), while the mean fairness weight, β, is lower (2.194 vs. 2.435). Both

Table 5: Estimation Results

	Partial Information			No Information		
Parameter	Full Sample	Low Earnings	High Earnings	Full Sample	Low Earnings	High Earnings
λ_E	0.278	0.377	0.189	0.469	0.650	0.216
	(0.053)	(0.089)	(0.063)	(0.062)	(0.087)	(0.079)
λ_L	0.398	0.266	0.574	0.315	0.215	0.588
	(0.059)	(0.075)	(0.082)	(0.059)	(0.082)	(0.093)
λ_M	0.325	0.357	0.236	0.215	0.135	0.196
	(0.058)	(0.088)	(0.074)	(0.056)	(0.069)	(0.080)
μ	2.435	3.242	2.397	2.194	4.967	-1.841
	(0.032)	(0.039)	(0.043)	(0.026)	(0.062)	(0.867)
σ	2.560	2.350	2.619	2.580	2.681	5.127
	(0.036)	(0.071)	(0.053)	(0.033)	(0.073)	(0.842)
γ	0.789	1.007	0.625	1.321	1.459	0.650
	(0.018)	(0.039)	(0.020)	(0.023)	(0.034)	(0.027)
$\log L$	-5,724.0	-2,683.3	-3,032.2	-5,458.6	-2,895.5	-2,609.7
N	108	52	56	104	54	50

of these differences suggest that participants act more self-interested when they face greater uncertainty about effort. One interpretation is that this behavior stems from ambiguity about whether their partner's earnings are justified by merit, leading participants to avoid the risk of overcompensating and instead keep more for themselves, placing less weight on fairness considerations.

To test whether individuals "choose" what they consider fair in a self-serving way, the sample was split into higher and lower earners[22][23] and the structural model was estimated for each subsample. Columns (3) and (4) show the results of the Partial Information treatment. Participants in the bottom half of the earnings distribution are more in favor of redistribution, with over 70% of participants supporting either egalitarian or meritocratic (conditional on their beliefs) fairness views. In contrast, only 43% of higher earners support any form of redistribution, with 57% adopting a libertarian view.

[22] The median earnings from the three treatments was used to divide the sample.

[23] Although the role of higher or lower earner varies with each decision, higher earners are defined based on the distribution of earnings in the sample, not relative to earnings in hypothetical situations, and this classification remains consistent across decisions. Fairness views are static within each environment, and while some individuals might adjust their views in self-serving ways with each decision, it would be difficult for them to justify these shifts as fair.

A similar but more pronounced pattern is observed in the No Information treatment. Among lower earners, 65% are egalitarian, compared to only 22% among higher earners, 59% of whom adopt a libertarian view. In the No Information treatment, there is also a substantial difference in the weight attached to fairness, with lower earners placing significantly more emphasis on fairness than higher earners.

This result aligns with Konow (2000) and suggests that not only participants' beliefs but also their fairness views may be shaped by self-serving motives. Specifically, higher personal earnings decrease the likelihood of egalitarian and meritocratic behavior, both of which would require high earners to redistribute more to their partners. Konow (2000) finds similar results, showing that fairness views differ between high and low earners by comparing redistribution decisions when they personally benefit versus when they act as spectators. Participants who take more for themselves also tend to allocate more to the advantaged party when acting as spectators, indicating a self-serving bias in fairness judgments.

6 Conclusion

This study investigates the impact of belief distortions and fairness views on redistribution decisions in environments with different levels of information about the sources of inequality—effort and luck. Using a controlled experimental setting, it is observed how participants adjust their beliefs about the deservedness of their earnings and those of their partners, ultimately influencing their redistribution choices. The results show that in environments with less information about the effort exerted, participants are more inclined to attribute others' success to luck and, in turn, justify keeping a larger share of the pooled earnings. This excuse-seeking behavior intensifies inequality, as observed in the No Information treatment, where inequality implemented after redistribution reaches levels comparable to Brazil, while in the Partial Information treatment, it remains relatively unchanged, comparable to the level in France.

The results from a choice model suggest that individuals not only distort their beliefs about fairness but may also selectively adopt fairness views that align with their interests. For example, participants with lower earnings are more likely to adopt egalitarian or meritocratic views that support redistribution, whereas higher earners frequently favor libertarian views that minimize redistribution.

The implications of these findings are significant. First, they suggest that policy interventions could effectively target informational asymmetries to mitigate inequality acceptance without the need for full transparency on effort and luck, which is not feasible. By providing population-level data on effort distributions, policymakers may reduce the acceptance of inequality. Second, the study highlights how fairness views and motivated beliefs can drive political polarization and social instability. When individuals interpret fairness in ways that benefit themselves, this can lead to greater social fragmentation, with the economically advantaged adopting views that justify minimal redistribution and the disadvantaged supporting increased redistribution policies.

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ONLINE APPENDIX

A Figures

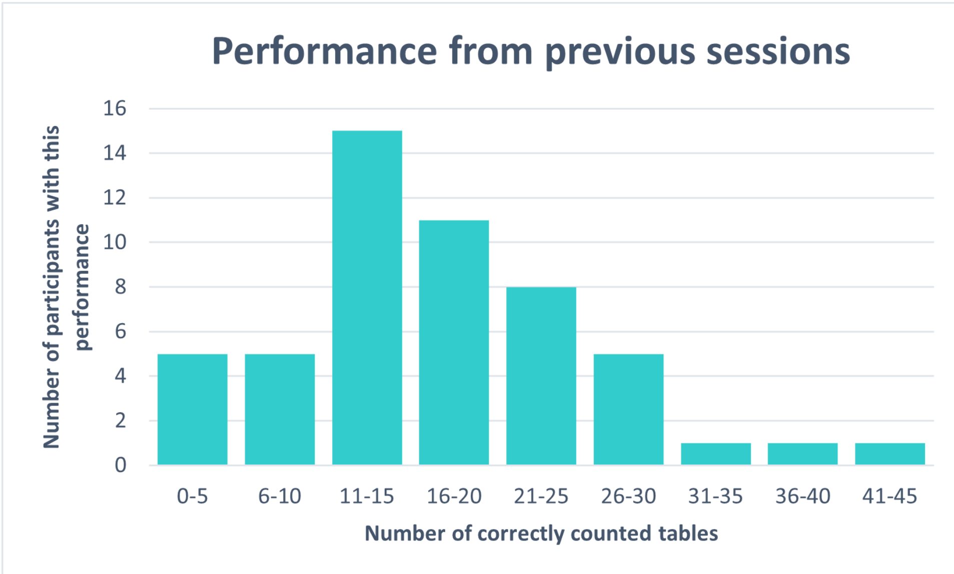


Figure A1: Effort Distribution Shown in Partial Information Treatment

B Tables

Table B1: Situation Summary

Situation			Treatment			
Earnings	Piece Rate	Effort	Full Information	Partial Information	No Information	Spectator
\$1.50	Low	9	x	x		x
\$2					x	
\$2.50	Low	16	x	x		
\$3					x	
\$3.50	Low	22	x	x		
\$4	High	8	x	x		
\$4.50	Low	29			x	x
\$5	Low	30	x	x	x	x
\$5.50	High	11	x	x	x	x
\$6	Low	38	x	x	x	
\$7	High	15			x	
\$7.50	High	15	x	x		x
\$8					x	
\$9.50					x	
\$11					x	
\$11.50	High	23	x	x		
\$16	High	32	x	x		

Table B2: Probability Other Participant Piece Rate was High

	Same Situations (1)	All Decisions (2)	Low Piece Rate (3)	High Piece Rate (4)
Spectator	-1.865	2.173	-0.474	-3.256
	(1.986)	(1.333)	(2.438)	(3.219)
Other Earnings	17.12***	9.709***	16.59***	17.66***
	(1.761)	(0.249)	(2.636)	(2.433)
Constant	-21.21	13.53	-123.9	17.85
	(24.33)	(14.94)	(81.56)	(25.86)
Observations	624	1560	312	312
Controls	Yes	Yes	Yes	Yes

Note: The table reports OLS estimates for participants in the No Information treatment for the belief elicitation for Spectators and Partners. The dependent variable is the belief about the probability that their partner's or another participant's piece rate was high (in %). The independent variable of interest is "Spectator", indicating whether the belief corresponds to the piece rate of the stage "Spectator" (a participant from another session) or to their partner. "Other Earnings" refers to the earnings their partner or the spectator received during the Production Stage. Column 1 ("Same Situations") includes only decisions where the other earnings were the same across treatments - \$4.5, \$5, and \$5.5. Column 2 ("All Decisions") includes all hypothetical decisions made by participants and all spectator decisions. Column 3 ("Low Piece Rate") presents results for the same situations as in Column 1 but only for decision makers who received the low piece rate, while Column 4 ("High Piece Rate") presents results for those with the high piece rate. All regressions include controls for age, number of incorrect answers on comprehension questions, and indicators for male gender, political affiliation, ethnicity, college year, high income, and liberal political views. Standard errors are in parentheses and are clustered at the individual level (104 clusters for Columns 1 and 2, 52 clusters for Column 3, and 52 for Column 4). $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

Table B3: Libertarian and Egalitarians

	Libertarians				Egalitarians			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No Info	-0.126**	-0.128**	-0.110**	-0.111**	0.026	0.028	0.014	0.014
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Age	-0.016	-0.013	-0.020	-0.019	0.029	0.027	0.032*	0.032*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Man	-0.032	-0.049	-0.017	-0.019	-0.016	-0.003	-0.027	-0.025
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Democrat	0.205**	0.233**	0.179**	0.183**	0.110	0.088	0.130*	0.127
	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
Independent	0.162*	0.185**	0.141	0.144*	0.172**	0.154**	0.188**	0.186**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
Not Say	0.041	0.044	-0.000	0.001	0.055	0.053	0.088	0.086
	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
College Year	-0.013	-0.021	-0.023	-0.024	-0.065*	-0.058*	-0.056*	-0.056*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
CQ Mistakes	-0.010	-0.011	-0.011	-0.011	0.001	0.001	0.002	0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Black	-0.117	-0.099	-0.067	-0.067	0.009	-0.006	-0.031	-0.031
	(0.08)	(0.08)	(0.07)	(0.07)	(0.10)	(0.10)	(0.10)	(0.10)
South Asian	-0.029	0.018	0.063	0.064	-0.070	-0.107	-0.141*	-0.142*
	(0.10)	(0.11)	(0.10)	(0.10)	(0.07)	(0.08)	(0.07)	(0.08)
Asian/P Islander	-0.081	-0.067	-0.067	-0.066	-0.043	-0.053	-0.053	-0.054
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Hispanic/Latino	0.006	0.045	0.082	0.083	-0.078	-0.108	-0.136	-0.137*
	(0.12)	(0.11)	(0.11)	(0.11)	(0.09)	(0.08)	(0.08)	(0.08)
Other	-0.109	-0.084	-0.060	-0.059	-0.084	-0.103	-0.122	-0.122
	(0.10)	(0.10)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)
Above Median	-0.092	-0.106	-0.092	-0.093	0.038	0.048	0.038	0.039
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Not Know	-0.103	-0.120	-0.082	-0.085	0.089	0.102	0.073	0.075
	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Liberal	-0.100	-0.112*	-0.095*	-0.097*	0.030	0.040	0.027	0.028
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
$\mathbb{E}$[Effort Share]		0.007***		0.001		-0.005**		-0.001
		(0.00)		(0.00)		(0.00)		(0.00)
Own Earnings			0.034***	0.033***			-0.026***	-0.025***
			(0.01)	(0.01)			(0.01)	(0.01)
Constant	0.694***	0.354	0.618**	0.588**	-0.377	-0.113	-0.318	-0.294
	(0.27)	(0.27)	(0.26)	(0.28)	(0.39)	(0.35)	(0.33)	(0.33)
Observations	636	636	636	636	636	636	636	636
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are in parentheses and are clustered at the individual level. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table B4: Meritocrats and Selfish

	Meritocrats				Selfish			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No Info	0.027	0.024	0.029	0.017	0.076	0.076	0.073	0.074
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Age	0.003	0.006	0.003	0.008	-0.017	-0.018	-0.016	-0.017
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Man	-0.026	-0.044	-0.024	-0.056	0.123**	0.127**	0.120**	0.123**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Democrat	0.081	0.111	0.079	0.132	-0.113	-0.120	-0.108	-0.113
	(0.09)	(0.09)	(0.09)	(0.09)	(0.12)	(0.12)	(0.12)	(0.12)
Independent	0.055	0.078	0.052	0.096	-0.146	-0.152	-0.143	-0.146
	(0.09)	(0.08)	(0.09)	(0.09)	(0.12)	(0.12)	(0.12)	(0.12)
Not Say	0.043	0.046	0.038	0.064	0.049	0.048	0.056	0.054
	(0.10)	(0.10)	(0.10)	(0.11)	(0.14)	(0.14)	(0.13)	(0.14)
College Year	-0.064**	-0.073**	-0.065**	-0.072**	0.084***	0.086***	0.086***	0.087***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
CQ Mistakes	-0.018	-0.019	-0.018	-0.019	-0.019	-0.019	-0.019	-0.019
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Black	0.031	0.051	0.037	0.037	0.137	0.132	0.128	0.128
	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
South Asian	-0.069	-0.020	-0.059	-0.040	-0.023	-0.035	-0.040	-0.042
	(0.09)	(0.09)	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)
Asian/P Islander	-0.028	-0.014	-0.026	-0.014	0.146**	0.142**	0.143**	0.142**
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Hispanic/Latino	-0.092	-0.051	-0.084	-0.067	-0.033	-0.043	-0.047	-0.048
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.10)	(0.10)	(0.10)
Other	-0.089	-0.062	-0.083	-0.073	0.118	0.112	0.109	0.108
	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)
Above Median	0.040	0.026	0.040	0.021	0.035	0.039	0.035	0.037
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Not Know	0.010	-0.007	0.012	-0.022	0.057	0.061	0.053	0.056
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Liberal	-0.064	-0.077	-0.063	-0.083	0.020	0.023	0.020	0.021
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
$\mathbb{E}$[Effort Share]		0.007***		0.009***		-0.002		-0.001
		(0.00)		(0.00)		(0.00)		(0.00)
Own Earnings			0.004	-0.014**			-0.006	-0.005
			(0.01)	(0.01)			(0.01)	(0.01)
Constant	0.345	-0.008	0.336	-0.107	0.240	0.324	0.254	0.291
	(0.26)	(0.28)	(0.26)	(0.28)	(0.23)	(0.25)	(0.23)	(0.25)
Observations	636	636	636	636	636	636	636	636
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are in parentheses and are clustered at the individual level. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table B5: Probability Partner Piece Rate was High

	Same Situations (1)	All Decisions (2)	Low Piece Rate (3)	High Piece Rate (4)
No Info	11.51***	14.83***	10.19***	16.68***
	(2.915)	(1.806)	(3.540)	(4.595)
Partner Earnings	9.175***	7.029***	10.49***	7.558***
	(1.577)	(0.152)	(1.914)	(2.683)
Age	-1.025	-0.306	1.832	-1.966***
	(0.692)	(0.489)	(1.733)	(0.663)
Man	0.849	-0.711	-6.178	6.428
	(3.201)	(1.844)	(4.018)	(4.823)
Democrat	-11.76**	-6.386*	0.534	-24.52***
	(5.931)	(3.571)	(6.335)	(9.057)
Independent	-8.383	-4.695	10.04	-29.97***
	(5.935)	(3.609)	(6.526)	(8.308)
Not Say	-7.802	-3.837	-1.331	-17.42**
	(5.816)	(3.567)	(6.932)	(8.080)
CQ Mistakes	-0.220	-0.588	-0.360	1.028
	(1.223)	(0.730)	(1.805)	(1.810)
Black	1.078	1.421	-10.28	4.055
	(6.154)	(3.629)	(11.42)	(7.393)
South Asian	6.774	7.080**	5.088	6.317
	(5.475)	(3.296)	(6.106)	(10.08)
Asian/P Islander	-0.197	0.308	2.514	-6.418
	(3.932)	(2.417)	(4.814)	(5.515)
Hispanic/Latino	14.68***	9.872***	10.40	5.718
	(4.569)	(3.684)	(6.547)	(6.658)
Other	6.342	5.477*	0.839	9.399
	(4.530)	(2.799)	(5.892)	(9.893)
College Year	1.201	0.557	-0.408	0.466
	(1.653)	(1.083)	(2.564)	(2.925)
Above Median	6.485	0.758	5.908	4.910
	(4.005)	(2.446)	(5.872)	(5.734)
Not Know	4.502	0.756	4.328	5.662
	(4.278)	(2.606)	(5.831)	(6.862)
Liberal	0.909	0.980	-0.685	0.259
	(3.784)	(2.423)	(4.292)	(6.335)
Constant	28.92*	17.73*	-36.54	65.79***
	(16.27)	(9.400)	(36.42)	(20.09)
Observations	636	2120	351	285
Controls	Yes	Yes	Yes	Yes

Note: The table reports OLS estimates for participants in the Partial and No Information treatments, where the dependent variable is the belief about the probability that their partner's piece rate was high (in %). The independent variable of interest is "No Info", indicating if the participant was in the No Information treatment. "Partner Earnings" refers to the earnings their partner received during the Production Stage. Column 1 ("Same Situations") includes only decisions where the partner's earnings were the same across treatments - \$5, \$5.5, and \$6. Column 2 ("All Decisions") includes all hypothetical decisions made by participants. Column 3 ("Low Piece Rate") presents results for the same situations as in Column 1 but only for participants who received the low piece rate, while Column 4 ("High Piece Rate") presents results for those with the high piece rate. All regressions include controls for age, number of incorrect answers on comprehension questions, and indicators for male gender, political affiliation, ethnicity, college year, high income, and liberal political views. Standard errors are in parentheses and are clustered at the individual level (212 clusters for Columns 1 and 2, 117 clusters for Column 3, and 95 for Column 4). $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

Table B6: Redistribution

	(1)	(2)	(3)	(4)	(5)
No Info	5.262*	3.357	3.770	9.779	4.206
	(2.719)	(2.792)	(2.726)	(10.69)	(2.727)
Partner Earnings	-1.147***	-1.147***	-0.601***	-0.700	0.545*
	(0.113)	(0.113)	(0.194)	(0.834)	(0.318)
Age		-0.622	-0.543	-0.320	-0.557
		(0.966)	(0.835)	(0.816)	(0.837)
Man		5.900**	5.169*	4.403	5.239*
		(2.943)	(2.918)	(2.974)	(2.923)
Democrat		-7.298	-6.367	-8.958	-6.376
		(6.057)	(5.575)	(5.437)	(5.608)
Independent		-8.724	-7.930	-10.48*	-7.939
		(5.864)	(5.434)	(5.352)	(5.462)
Not Say		0.990	0.741	0.506	0.767
		(6.569)	(6.161)	(6.027)	(6.190)
CQ Mistakes		-0.582	-0.572	-0.506	-0.579
		(1.093)	(1.054)	(1.075)	(1.056)
College Year		5.258***	4.828***	5.552***	4.863***
		(1.826)	(1.751)	(1.784)	(1.753)
Black		8.354*	9.325*	8.078	9.258*
		(4.966)	(4.979)	(5.458)	(4.991)
South Asian		-1.500	1.055	1.919	0.820
		(4.716)	(4.681)	(4.693)	(4.685)
Asian/P Islander		8.373**	9.032**	9.745**	8.993**
		(3.640)	(3.700)	(3.857)	(3.700)
Hispanic/Latino		-10.93*	-8.430	-8.046	-8.592
		(5.604)	(5.416)	(5.944)	(5.426)
Other		8.672	10.01	10.88	9.877
		(6.607)	(6.756)	(6.789)	(6.756)
Above Median		-0.00616	-0.200	-0.247	-0.124
		(3.524)	(3.577)	(3.742)	(3.577)
Not Know		2.066	1.558	1.034	1.608
		(3.788)	(3.817)	(3.971)	(3.818)
Liberal		0.378	-0.229	2.282	-0.237
		(3.515)	(3.467)	(3.568)	(3.474)
$\mathbb{E}$[Effort Share]			0.346***	0.409***	0.500***
			(0.101)	(0.142)	(0.0843)
No Info × $\mathbb{E}$[Effort Share]				-0.110	
				(0.222)	
$\mathbb{E}$[Effort Share] × Partner Earnings					-0.0276***
					(0.00887)
Constant	69.71***	70.83***	50.35***	40.43**	43.47**
	(1.718)	(19.23)	(18.34)	(18.86)	(18.02)
Observations	2120	2120	2120	636	2120
Controls	No	Yes	Yes	Yes	Yes

Note: Standard errors are in parentheses and clustered at the individual level. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

C Partial Information: Beliefs vs Bayesian Benchmark

This section compares participants' beliefs about their own and their partner's luck for the Partial Information treatment with the Bayesian benchmark. This analysis is not conducted for the No Information treatment because participants do not observe the distribution of effort and, therefore, could not apply Bayes' rules. First, it discusses how the Bayesian benchmark is calculated, as well as factors that could affect belief updating beyond motivated reasoning. In the second part, the analysis comparing the Bayesian posteriors with the elicited beliefs is discussed.

C.1 Bayesian Benchmark

In the belief elicitation, participants are asked to report the probability they think someone (their partner or themselves) has the high (and low) piece rate after observing the earnings and the effort distribution. The Bayesian posterior is given by:

$$\Pr(p = H|w) = \frac{\Pr(w|p = H)\Pr(p = H)}{\Pr(w|p = H)\Pr(p = H) + \Pr(w|p = L)\Pr(p = L)}$$

where $p \in \{L, H\}$ is the piece rate and w is the earnings from the real effort task. The prior probability of having the high or low piece rate is 50%, therefore is not necessary to include the prior in the calculations, and beliefs are not affected by base-rate neglect.

To be able to find the probability of having earnings w conditional on the piece rate, the payment structure and effort distribution are needed. With the high piece rate, participants get 50 cents for each correctly counted table, and with the low piece rate, 50 cents for every three correctly counted tables. This means that there are three possible effort levels for the same earnings with the low piece rate and only one with the high piece rate. For example, if someone earned \$6 and got the high piece rate, that means that they correctly counted 12 tables, but if they got the low piece rate, they correctly counted 18, 19, or 20 tables. Let's denote e_H the effort level if the piece rate was high, and e_{L1}, e_{L2}, and e_{L3} the three possible effort levels if the piece rate was low. Then, the Bayesian posterior is:

$$\Pr(p = H|w) = \frac{\Pr(w|p = H)}{\Pr(w|p = H) + \Pr(w|p = L)} = \frac{\Pr(e_H(w))}{\Pr(e_H(w)) + \Pr(e_{L1}(w)) + \Pr(e_{L2}(w)) + \Pr(e_{L3}(w))}$$

This payment structure makes it more challenging to find the Bayesian posterior because it needs to include the probability for each effort level, increasing complexity, and participants might not consider this when updating their beliefs. For example, they might only consider one effort level for the low piece rate.

Figure D1 illustrates the Bayesian posteriors, with the dashed blue line representing the posteriors using only one low effort level and the solid blue line representing the posteriors with the three low effort levels[24]. The difference is substantial between both, and using only one effort level weakly overestimates the effect of luck (the probability of having the high piece rate is higher) for every possible earnings, and strictly for earnings up to $7, and in some cases, the posterior is more than 30 percentage points higher.

Another factor that makes finding the posteriors more challenging is the effort distribution. Figure A1 in Appendix A shows the effort distribution shown to participants in the Partial Information treatment, which corresponds to the effort distribution of the participants from the Full Information treatment. The figure does not show the exact number of participants that did each possible effort level but rather shows them in ranges of five. For example, it shows that 15 participants had between 11 and 15 correctly counted tables. How participants use this information depends on their beliefs about the effort distribution in each bracket. For example, out of the 15 people who correctly counted between 11 and 15 tables, participants might believe that it is more likely that a majority of those 15 people counted 14 or 15 tables rather than 11 or 12. To calculate the posteriors, it will be assumed that the effort levels are uniformly distributed in each bracket, this is with loss of generality.

Panel D2a shows the Bayesian posterior of having the high piece rate for every level of earnings using the effort from the Full Information treatment. The dashed line shows the posterior if

[24] Bayes is calculated assuming the three low piece rate efforts are equally likely. If participants are only paid every three tables, when there is not much time left, they might stop working if they need to correctly count two more tables to increase their payment by 50 cents, making e_{L1} more likely than the other two low effort levels. For this experiment, this strategy was very unlikely because participants did not know which piece rate they got while doing the task, leading to earning less money on expectation. There was also no feedback, so they did not know if they counted all the tables correctly or if they made a mistake. Each table consisted of 150 zeros and ones, with the number of zeros varying (on average) between 50 and 100 zeros, so mistakes were likely. Participants neither knew how many tables they solved (correctly or incorrectly). For all of these reasons, it is very unlikely that participants followed the aforementioned strategy, and assuming the three low piece rate efforts are equally likely is without loss of generality.

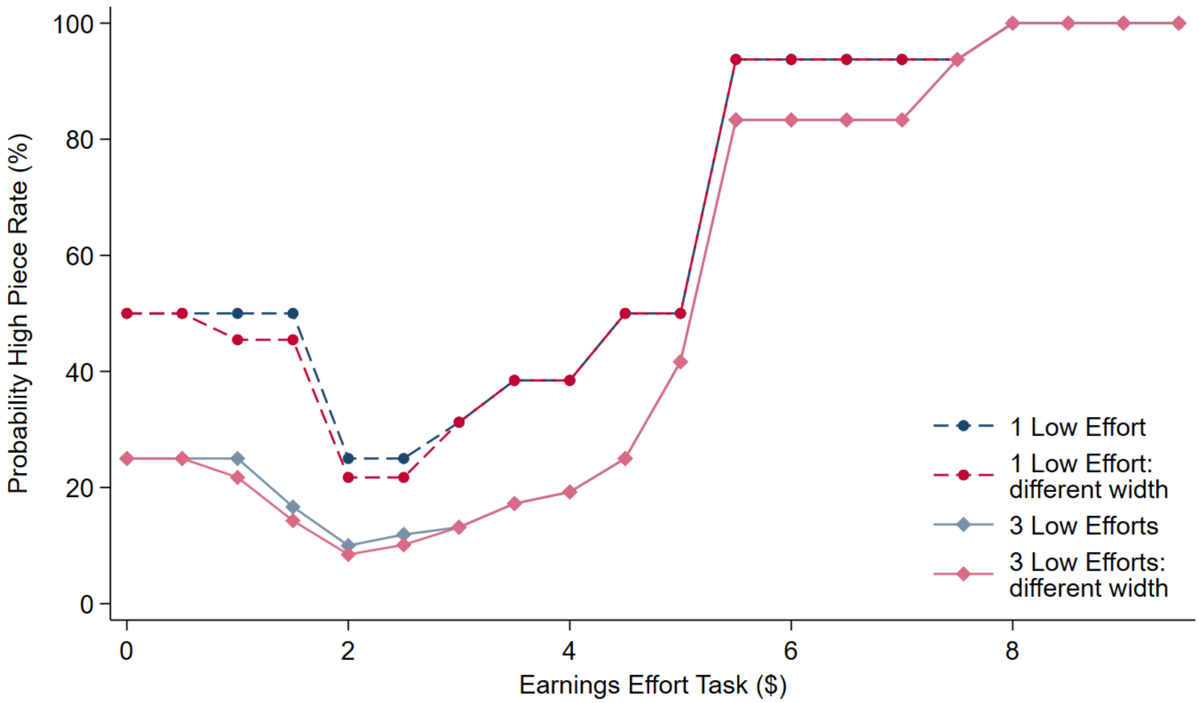
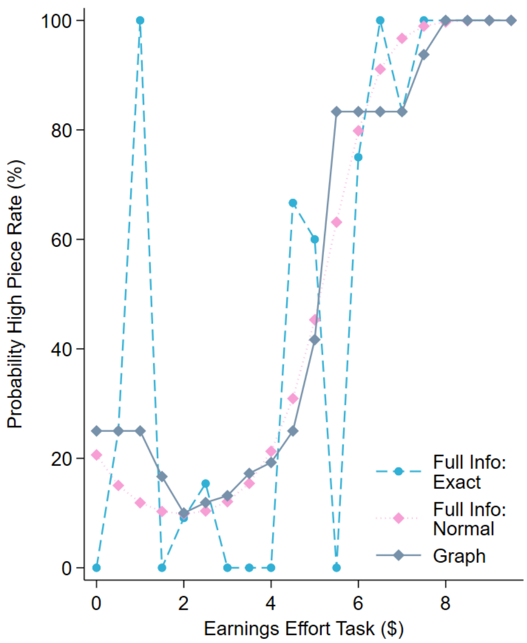


Figure D1: Alternative Bayesian posteriors

Notes: Bayesian posteriors are calculated taking into account the challenges described above. All posteriors are calculated assuming the probability of any effort in each bar is the same. In blue, the posteriors are calculated assuming each bar on the distribution shown to participants is the same width, ignoring that the first bar shows the frequency of efforts 0 to 5. In red, the posteriors are calculated taking into account the difference in width of the first bar. The dotted lines show the posteriors if participants did not consider that with the low piece rate, there are three possible effort levels, while the solid lines do include them.



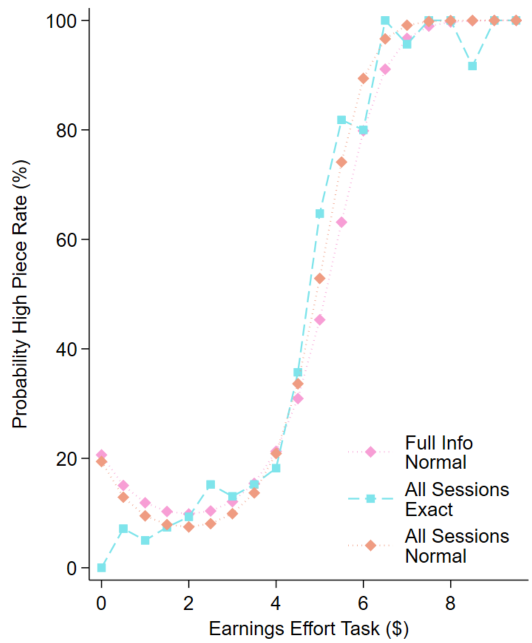


Figure D2: Bayesian Approximations

Notes: Panel D2a shows with the dashed line the Bayesian posterior of having the high piece rate using the exact distribution of effort from the Full Information treatment; with the dotted line, it shows the Bayesian posterior using the normal approximation of effort from the Full Information treatment, and with the solid line, it shows the Bayesian posterior from the distribution shown to participants. Panel D2b shows with dotted lines the Bayesian posterior using the normal approximation of the Full Information treatment (pink) and the pooled sample (orange); with the dashed line, it shows the Bayesian posterior using the exact distribution of effort from the pooled sample.

participants had seen the exact effort distribution (instead of in ranges). The dotted line shows the Bayesian posterior using the normal approximation for the effort distribution in the Full Information treatment[25]. The solid line shows the posteriors using the distribution shown to participants assuming efforts are uniformly distributed in each range. As depicted in the graph, showing the exact effort distribution would have led to very different posteriors (given the small sample). The posteriors using the normal approximation and the ones from the graph shown are similar between \$2 and \$5, and above \$8, but are different for most part of the rest. The normal approximation will be used to discuss the implications of assuming the effort levels are uniformly distributed in each bracket.

Another concern is that every bar on the graph has the same width except for the first bar,

[25] As discussed in Appendix D.3, normality tests cannot reject that the distribution of effort in the Full Information treatment does not follow a normal distribution.

where the range is size 6 because it includes the possibility of 0 tables counted correctly. This could cause two potential issues: one is that participants did not notice the difference in width and update beliefs assuming each bar had the same width. The other issue could be that because participants had 25 minutes to work on the task, it is very unlikely that anyone got any of them right, and therefore they assume that no one got 0 tables counted correctly[26]. For the main analysis, it will be assumed that each bar had the same width. There are two reasons for this: one is that it seems more likely that this is the mistake participants could make, and second, as depicted in Figure D1 with the red lines, using this approach has no effect on posteriors for most of the range of earnings. When there is an effect, for earnings between \$1 and \$2.5, the posteriors are slightly higher, which for the case of partners, would decrease the effects of motivated beliefs, making it a lower bound for any possible effect found.

Finally, the effort distribution shown was not from the session, but from previous sessions (the Full Information treatment). Participants could believe that the distribution does not represent the real effort distribution of their session, and take it as a lower or upper bound, depending on if they think they are better or worse at the task that the distribution shows. This possibility seems unlikely, participants are told in the instruction that the distribution comes from participants in a different session from the week before. Therefore, there will be no reason to believe students from the same university in the same period of time perform better or worse than them. Panel D2b in Figure D2 compares the posteriors using the normal approximation for the Full Information treatment (in pink) with the Pooled sample (in blue). It also shows the posteriors using the exact effort distribution of the pooled sample. The normal approximations are not much different using the Full Information treatment or the pooled sample. The posteriors using the exact effort distribution of the pooled sample also do not differ greatly.

C.2 Partial Information vs Bayesian

Figure D4 shows the mean across participants for the belief they got the high piece rate and the mean across participants and all partner's earnings, for the belief their partner got the high piece

[26]This would generate different beliefs only if a participant earned \$0, but only one participant in the sample earned \$0 in the real effort task and was part of the Full Information treatment; therefore, this assumption does not affect beliefs.

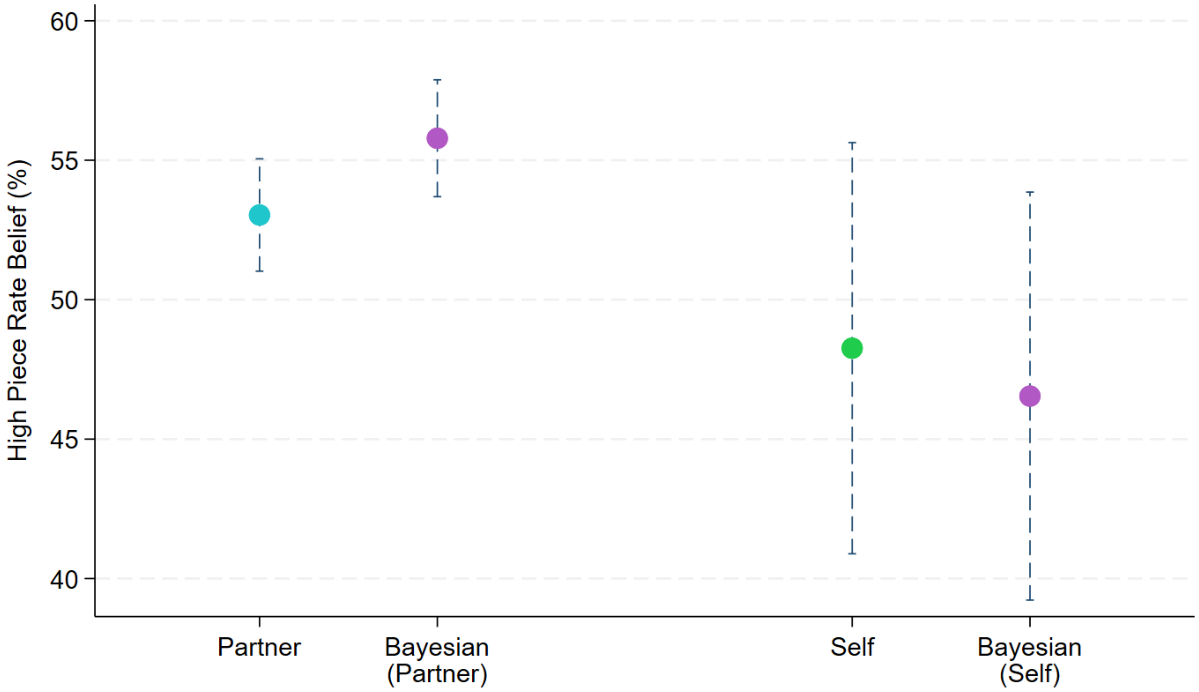


Figure D4: Beliefs by type of Decision

Notes: Mean of the belief the piece rate was high, across participants and earnings levels, for the partner and self. The Bayesian is the average posterior across all earnings levels, separately for partner and self. Both posteriors are different because the earnings are not the same between partner and self.

rate. Motivated beliefs to excuse selfishness and believe they are more deserving than their partner would imply that they think the partner was luckier and/or they were less lucky than a Bayesian would. Figure D4 shows the opposite pattern, for their partner, they think they were less lucky than the Bayesian posterior by 2.75% ($p < 0.001$), and for themselves, they think they were more lucky by 1.7% but this difference is not significant ($p = 0.494$). Table D1 shows the results for the paired differences in mean tests. Notice that the Bayesian posteriors for partner and self are different, that is because the partner's and the self's earnings are not the same.

Figure D4 also shows that the belief about the partner's piece rate is on average higher than the belief about themselves, although not significant ($p = 0.1829$). This can be explained by the difference in the distribution of earnings in the situations for partners and in their own earnings. Figure D5 shows the average belief of having the high piece rate for each earnings level and type of decision. As expected, the beliefs seem to be increasing in earnings, for both partner and self, although it does not look like there is a significant difference between belief types. Table D2 confirms

Table D1: Beliefs: Partner and Self

	Obs	Mean Earnings	Mean Belief	Bayesian	Difference	p-value
Partner	1,188	6.22	53.04	55.79	-2.75	0.000
		(4.17)	(35.38)	(36.81)	(24.86)	
Self	108	5.41	48.26	46.54	1.72	0.494
		(3.85)	(38.64)	(38.36)	(25.99)	

Note: Average across participants and earnings levels for the belief the piece rate was high. Paired test for differences in means with the Bayesian posterior.

this result and also shows the effect of earnings and the Bayesian posterior on the belief of having the high piece rate. Although the posteriors and the earnings are correlated, both measures differ in two important factors. First, the Bayesian posteriors are bounded to 100, and for earnings above \$8, the Bayesian posterior is the same. And second, the Bayesian is not monotonically increasing, for earnings of \$2 and below, the Bayesian decreases and only at \$4.50 reaches the same level as for the lower earnings. Column 2 in Table D2 shows that increasing \$1 the earnings, increase on average 6.44% the belief. Column 3 shows that a 1% increase in the Bayesian posterior increases the belief in 0.74%. Columns 4 and 5 show the combined effect of earnings and the Bayesian with and without demographic controls. Both coefficients remain highly significant but are smaller than when the other variable was not included. In all of these five specifications, the type of belief (self or partner) is insignificant.

Although the previous results show that on average the beliefs about partner and self are not significantly different, it does not help us understand why Figure D4 shows the opposite pattern to the one expected about motivated beliefs. One explanation for this is the belief elicitation method used (BSR). In Danz, Vesterlund and Wilson (2022), they found that using BSR made participants report beliefs centered to the middle, and this pattern was even found (but diminished) in the No Information treatment in Danz, Vesterlund and Wilson (2022), where participants only knew that the best thing was to report their true belief (and not information about how the payment is calculated). Here, the same procedures as in the No Information treatment in Danz, Vesterlund and Wilson (2022) were followed.

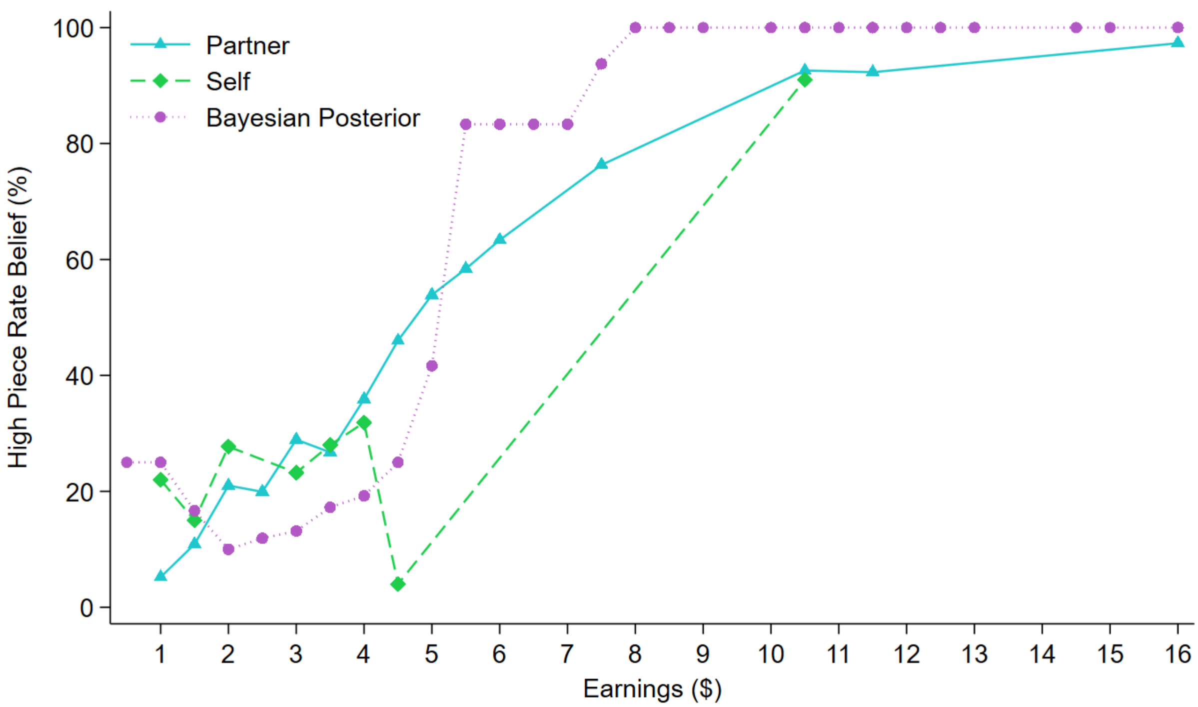


Figure D5: Beliefs by Earnings

Notes: Mean of beliefs across participants for each earnings level, for the partner and self, and for the Bayesian posterior. The plot shows the means for each earning level only for earnings with 5 or more observations.

Table D2: Belief about my own vs partner

	(1)	(2)	(3)	(4)	(5)
Self Belief	-4.78	0.42	2.05	1.89	1.91
	(4.01)	(2.57)	(2.46)	(2.36)	(2.38)
Earnings		6.44***		3.17***	3.15***
		(0.16)		(0.22)	(0.22)
Bayesian Posterior			0.74***	0.44***	0.45***
			(0.02)	(0.03)	(0.03)
Constant	53.04***	12.99***	11.87***	8.52***	7.02
	(1.17)	(1.84)	(1.83)	(1.89)	(11.50)
Observations	1296	1296	1296	1296	1296
R^2	0.00	0.56	0.58	0.63	0.64
Controls	No	No	No	No	Yes

Note: The table reports OLS estimates for participants in the Partial Information treatment, where the dependent variable is the probability the piece rate was high (%). The independent variable of interest is Self Belief which indicates if the decision was about their own piece rate (1) or about their partner (0). Earnings are the earnings for which they are making the guess. Controls include age and number of incorrect answers in comprehension questions, and indicators for male gender, political party, ethnicity, college year, being high income, and being liberal. Standard errors in parentheses and clustered at the individual level. ${}^{*}p < 0.1, {}^{**}p < 0.05, {}^{***}p < 0.01$.

This would imply that for earnings with posteriors below 50%, participants will report higher beliefs, and for earnings with posteriors above 50%, participants will report lower beliefs (independently if it is about partner or self). Therefore, for earnings $5 and below, participants will report higher beliefs, and for earnings above $5, they will report lower (Table D4, column 5). Figure D6 shows the difference between the belief and the Bayesian posterior for each earnings level, for both the partner and self where the aforementioned pattern is observed; for all the earnings above $5, participants report beliefs lower than the Bayesian posterior for both partners and self and for a majority of earnings of $5 or below, beliefs are above the Bayesian posterior. Because a greater proportion of the sample is $5 or less for self than partner (62.96% vs 51.18%, Column 3 in Tables D5 and D4) this could explain the pattern observed in Figure D4.

Table D3 shows the effect of the type of decision in the relative difference of the belief with the Bayesian posterior, $100 \times \frac{Guess - Bayesian}{Bayesian}$, where positive values indicate beliefs greater than the Bayesian and negative values beliefs lower than the Bayesian. Column 1 shows that if the decision is about their own earnings, the belief is higher and greater than the Bayesian, and this is

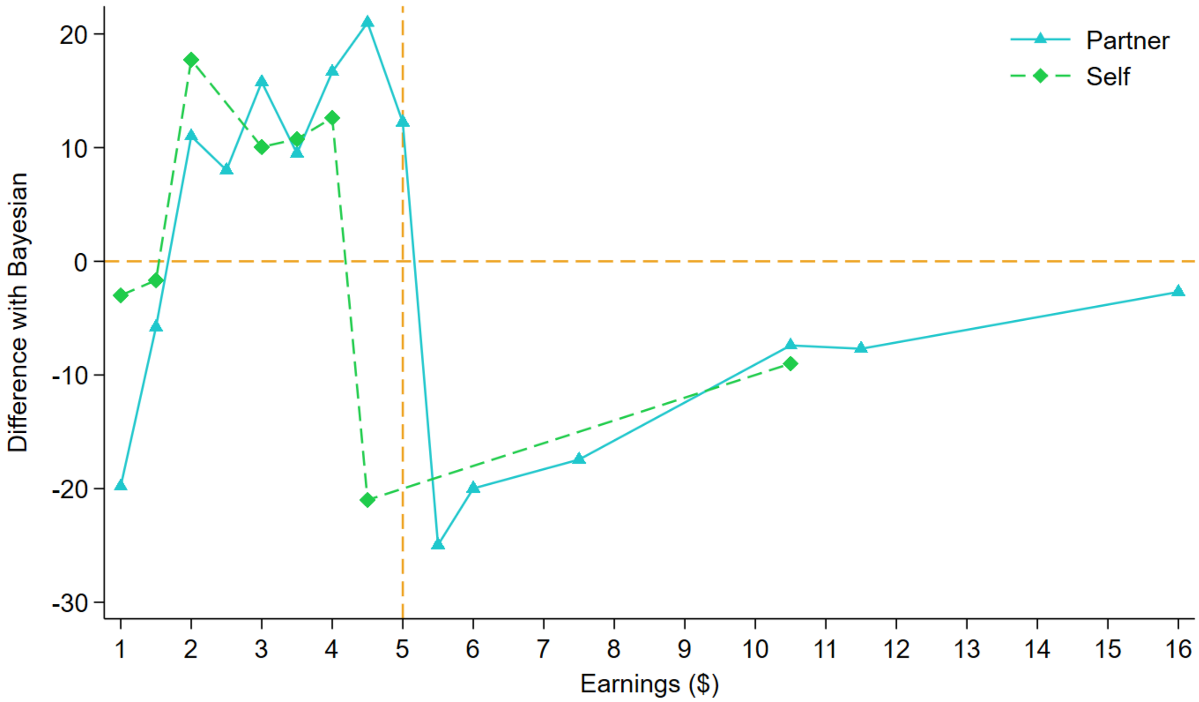


Figure D6: Difference between beliefs and Bayesian by Earnings

Notes: Mean of the difference in beliefs with the Bayesian posterior (Guess - Bayesian) across participants for each earnings level, for the partner and self. Differences above zero represent participants thinking there was more luck than a Bayesian would and differences below zero represent less luck. The plot shows the means for each earning level only for earnings with 5 or more observations.

significant at the 10% level. This result goes against the hypothesis of motivated belief but once it is controlled by earnings and/or the Bayesian posterior, the type of belief becomes insignificant.

Table D3: Difference between Belief and Bayesian Posterior

	(1)	(2)	(3)	(4)	(5)
Self Belief	22.42*	19.45	14.97	14.64	14.72
	(13.18)	(12.95)	(12.67)	(12.49)	(12.59)
Earnings		-3.68***		7.00***	6.91***
		(0.84)		(0.44)	(0.45)
Bayesian Posterior			-0.80***	-1.45***	-1.43***
			(0.12)	(0.15)	(0.15)
Constant	14.02***	36.89***	58.92***	51.52***	11.95
	(4.61)	(9.62)	(11.18)	(11.00)	(45.99)
Observations	1296	1296	1296	1296	1296
R^2	0.00	0.02	0.08	0.11	0.15
Controls	No	No	No	No	Yes

Note: The table reports OLS estimates for participants in the Partial Information treatment, where the dependent variable is the percentage difference between the belief and the Bayesian posterior (%), $100 * \frac{(Guess-Bayesian)}{Bayesian}$. The independent variable of interest is Self Belief which indicates if the decision was about their own piece rate (1) or about their partner (0). Earnings are the earnings for which they are making the guess. Controls include age and number of incorrect answers in comprehension questions, and indicators for male gender, political party, ethnicity, college year, being high income, and being liberal. Standard errors in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table D4: Belief High Piece Rate by Earnings: Partner

	Observations	Cumulative (%)	Belief	Bayesian	Difference	p-value
.5	1	0.08	0.00	25.00	-25.00	.
1	5	0.51	5.20	25.00	-19.80	0.001
1.5	116	10.27	10.87	16.67	-5.80	0.001
2	11	11.20	21.00	10.00	11.00	0.127
2.5	111	20.54	19.92	11.90	8.01	0.000
3	14	21.72	28.93	13.16	15.77	0.026
3.5	118	31.65	26.73	17.24	9.49	0.000
4	115	41.33	35.90	19.23	16.66	0.000
4.5	5	41.75	46.00	25.00	21.00	0.064
5	112	51.18	53.89	41.67	12.23	0.000
5.5	111	60.52	58.38	83.33	-24.95	0.000
6	109	69.70	63.35	83.33	-19.98	0.000
6.5	2	69.87	82.50	83.33	-0.83	0.795
7	4	70.20	77.50	83.33	-5.83	0.684
7.5	111	79.55	76.31	93.75	-17.44	0.000
8	2	79.71	60.00	100.00	-40.00	0.500
8.5	2	79.88	100.00	100.00	0.00	.
9	1	79.97	80.00	100.00	-20.00	.
10	2	80.13	100.00	100.00	0.00	.
10.5	5	80.56	92.60	100.00	-7.40	0.196
11	2	80.72	97.50	100.00	-2.50	0.500
11.5	111	90.07	92.31	100.00	-7.69	0.000
12	2	90.24	100.00	100.00	0.00	.
12.5	3	90.49	98.33	100.00	-1.67	0.423
13	2	90.66	95.00	100.00	-5.00	0.500
14.5	1	90.74	100.00	100.00	0.00	.
15	1	90.82	100.00	100.00	0.00	.
16	109	100.00	97.30	100.00	-2.70	0.000

Note: Aggregate beliefs across participants and partner's earnings. P-value from paired test between average belief and Bayesian posterior. Participants completed 10 hypothetical belief elicitation that are the same across them and another belief elicitation about the assigned partner which differ in earnings across participants, this is why some earnings levels have a handful of observations. Cumulative (%) corresponds to the cumulative distribution of earnings of the partner.

Table D5: Belief High Piece Rate by Earnings: Self

	Observations	Cumulative (%)	Belief	Bayesian	Difference	p-value
.5	1	0.93	25.00	25.00	0.00	.
1	5	5.56	22.00	25.00	-3.00	0.878
1.5	8	12.96	15.00	16.67	-1.67	0.774
2	11	23.15	27.73	10.00	17.73	0.033
2.5	3	25.93	33.33	11.90	21.43	0.467
3	14	38.89	23.21	13.16	10.06	0.090
3.5	10	48.15	28.00	17.24	10.76	0.161
4	7	54.63	31.86	19.23	12.63	0.408
4.5	5	59.26	4.00	25.00	-21.00	0.001
5	4	62.96	72.50	41.67	30.83	0.185
5.5	3	65.74	42.00	83.33	-41.33	0.211
6	1	66.67	20.00	83.33	-63.33	.
6.5	2	68.52	90.00	83.33	6.67	0.626
7	4	72.22	76.25	83.33	-7.08	0.231
7.5	3	75.00	76.67	93.75	-17.08	0.291
8	2	76.85	95.00	100.00	-5.00	0.500
8.5	2	78.70	97.50	100.00	-2.50	0.500
9	1	79.63	100.00	100.00	0.00	.
10	2	81.48	99.50	100.00	-0.50	0.500
10.5	5	86.11	91.00	100.00	-9.00	0.181
11	2	87.96	95.00	100.00	-5.00	0.500
11.5	3	90.74	100.00	100.00	0.00	.
12	2	92.59	100.00	100.00	0.00	.
12.5	3	95.37	94.67	100.00	-5.33	0.386
13	2	97.22	85.00	100.00	-15.00	0.500
14.5	1	98.15	100.00	100.00	0.00	.
15	1	99.07	100.00	100.00	0.00	.
16	1	100.00	70.00	100.00	-30.00	.

Note: For each earnings, mean of belief elicitation about the probability of themselves having the high piece rate. P-value from paired test between average belief and Bayesian posterior. Cumulative (%) corresponds to the cumulative distribution of earnings of themselves.

D Production Stage

D.1 Real Effort Task

Participants perform the counting zero task (Abeler et al., 2011) for 25 minutes. Participants were not allowed to talk to each other, move, or use their phones, but they could use the browser, as pointed out in the instructions. They could solve as many tables as they could, and there was no restriction on the amount of time they needed to spend on each table.

Each table consisted of 15 columns and 10 rows, with a total of 150 zeros and ones, and was generated as follows: First, a probability was randomly chosen from the values $35, 42, 50, 54, 58$, and 65. This probability was then used to determine if each digit on the table would be a zero or a one. For example, if the probability chosen was 42%, then each digit would independently have a 42% chance of being a zero. On average, each table generated with a 42% probability would have 63 zeros with a standard deviation of 6.04. Every time a new table was generated, a new probability was drawn. This method was used to avoid limiting the number of different tables participants could solve and to prevent all tables from having the same answers or being too easy to solve. Figure E1 shows an example of a table.

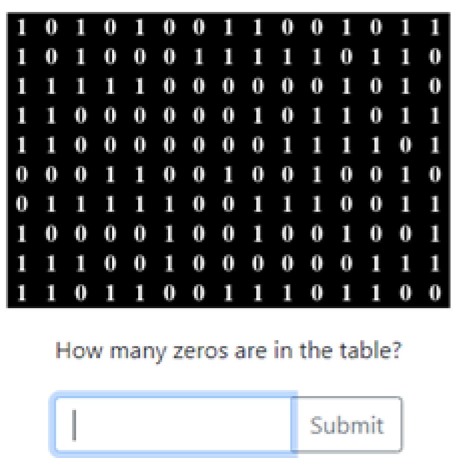


Figure E1: Counting Zeros Task

D.2 Piece Rate

Participants had a 50% chance of getting the high piece rate in the production stage. Figure E2 shows the proportion of participants by treatment who got the high piece rate. Because the probability of getting the high piece rate was independent between participants, 51.9% got it in the Full Information treatment and 39.8% in the Partial Information treatment. Although the difference between treatments is 12.1%, the difference is not significant ($p = 0.148$). To avoid this for the No Information treatment, balance was imposed. The difference between the Partial and No Information treatments is 10.2%, but it is neither significant ($p = 0.136$).

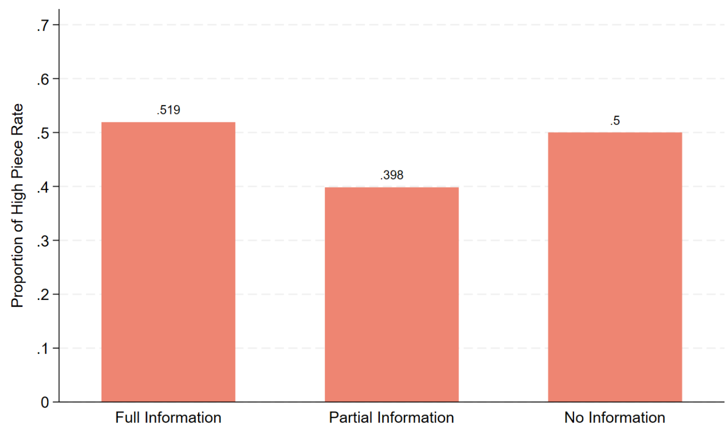


Figure E2: Piece Rate by Treatment

Notes: Proportion of participants by treatment who got the high piece rate in the production task.

D.3 Correctly Counted Tables

This section studies the effort exerted by participants in each treatment. Because there was no limit on the total number of tables participants could count or a minimum time they needed to stay on each table, they could have tried to guess the number of zeros instead of counting them. For this reason, effort is defined as the number of correctly counted tables. If effort is different in each treatment, differences in beliefs and redistribution could be driven by differences in effort levels. Also, the effort distribution shown in the Partial Information treatment comes from the Full Information treatment; if the effort distributions are different or if they believe it, their posteriors will differ from the Bayesian benchmark. In section C.1, the effects of belief updating are discussed.

Figure E3a shows the mean of effort by treatment. In the Full Information treatment, the mean is 17.39 correctly counted tables, and in the Partial and No Information treatments is 18.47 and 15.94, respectively. Table E1 shows the summary statistics. The difference in means between treatments is only significant between the Partial and No Information treatments ($p = 0.0102$) but not between the Full and Partial Information treatments ($p = 0.418$) or between the Full and No Information treatments ($p = 0.239$).

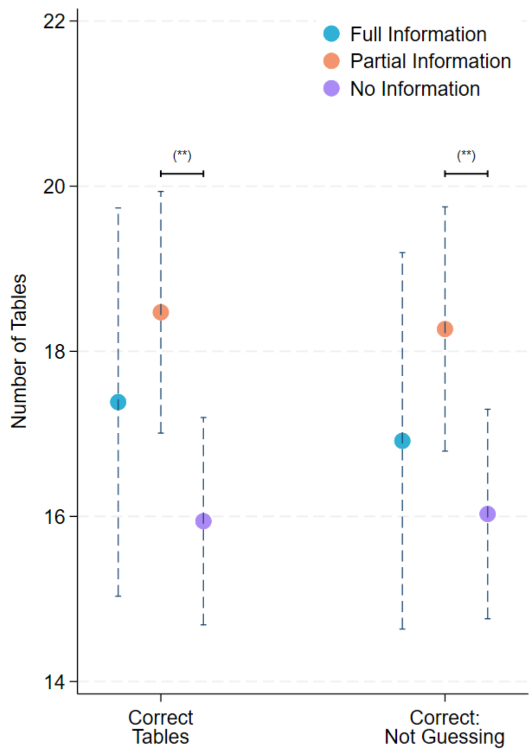
Assuming that at least each table takes 25 seconds to solve, if someone counted more than 60 tables, they will be considered as guessing the number of zeros. For robustness, the analysis will also be done excluding these participants. Figure E3a and Table E1 show the summary statistics by treatment for this restricted sample. The differences between treatments remain almost the same, with the difference in means between the Partial and No Information treatments being the only one significant ($p = 0.0239$). This is expected given that the tables were designed such that guessing correctly would be unlikely.

Figure E3b shows the cumulative effort distribution by treatment for the full sample. A Kolmogorov-Smirnov test for equality of distributions cannot reject that the distributions of efforts are different between treatments, comparing two treatments at a time. For the Partial and No Information treatment, where the difference in means is significant, the equality of distributions cannot be rejected, although the p-value is low ($p = 0.160$).

Figure E5 shows the distribution of correctly counted tables by treatment and for the pooled sample. The kernel density estimation is shown in blue and the normal estimation in red. For the pooled sample, both estimations are very similar. In the Full Information treatment, 34.6% of the sample correctly counted between 14 and 19 tables, 15.4% counted correctly more than 25, and only 5.8% less than 5 tables. In the Partial Information treatment, 30.6% of the sample correctly counted between 14 and 19 tables, 13.9% counted correctly more than 25, and only 0.9% less than 5 tables. In the No Information treatment, 35.6% of the sample correctly counted between 14 and 19 tables, 7.7% counted correctly more than 25, and only 3.9% less than 5 tables.

To calculate the Bayesian benchmark of the probability of having the high piece rate conditional on earnings, it is necessary to know the effort distribution. Two different normality tests were conducted: the Shapiro-Wilk test and a skewness and kurtosis join tests. Both test shows that the

(a) Effort by Treatment



(b) Cumulative Distributions of Effort by Treatment

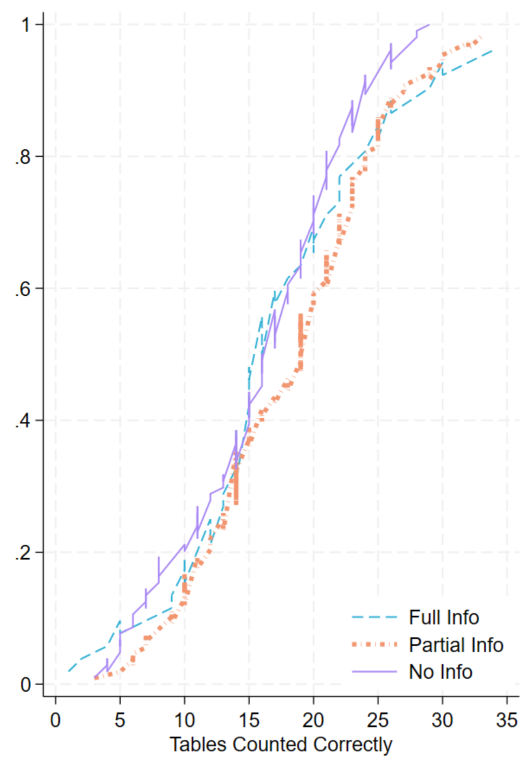


Figure E3: Correctly Counted Tables

Notes: Panel E3a shows the mean of correctly counted tables by treatment, with 95% confidence interval. It also shows the mean of correctly counted tables excluding participants who randomly guessed the number of zeros. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Panel E3b shows the cumulative distribution of effort by treatment for the full sample.

Table E1: Summary Statistics

	Full Sample				Excluding Guessing			
	Obs	Mean	Min	Max	Obs	Mean	Min	Max
Full Information	52	17.385	1	42	47	16.915	1	36
		(8.444)				(7.762)		
Partial Information	108	18.472	3	51	104	18.269	3	51
		(7.673)				(7.606)		
No Information	104	15.942	3	29	102	16.030	3	29
		(6.458)				(6.460)		
Pooled Sample	264	17.261	1	51	253	17.115	1	51
		(7.443)				(7.239)		

Note: Summary statistics of effort distribution by treatment and for the pooled sample. Standard deviation in parenthesis. The excluded participants are those who counted more than 60 tables (correctly or incorrectly).

effort distribution for the Partial Information and the No Information treatments do not follow a normal distribution. Only for the effort distribution in the Full Information treatment, it cannot be rejected that it follows a normal distribution ($p = 0.270$ and $p = 0.113$ for the Shapiro-Wilk test and a skewness and kurtosis join tests, respectively). Section C.2 shows the Bayesian analysis.

D.4 Total and Incorrect Counted Tables

Because participants did not receive feedback during the real effort task, their beliefs could be affected not only by the correct number of tables counted but also by the tables they got wrong. For example, if someone correctly solved 6 tables but 12 incorrectly, their beliefs about having the high piece rate would be different from someone who solved 6 tables correctly and only 6 incorrectly. If both of them got the high piece rate, their earnings would have been \$3. If they have perfect recall of the number of tables solved[27], to believe they got the low piece rate, they would need to solve correctly at least 18 tables. Therefore, the person with only 6 mistakes would know for sure they got the high piece rate, but for the person who solved 18 tables, 12 of those wrong, it could be feasible to have gotten the low piece rate if every table had been correct. For this, it is important to compare the distribution of incorrect and total tables between treatments.

Figure E6 shows the mean and distribution for the number of tables counted incorrectly. Panel

[27] They perform the task for 25 minutes and information of how many tables they have solved is not provided, they would need to keep their own count of tables to perfectly know.

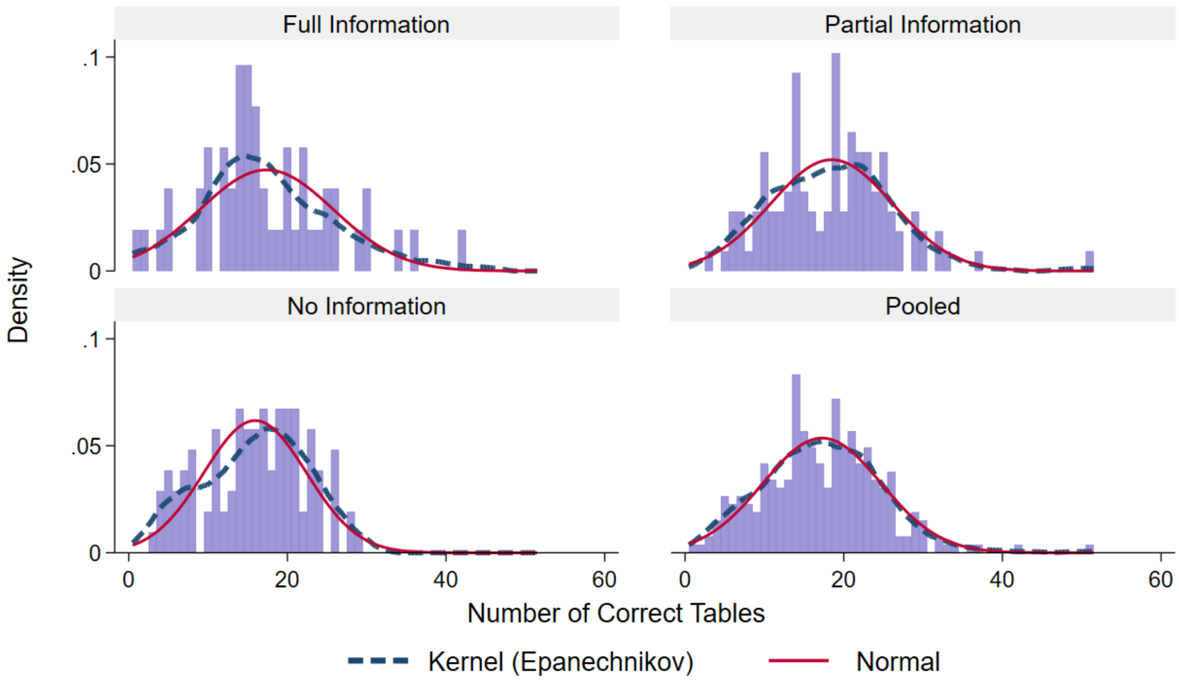


Figure E5: Effort Distribution by Treatment

E6a shows the mean by treatment, the only differences significant at 10% or less is between the Full and No Information treatments ($p = 0.037$), although for the Full and Partial Information treatments, it is close ($p = 0.108$). Excluding those participants defined as guessing (more than 60 tables counted), the difference between treatments disappears, which means that any differences between beliefs will not be driven by the participant's perception of mistakes made. Table E2 shows the summary statistics for the incorrectly counted tables.

Panel E6b shows the cumulative distribution for the incorrectly counted tables (truncated at 25 tables, as shown in Table E2 the difference for the maximum number of mistakes is more than 1,000 tables). Kolmogorov-Smirnov test for equality of distributions cannot reject that the distributions of incorrectly counted tables are different between treatments (with all $p > 0.75$).

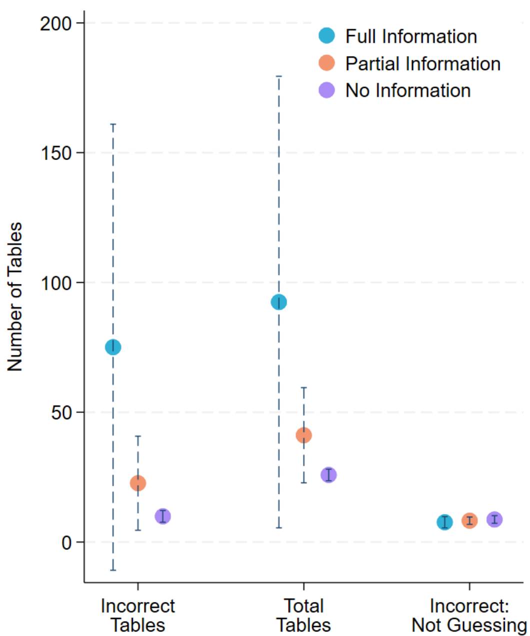
Given the high means in incorrectly counted tables relative to correctly, as expected, the total tables counted (correctly and incorrectly) follow a similar pattern as the incorrectly counted tables, as shown in Panel E6a and Table E2. Specifically, the difference between treatments becomes insignificant for the restricted sample.

Table E2: Summary Statistics: Total and Incorrect Tables

	Full Sample							Excluding Guessing			
		Incorrectly Counted			Total Counted			Incorrectly Counted			
	Obs	Mean	Min	Max	Mean	Min	Max	Obs	Mean	Min	Max
Full Information	52	75.06	0	1987	92.44	5	2029	47	7.62	0	48
		(308.66)			(312.44)				(7.40)		
Partial Information	108	22.67	0	717	41.14	9	749	104	8.22	0	50
		(94.97)			(96.08)				(7.23)		
No Information	104	9.89	0	87	25.84	8	94	102	8.68	0	40
		(11.64)			(11.38)				(7.46)		

Note: Summary statistics for the total and incorrectly counted tables. Standard deviations in parenthesis. The last four columns exclude participants who counted more than 60 tables.

(a) Mean



(b) Cumulative Distributions of Incorrectly Counted Tables

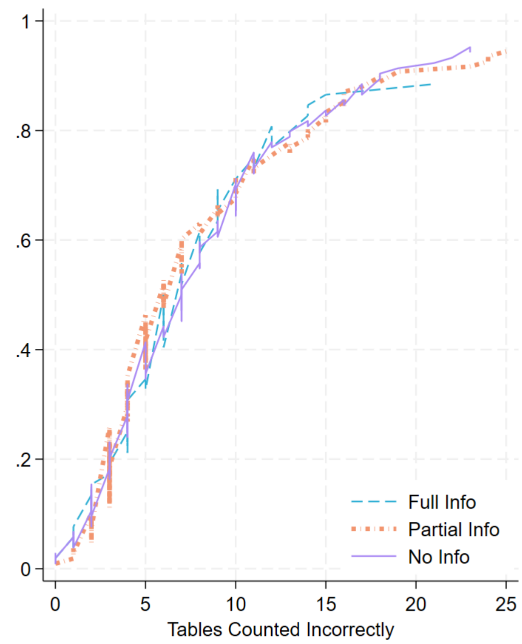


Figure E6: Total and Incorrect Counted Tables

Notes: Panel E6a shows the mean (with 95% confidence interval) of incorrectly counted tables and the total tables counted by treatment. It also shows the mean of incorrectly counted tables excluding participants who guessed randomly the number of zeros. Assuming that at least each table takes 25 seconds to be solved, if someone counted more than 60 tables, they will be considered as guessing. Panel E6b shows the cumulative distribution of incorrectly counted tables, truncated at 25 tables.

D.5 Earnings

Figure E8 and Table E3 show the difference in earnings from the production stage by treatment. The differences in mean between treatments are not significant for the full and restricted sample.

For the full sample, the difference between the Full and Partial Information treatments is \$0.41 ($p = 0.557$), \$0.76 ($p = 0.258$) for the Full and No Information treatments, and \$0.34 ($p = 0.494$) for the Partial and No Information treatments. Kolmogorov-Smirnov tests also show no significant differences in the distributions between treatments.

(a) Mean (b) Cumulative Distributions

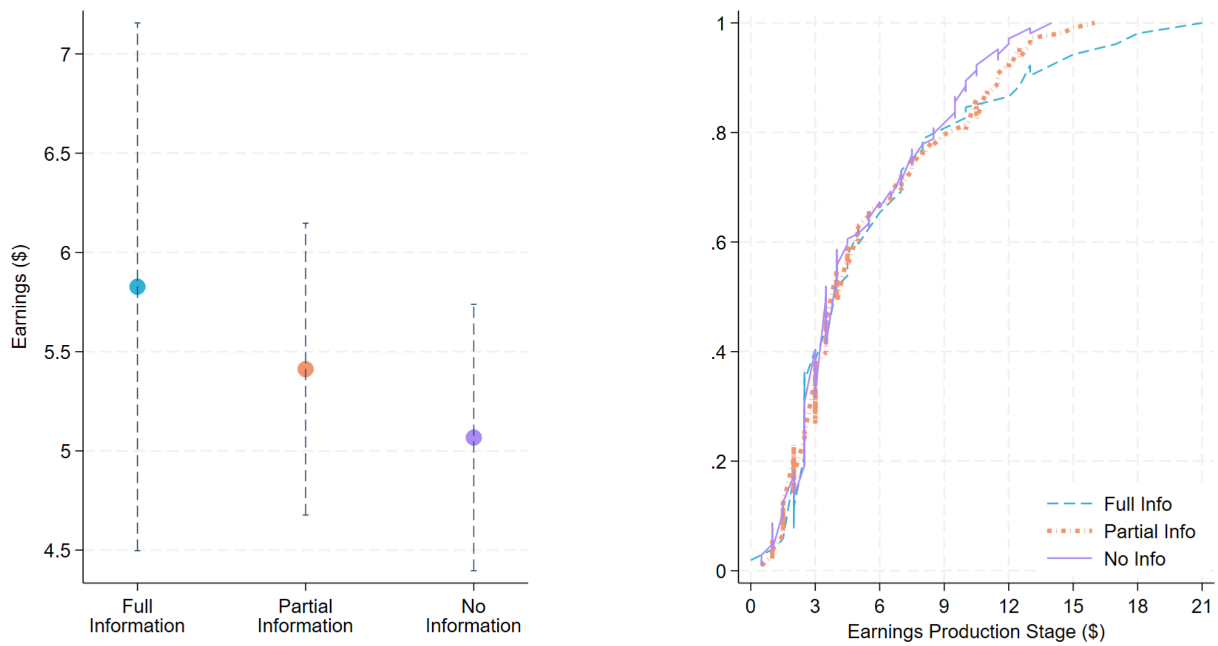


Figure E8: Production Stage Earnings

Notes: Panel E8a shows the mean (with 95% confidence interval) of earnings. Panel E8b shows the cumulative distribution.

Table E3: Production Stage Earnings

	Full Sample				Excluding Guessing			
	Obs	Mean	Min	Max	Obs	Mean	Min	Max
Full Information	52	5.83	0	21	47	5.55	0	18
		(4.78)				(4.17)		
Partial Information	108	5.41	0.50	16	104	5.23	0.50	14.50
		(3.85)				(3.65)		
No Information	104	5.07	0.50	14	102	5.11	0.50	14
		(3.45)				(3.47)		
Pooled Sample	264	5.36	0	21	253	5.24	0	18
		(3.90)				(3.67)		

Note: Summary statistics of earnings by treatment and for the pooled sample. Standard deviation in parenthesis. The excluded participants are those who counted more than 60 tables (correctly or incorrectly).