Beliefs and self-selection in a dual labor markets: an experiment

Autor

Steffanny Romero

Trabajo presentado como requisito para optar por el título de Magíster en Economía

Director, Tutor

César Mantilla

Facultad de Economía

Maestría en Economía

Universidad del Rosario

Bogotá - Colombia

2022

Beliefs and self-selection in a dual labor markets: an experiment *

Steffanny Romero†

April 28, 2022

Abstract

In a dual labor market experiment, we examine how information and beliefs about teammates' decisions affect the individual selection of contribution and productivity. Participants must choose either a contributive (Market C) or a non-contributive labor market (Market NC) over five rounds. We randomized two types of information: in the *Baseline* treatment group, the participants receive individual performance-related details; in the *Market Info* we additionally present teammate's market selection and the earnings in each market. We find that i) *Market Info* increases the likelihood to select Market C; ii) Market selection is affected by beliefs, the higher the expected number of group-mates opting for Market C, the higher the probability to mimic their choice; and iii) the average productivity changes neither between markets nor treatments arms as we expected. However, we have some suggestive evidence that productivity changes across beliefs.

Keywords: Online Experiments, Contributions, Beliefs, Information, Coordination, Labor Markets

JEL Classification Codes: C90, O17

*I thank my advisor César Mantilla for his priceless guidance, comments, and support during this project. I am grateful for the useful comments and suggestions to enrich this document by Felipe Coy, Daniel Gómez, and Camilo Ríos. Finally, I thank Laura Prada and Ferley Rincón for their support during the programming and execution of the experiment. Financial Support from the program *"Inclusión productiva y social: programas y políticas para la promoción de una economía formal, código 60185, que conforma la Alianza EFI, bajo el Contrato de Recuperación Contingente No. FP44842-220-2018."* is gratefully acknowledged. IRB approval was received from CEI-UR (Case #405-CS26).

†Department of Economics, Universidad del Rosario.

1 Introduction

Understanding the dynamics of labor markets is of great interest in developing countries. A key concept is "dual markets". This concept postulates the coexistence of a primary and a secondary labor market. The primary labor is characterized by high salaries and returns to education, job security, stability, the possibility of promotion, and greater responsibility. On the other hand, secondary market jobs have low wages and low returns to education, causal linkages between employees and employers, and no internal job promotions (Bulow & Summers, 1986; Rosenzweig, 1988).

In this regard, De Soto, 1989, Perry et al., 2007, and Bromley and Wilson, 2018 outline the existence of two dimensions through which informality can be addressed: exit and exclusion. The concept of exclusion has been of great importance in the literature. Academics have explained this phenomenon by using the rigidities of the labor market, market failures, and the exclusion of the benefits granted by the government to explain how individuals end up in the informal labor market without making a choice (Portes & Haller, 2010). Less explored is the dimension of exit, which suggests that when economic agents find no utility in interacting with the State or feel dissatisfied with their performance, they opt for informality (Maloney, 2004). After analyzing the benefits generated by formality and the State's capacity to comply with the law, both individuals and companies choose their optimal level of relationship with the government.

Our goal is to explore the exit decision through a laboratory experiment. This decision can be conceived as a coordination game when there is a high level of formality in the market. Besides, individuals have a higher incentive to stay because the social security burden is better distributed along with individuals. The opposite occurs in the setup with a low level of formality. The burden on those individuals who remain in the market gets heavier, incentivizing them to leave. In these contexts, beliefs about others' actions are essential Schelling, 1978. We study the role that beliefs and information on net wages have in selecting a formal or an informal labor market. One reason why beliefs are essential is that a worker's best response is to select the market she thinks the majority of group members will also select.

As informality and contribution increase, the probability of exiting the formal market may also increase. Being informed about this matter can generate a behavior change and prevent participants from falling into the classic self-serving bias that reduces cooperation in public goods games (Fischbacher et al., 2001). Also, comparing average earnings across markets can serve as a focal point to explain equilibrium selection (Myerson, 2009; Schelling, 1960). In this experiment, participants either decide to go to a market where they must contribute (emulating the formal market) or to a market with no contributions (emulating the informal market). Then, the main

contribution of this paper is to conceive market selection as a coordination problem. We propose an experiment in which the total participation of each market is at equilibrium when productivity along individuals is similar. After deciding which market they will go to, participants perform a real effort task that entails a piece-rate payment. Our game offers the opportunity to understand better whether participants perceive any moral obligation to select the "contributory" labor market or whether existing rules on informal market participation and bureaucracy cost too much, the basin of attraction of the "non-contributory" market.

We contribute to the experimental literature on contract selection inspired by Lazear and Rosen's theoretical work on intra-firm incentives lazear1981rank. We can analyze the decisions at the individual level made by informal economic agents in the context of economic duality using incentive measurements. Some studies in labor market contexts like Eriksson et al., 2009 show that when subjects choose to enter a tournament instead of a pay-per-piece scheme (i.e., pay for a task they perform), the average effort is higher. At the same time, the between-subject variation is substantially lower than when the same payment scheme is imposed. Gneezy et al., 2003 show that women tend to self-select outside of tournaments. Furthermore, they find that there is no significant gender difference in performance when participants are paid per piece, contrary to the results under the tournament scheme. Most labor economics studies with an experimental self-selection approach have focused on how individuals perform after their election. Therefore, analysis of the reasons behind the choices of individuals is little explored, we contributed to the literature in this focus.

On the other hand, experiments have also been used to understand the behavior of tax compliance (Alm, 2012; Alm & Malézieux, 2021) and sanctions (Gërxhani & Schram, 2006; Lefebvre et al., 2015), as well as income declaration and the role of simplifying the calculation in tax obligations (Gërxhani & Schram, 2006; Lefebvre et al., 2015). Previous studies investigate how profitable it is to declare income; for example, literature studies the role of exogenous messages on tax compliance, as done by Lefebvre et al., 2015. In our game, the endogenous information is the participation of workers in the formal and informal market and their average earnings.

We find that revealing information about groupmates' decisions and earnings increases the likelihood of contributing, the selection of *Market C* increases six percentage points (from 64% to 70%). Also, this information increases the accuracy of beliefs about labor market composition. As one would expect in a coordination game, beliefs play a crucial role in market selection: the greater the expected number of group mates who choose to contribute, the greater the probability of imitating this selection. Also, we found that the average productivity changes neither between markets nor treatments arms. However, we have some suggestive evidence that productivity changes across beliefs.

2 Experimental Design

2.1 Game Theoretical Framework

We emulate a dual labor market, in which participants must choose between a market with contributions to the social security system (*Market C*) and a market with null contributions (*Market NC*) for five rounds. Participants' decisions in round r are not conditioned to choices made in previous rounds $r < R$. Markets and their respective payment schemes are drawn as follows:

- *Market C*: participants receive a payment X_c for every completed task M_i. A fixed part (δ) of the payment is retained as a contribution to a common fund that is ultimately redistributed among all participants, regardless of the market to which they belong. The redistribution among the participants of *Market C* will be increased by a multiplier α_c. Hence the payouts per round in this market are given by:

$$\pi_{i,C} = (1-\delta)(X_C M_i) + \alpha_C \frac{\delta\,(X_C M_C)}{T} \quad ; \quad M_C = \sum_{i \epsilon C} M_i \tag{1}$$

- *Market NC*: participants receive a payment $X_{NC} < X_C$ for every completed task (M_i). They do not make contributions to the common fund but receive a benefit from the redistribution process, increased by a multiplier α_{NC}. Payments in this market follow the equation:

$$\pi_{i,NC} = X_{NC} M_i + \alpha_{NC} \frac{\delta\,(X_C M_C)}{T} \tag{2}$$

Where M_C is the average amount of tasks completed by members of *Market C*, and T is the total number of participants in the group. Thus, participant j will prefer to go to *Market C* whenever the following condition is met:

$$\pi_{j,C} > \pi_{j,NC}$$

If α_C and α_{NC} are equal to 1, the solution is straightforward. The right terms of both equations would be canceled out. Therefore, if we fix the payout for every completed task as equal in both markets, participants would be better off in the market NC when $alpha$ is greater than 0. Then, there is no incentive to contribute, and the game is meaningless. For that reason, we include α_C as greater than α_{NC}. This would imply that if the common fund is greater than 0, the left term of equation 1 would be greater than equation 2 left term. This increases the incentive of individuals to select Market C, compensating the contribution made by the participant.

In this game, we abstracted from mobility barriers between markets because we want to focus on self-selection and we use a model with multiple Schelling equilibria that depend on the beliefs

Table 1: Parameterization

	τ	X_{NC} [kCOP]	$\frac{X_C}{X_{NC}}$	$\bar{M_{i,NC}}$	$\frac{M_{i,C}}{\bar{M_{i,NC}}}$	α_{NC}	α_C
Selected parameters	0.5	3	1.6	7.6[a]	1	0.9	1.2
Range for multiple-equilibria	[0.47, 0.59]	[2.88, 3.28]	[1.46, 1.66]	[5.66, 10.26]	[0.92, 1.25]	[0, 1.13]	(1, 1.5)

[a] This value of $\bar{M_{i,NC}}$ corresponds to the average number of solved tasks per round in our experiment.

of the participants (Schelling, 1978). We use simulations of the parameters that influence the payoff of each market to calibrate the game so that there are two equilibria. These equilibria depend on beliefs about the proportion of participants choosing *Market C*, and their expected profit. The first equilibrium that we propose is one in which participants choose *Market C*. In the second one, everyone goes to *Market NC*. If most of the group members choose *Market C*, individual j's best response is to choose *Market C*. Similarly, j's best response is to choose *Market NC* if the majority of the group pick *Market NC*. Any deviation from these scenarios generates a lower payment for the participant. We used the parameters that satisfy the double equilibrium condition shows in Table 1. We assume an average and homogeneous productivity among markets because the payments are not very different. However, equilibria hold if productivity changes across markets.

2.2 The experiment

Participants in each session were randomly assigned in groups of 6 people, and such groups were fixed between rounds [1]. The experiment consists of 5 rounds, and each round has 4 stages. First, participants choose one of the two labor markets (S_1). Second, participants report what they believe that the rest of the group decided (S_2). In the third stage, participants perform an encryption task (S_3). Finally, participants receive information about the latest round (S_4). We explain the details of each stage in the following subsections.

2.2.1 Market Selection

Participants must choose a market they prefer. Participants' payments depend on the market selection, as we explained in the previous section, and this is the unique difference between markets. Market selection is repeated in every round.

[1] The experiment continued whenever a participant dropped the game. In such a case, a bot decided for the missing participant by following the group's majority pick.

2.2.2 Belief elicitation

Before starting the tasks in S_2, we asked participants how many of their five teammates selected *Market C* for the current round. We offered monetary incentives for accurately predicting behavior group. If the participant's belief is correct in the round selected for payment, she earns a bonus of 3,000 COP (around 0.75 USD).

2.2.3 Encryption task

In both markets, participants conduct the same real-effort task. We use a modified version from Erkal et al., 2018 and Benndorf et al., 2019 for the encryption task. Participants are requested to translate 5 numbers to 5 letters in our version. The letters are always the same (Z, D, J, K and L) and the corresponding numbers change whenever a task is completed. A completed task is correct when the translation corresponds exactly to the key. Participants had 90 seconds per round to complete as many tasks as possible. At the beginning of the experiment, the participants practiced for 60 seconds to get used to the task. Figure 1 shows an example for an encryption task.

2.2.4 Feedback and Treatments

When the participants finish the task stage, they receive information about the earnings in the latest round. We believe that information can shape the individual's decision (Berninghaus and Ehrhart, 2001), so we randomize two types of information. The treatments are:

- **Baseline information "*Baseline*":** at the end of the round, we show the results to the participants. In this treatment, we give information on individual earnings. Specifically, i) we remind the participant of the market she selected in the round; ii) we tell her how many correct tasks she performed and the earnings from those tasks; iii) she is informed of the earnings she receives from the redistribution of the tasks completed in *Market C*; and iv) she is presented with the total profit of the round.

- **Relative information "*Market Info*":** In this treatment, we present the information of *Baseline* plus additional pieces of information regarding the two markets: how many group members selected each market and the average earnings perceived in each market.

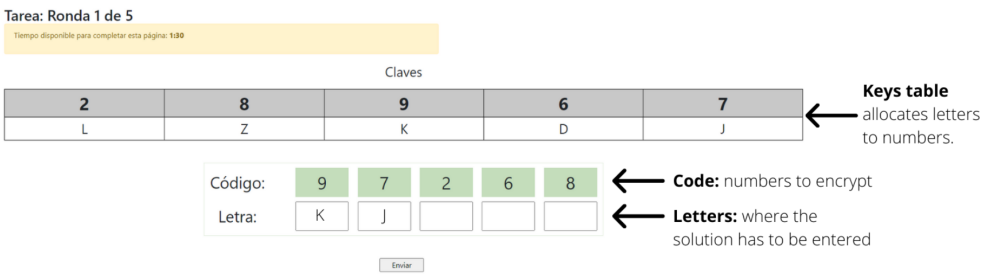
2.2.5 Payments, sampling and implementation

After the five rounds concluded, the participants completed a survey on demographics questions and incentivized risk-aversion staircase questionnaire adapted from falk2018global. We randomly

selected one of the five rounds to pay the participants through bank accounts. The participant's payment is made up of three parts: payment from market rounds, beliefs elicitation, and risk-aversion staircase. On average, participants received 36,150 COP.

We conducted an online experiment through the Rosario Experimental and Behavioral Economics Lab - REBEL [2], with two populations, students and non-students. Students were invited from the REBEL subject pool sample. Non-students were called via social media (i.e., Facebook, Twitter, and e-mail) to complete an enrollment survey to validate their work status. In the survey, participants gave us the consent to be contacted by e-mail and receive the online payment. The experiment was conducted with 216 participants in 15 sessions. Four participants dropped out during the session, and one participant performed the activity twice, so we kept the earlier observation. Each session lasted approximately 45 minutes. Treatment randomization was at the session-level. We conducted the sessions with each type of population separately between September and November 2021. The experiment was programmed in oTree (Chen et al., 2016).

Figure 1: Encryption task example



2.3 Hypotheses

Hypothesis 1 (H1): *Market Info* increases the selection of *Market C*, compared to the *Baseline* treatment. The intuition behind our hypothesis is as follows. If more participants go to *Market C*, the average payments would increase, revealing how good *Market C* is, and inducing more participants to go to this market. In other words, individuals use market information to determine if people are selecting *Market C*.

Hypothesis 2 (H2): Beliefs about market participation are more accurate under the *Market Info* treatment. With information, participants' beliefs about how many people are participating in the market are updated. Then, those beliefs would be closer to the real participation since they have knowledge about previous rounds.

[2]We obtained approval from the Ethics Committee at Universidad del Rosario in Bogotá

Hypothesis 3 (H3): We expect higher productivity in *Market C* when participants receive individual information than when they receive relative information. First, individuals may realize they can reduce their effort given the current productivity of members of *Market C*. It means participants use the relative information to calculate if the net payoff they receive is better off by reducing their effort. Second, individuals could demotivate if they realize that other members of *Market C* are not striving enough. In other words, they use the relative information to determine if they are working harder than others.

3 Results

3.1 Descriptive statistics

We check balance across treatment groups in Table A1 and descriptive statistics for our demographics variables. We present the statistics separately by type of population recruitment. We have 211 participants, 66 students reported in Panel A, and a sample for 145 non-students reported in Panel B. On average, students in our sample are 20.6 years of age, 65 percent are women, and 5 percent have a job. Only 23 percent of the students report being contributors to the health system, this value can be explained because they are beneficiaries of their parents; fourteen percent of them inform to have a type of long-term savings plan for retirement. In terms of the device for the activity, 83 percent used a laptop, and 44 percent used a mouse. For the non-student sample, the reported average age is 30.5 years old, and the majority of the observations were females (64%). More than half of the individuals had a university education level (65%). When we asked them about social security, 19% reported having contributory health insurance, and 58% reported having a type of long-term savings plan for retirement. Eighty percent of participants performed the activity from a laptop, and 56% used a mouse.

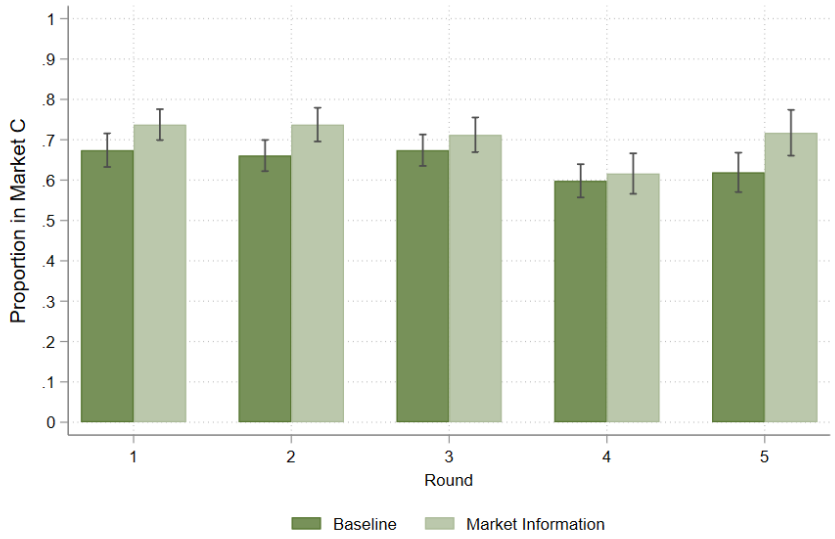
We do not find any statistical difference between *Market Info* and *Baseline* treatments for the non-student participants. For the students, both treatments arms are balance in most of the characteristics except for having a job, retirement plan, and mouse variables. These differences may be related to the size of the sample, the students in our sample are less than half the number of non-students.

3.2 Market selection

Figure 2 displays the distribution of market selection across treatment groups and rounds. It shows the average proportion of participants who selected *Market C*. We observe that the proportion in Market C is greater in the Market Information compared to the Baseline group for all

rounds ($p < 0.001$, one-tailed t-test; diff = *Baseline* - *Market Info*$\geq$0). We estimated the impacts of receiving *Market Info* compare to *Baseline* on market selection.

Figure 2: Distribution of market selection



We perform a statistical analysis using an OLS regression with robust standard errors. Although the treatment was assigned at the session level, it is not recommended to cluster at this level because we conducted only 15 sessions. Cameron and Miller, 2015 note that under a small number of clusters, the cluster-corrected estimators of the variance-covariance matrix are biased. Even though there is no exact number for how many clusters are few, 50 is generally the cut-off point. Nevertheless, we report standard errors clustered at the session level in squared brackets, though they must be interpreted with caution.

Table 2 shows the OLS coefficients of the model with a dichotomous variable for the *Market Info* treatment; the coefficient reports the absolute difference in Market C selection between treatments. Individual controls include age, sex, whether the participant was a student, the individual risk parameter obtained from the staircase procedure, and device controls (use of mouse and laptop). We also include round and group fixed effects. This result confirms what we observed in Figure 2: in the presence of information about the composition of the group and its average payments, participants are 6.6 percentage points (pp hereafter) more likely to choose Market C. The effects remain robust to adding individual controls and group fixed effects. As a robustness check, we present in Table A2 the estimations without the participants in groups in which bots replaced the dropped member. The results are in the same line, although we observe a reduction in the

statistical significance.

Table 2: OLS model explaining the treatment effect on market selection

	Outcome: Selection of Market C		
	(1)	(2)	(3)
Market Info	0.056	0.059	0.066
	(0.029)*	(0.029)*	(0.029)**
	[0.061]	[0.062]	[0.050]
Female			-0.054
			(0.030)*
			[0.036]
Student			-0.111
			(0.045)**
			[0.091]
Mean of Dep. Var (Baseline)	0.64	0.64	0.64
Observations	1,055	1,055	1,055
R-squared	0.009	0.040	0.064
Round FE	Yes	Yes	Yes
Group FE	No	Yes	Yes
Individual Controls	No	No	Yes

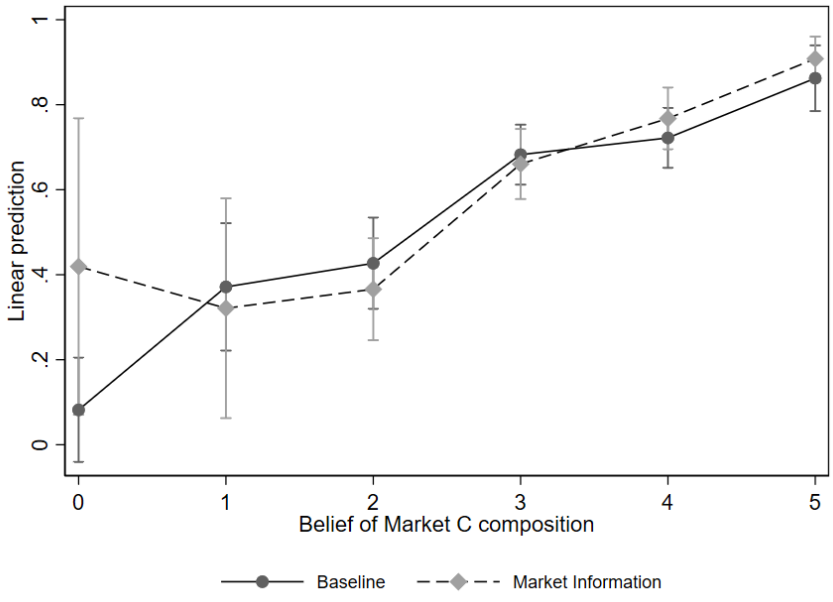
Notes: Model 3 includes as additional covariates: age, the individual risk parameters and device controls (use of mouse and laptop). Robust standard errors in parentheses. Clustered-session standard errors in squared brackets. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Relative to men, we find that females are 5.4 pp less likely to choose *Market C*. This result is aligned with the literature. In Fellner and Maciejovsky, 2007 women engage in less market activity than men, submit fewer bids, and conclude fewer contracts; Gallo et al., 2018 show participation in a pension fund and a change from non-participation to participation are negatively related to being female and risk aversion. These findings can be attributed to risk attitudes: attitudes toward ambiguity, competence, overconfidence, or performance differences between women and men in competitive settings (Gneezy et al., 2003; Gysler et al., 2002). We show that women are less productive in our real effort task. Similarly, participants whose principal occupation is studying present 11 pp less likely to choose *Market C* than the workers. Given this result, we explore the effects by separating our samples, Table A3 reports a similar regression to model 3. The effect of *Market Info* treatment is positive for students and non-students but is only statistically significant for the sample of students. For the rest of the estimations, we present the results for the pooled sample.

3.3 The role of beliefs in market selection

As we hypothesized, the type of information matters in the decisions; *Market Info* increases the number of people who go to the contribution market. In order to understand this effect, we explore how beliefs and accuracy led to the decision when choosing a market. Table 3 reports the OLS coefficients for the precision of beliefs, explained by our treatment variable, and isolating the effect of round 1 because, in that round, the Market information has not provided any additional information to the treated participants. The outcome used in this table is a dummy equal to one if the reported belief corresponds to the total participants who selected *Market C* in round *r* without her taking into account. The table shows that the beliefs are closer to the real participation since they have knowledge about previous rounds obtained by *Market Info*. On average, participants in *Market Info* are 17 pp (from 26% to 43%) more probable to report a correct belief. We report in Table A4 a robustness check where the outcome is a continuous accuracy measure. The difference between the participant's belief and the correct number of group-mates in *Market C* is our dependent variable; the result shows a reduction in this distance, *Market Info* reduces the bias in 0.19 units.

Figure 3: Marginal effects per Treatment Groups



Notes: Participants' market decision as a function of the beliefs about teammate's decision. Error bars show 95% confidence intervals. The marginal effects was obtained from regression in Table A5

Table 3: OLS model for correct beliefs about market selection.

	Outcome: Correct Belief	
	(1)	(2)
Market Info	0.171	0.171
	(0.032)**	(0.032)**
	[0.040]*	[0.041]*
Round 1	0.035	0.036
	(0.056)	(0.056)
	[0.063]	[0.063]
Market Info × Round 1	-0.121	-0.121
	(0.070)*	(0.070)*
	[0.097]	[0.098]
Test for linear combination		
Market Info + Market Info × Round 1	-0.050	-0.050
	(0.062)	(0.062)
	[0.074]	[0.074]
Mean of Dep. Var (Baseline)	0.26	0.26
Observations	1,055	1,055
R-squared	0.028	0.031
Round FE	Yes	Yes
Group FE	Yes	Yes
Individual Controls	No	Yes

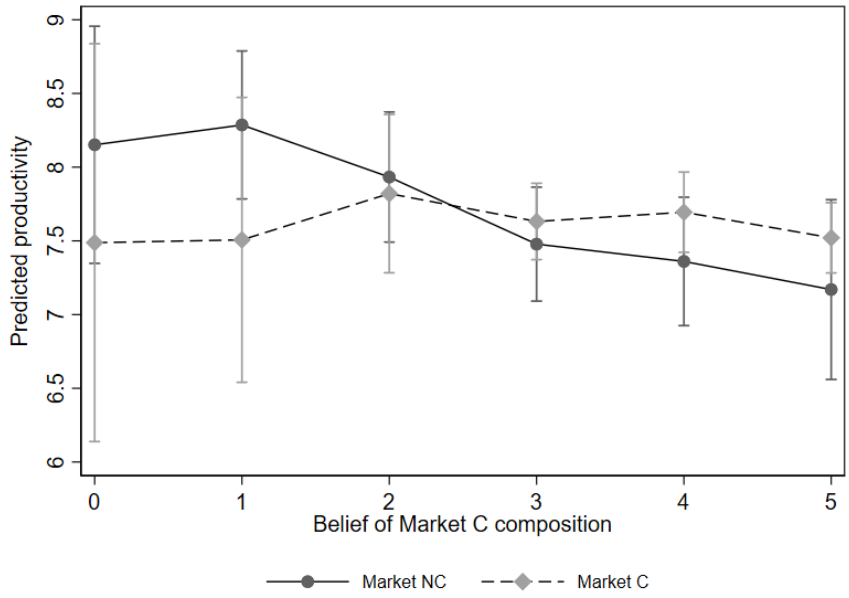
Notes: Model 2 includes as additional non-significant covariates: age, the individual risk parameters, a dummy capturing whether the participant is a student, and device controls (use of mouse and laptop). Robust standard errors are in parentheses. Clustered-session standard errors in squared brackets. *** p<0.01, ** p<0.05, * p<0.1.

We explore the participants' market decision as a function of the beliefs, and results are shown graphically in Figure 3, we estimate marginal effects from predictions of model reported in Table A5. We observe that the probability of choosing Market C increases with the belief about the groupmates' decision; this occurs similarly in both treatment groups, validating that the beliefs are fundamental in opting for one of the markets. Even if the beliefs are not entirely accurate, the participants respond reciprocally. Hence, both equilibria can be reached, depending on the groupmates' choices and the correct prediction of this behavior.

3.4 Productivity in Encryption task

We use an ordinary least squares (OLS) model to test the statistical significance of the differences across treatment groups on participants' productivity on the encryption task (i.e., the number of completed tasks within the time limit) in Table 4. We did not find a statistical difference between treatments. We observe that the number of tasks completed decreases with age, one additional year reduces 0.92% the number of tasks with respect to the mean in *Baseline* group, this effect is significant but small in magnitude. Likewise, if the participant is female, the number of tasks decreases by 0.25. The students in our sample have a slightly higher productivity, the number of tasks increases by 0.9 when the participant is a student.

Figure 4: Marginal effects per markets and beliefs



Notes: Participants' productivity as a function of the beliefs about teammate's decision. Error bars show 95% confidence intervals. The marginal effects was obtained from regression in Table A6

We explore the productivity outcomes across participants in both markets. First, it seems that in our preferred regression with controls, there is no significant difference in the average productivity between participants in *Market C* and *Market NC*. According to Table A6, productivity negatively correlates with the intensity of beliefs. Participants are less productive when they believe more people are selecting *Market C*. This significant correlation is not heterogeneous across *Market C* and *Market NC* participants. However, patterns in both markets seem to be different.

As Figure 1 shows, there is a drop in productivity in participants in *Market NC* when they believe more people are selecting *Market C*. On the contrary, participants' productivity in *Market C* remains constant with the belief. We interpret that the participants in *Market NC* relax their effort when they think more people are going to *Market C* and the common fund is more significant.

Table 4: OLS regresssions explaining productivity across treatments and markets

	Outcome: Productivity		
	(1)	(2)	(3)
Market Info	-0.083	-0.348	-0.107
	(0.127)	(0.231)	(0.218)
	[0.454]	[0.561]	[0.239]
Market C		-0.342	-0.197
		(0.200)*	(0.179)
		[0.232]	[0.137]
Market Info × Market C		0.404	0.304
		(0.281)	(0.260)
		[0.305]	[0.211]
Female			-0.251
			(0.126)**
			[0.210]
Age			-0.071
			(0.014)***
			[0.021]***
Student			0.858
			(0.187)***
			[0.307]**
Mean of Dep.Var (Baseline)	7.68	7.68	7.68
Observations	1,055	1,055	1,055
R-squared	0.058	0.062	0.222
Round FE	Yes	Yes	Yes
Group FE	Yes	Yes	Yes
Individual Controls	No	No	Yes

Notes: Model 3 includes as additional covariates: the individual risk parameters and device controls (use of mouse and laptop). Robust standard errors are in parentheses. Clustered-session standard errors in squared brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.5 Dynamics of market selection

Table 5 reports transition probabilities, which means the change in the market selection over rounds by treatment groups. The rows of both panels reflect the initial values t, and the columns reflect the values in period $t+1$. In Panel A, in the baseline group, people that select *Market NC* in period t, has a probability of 63.7% of selecting the same market in period $t+1$. However, in the treatment group, people that select *Market NC* in the period t, have just a probability of 50.4% of remaining in the same market. Now, transition probabilities for participants that select *Market C* in both treatment arms do not change that much. For example, participants choosing *Market C* in the baseline group have a 78.7% probability of remaining in the same market; similarly, the treated participants have a 77.62% chance of staying in *Market C* in period $t+1$. We interpret that receiving Market Information, conditional in selecting *Market NC*, eases the path of Market transition.

Table 5: Transition probability matrices across treatments

Panel A. Baseline		
	Market NC_t	Market C_t
Market NC_{t-1}	63.7	36.3
Market C_{t-1}	21.3	78.7

Panel B. Market Info		
	Market NC_t	Market C_t
Market NC_{t-1}	50.4	49.6
Market C_{t-1}	22.4	77.6

4 Concluding discussion

We conducted an online experiment emulating a dual labor market, one of them with a contribution in a common fund to understand if the participants´ decision to contribute depends on the information they receive about the choices and earnings of their teammates. First, we find that receiving Market Information increases the proportion of people that go to *Market C*. Second, we observe that beliefs are a decision mechanism and can explain that the participants are highly cooperative; we show a monotonic correlation between the expectation of the composition of *Market C* and the probability of selecting it. Specifically, when a participant expects that only a one-person chooses market C, the probability of selecting *Market C* is less than 40%. However, when a participant expects everyone to go to *Market C*, the probability is 88%.

We found that the average productivity changes neither between markets nor treatments arms as we expected. However, we have some suggestive evidence that productivity changes across beliefs. We observe that participants who selected *Market C* reduce their productivity when they believe more people are selecting *Market C*. In other words, if participants can choose their level of effort and their market, selecting *Market NC* is a profitable strategy when they believe more people

are going to *Market C*. We do not explore convergence due to the few rounds of our experiment. However, the transition probabilities indicate that *Market Info* prevents *Market C* becomes too absorbing and eases the path of market transition. We can learn what happens when the duties and benefits of formal work become dependent on beliefs in a coordination problem. Our experiment contributes to the discussion about whether the exit from formal labor markets results from an incomplete or uninformed cost-benefit analysis. Distrust in government can induce individuals to make uninformed and unconscious decisions that may well be at their disadvantage. We recommend the media's involvement to reduce information asymmetries between the government and individuals.

We observe that providing information about market benefits may work as a focal point that increases participation in the formal market and that beliefs are a powerful coordination mechanism. Based on the results, we believe that policies should enhance the perceived benefits of formality through effective communication and financial literacy to increase participation and decision consciousness. In particular, the government can show how they protect people from shocks and provide them with retirement benefits; these policies could help combat the notion of a bureaucratic and inefficient role for the state in social security provision. The mechanisms of a higher informal labor force can be explored using future experiments involving shocks (for example, one participant in each round may be shocked and more hedged in Market C) or the correlation between choosing contributing markets and inter-temporal preferences.

References

Alm, J. (2012). Measuring, explaining, and controlling tax evasion: Lessons from theory, experiments, and field studies. *International Tax and Public Finance*, *19*(1), 54–77.

Alm, J., & Malézieux, A. (2021). 40 years of tax evasion games: A meta-analysis. *Experimental Economics*, *24*(3), 699–750.

Benndorf, V., Rau, H. A., & Sölch, C. (2019). Minimizing learning in repeated real-effort tasks. *Journal of Behavioral and Experimental Finance*, *22*, 239–248.

Berninghaus, S. K., & Ehrhart, K.-M. (2001). Coordination and information: Recent experimental evidence. *Economics Letters*, *73*(3), 345–351.

Bromley, R., & Wilson, T. D. (2018). Introduction: The urban informal economy revisited.

Bulow, J. I., & Summers, L. H. (1986). A theory of dual labor markets with application to industrial policy, discrimination, and Keynesian unemployment. *Journal of Labor Economics*, *4*(3, Part 1), 376–414.

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources*, *50*(2), 317–372.

Chen, D. L., Schonger, M., & Wickens, C. (2016). OTree—an open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97.

De Soto, H. (1989). Ther other path: The invisible revolution in the third world.

Eriksson, T., Teyssier, S., & Villeval, M.-C. (2009). Self-selection and the efficiency of tournaments. *Economic Inquiry*, *47*(3), 530–548.

Erkal, N., Gangadharan, L., & Koh, B. H. (2018). Monetary and non-monetary incentives in real-effort tournaments. *European Economic Review*, *101*, 528–545.

Fellner, G., & Maciejovsky, B. (2007). Risk attitude and market behavior: Evidence from experimental asset markets. *Journal of Economic Psychology*, *28*(3), 338–350.

Fischbacher, U., Gächter, S., & Fehr, E. (2001). Are people conditionally cooperative? evidence from a public goods experiment. *Economics Letters*, *71*(3), 397–404.

Gallo, G., Torricelli, C., & Van Soest, A. (2018). Individual heterogeneity and pension choices: Evidence from italy. *Journal of Economic Behavior & Organization*, *148*, 260–281.

Gërxhani, K., & Schram, A. (2006). Tax evasion and income source: A comparative experimental study. *Journal of Economic Psychology*, *27*(3), 402–422.

Gneezy, U., Niederle, M., & Rustichini, A. (2003). Performance in competitive environments: Gender differences. *The Quarterly Journal of Economics*, *118*(3), 1049–1074.

Gysler, M., Brown Kruse, J., & Schubert, R. (2002). Ambiguity and gender differences in financial decision making: An experimental examination of competence and confidence effects. *Working papers/WIF*, *2002*(23).

Lazear, E. P., & Rosen, S. (1981). Rank-order tournaments as optimum labor contracts. *Journal of Political Economy*, *89*(5), 841–864.

Lefebvre, M., Pestieau, P., Riedl, A., & Villeval, M. C. (2015). Tax evasion and social information: An experiment in Belgium, France, and the Netherlands. *International Tax and Public Finance*, *22*(3), 401–425.

Maloney, W. F. (2004). Informality revisited. *World Development*, *32*(7), 1159–1178.

Myerson, R. B. (2009). Learning from Schelling's strategy of conflict. *Journal of Economic Literature*, *47*(4), 1109–25.

Perry, G. E., Arias, O., Fajnzylber, P., Maloney, W. F., Mason, A., & Saavedra-Chanduvi, J. (2007). *Informality: Exit and exclusion*. The World Bank.

Portes, A., & Haller, W. (2010). The informal economy. *The Handbook of Economic Sociology*, *403*.

Rosenzweig, M. R. (1988). Labor markets in low-income countries. *Handbook of Development Economics*, *1*, 713–762.

Schelling, T. C. (1960). The strategy of conflict. Cambridge, Massachusetts: Harvard University Press.

Schelling, T. C. (1978). Sorting and mixing. *Micromotives and Macrobehavior*.

Appendix Tables and Figures

Table A1: Summary statistics and balance tests

	Obs.	Mean	Std. Dev.	Mean Baseline	Mean Market Info	$p-$value from test
Panel A. Student sample						
Female	66	0.65	0.48	0.64	0.67	0.817
Age (years)	66	20.64	1.79	20.47	20.83	0.418
Have a job	66	0.05	0.21	0.00	0.10	0.053
Social protection	66	0.23	0.42	0.19	0.27	0.493
Retirement plan	66	0.14	0.35	0.03	0.27	0.004
Trust [1-4 scale]						
Government	66	2.20	0.83	2.11	2.30	0.359
Ministerio de Salud y Protección Social	66	2.52	0.68	2.44	2.60	0.362
ADRES	66	2.36	0.74	2.31	2.43	0.487
Colpensiones	66	2.61	0.84	2.58	2.63	0.812
Altruism [1-5 scale]						
I felt great afterwards helping others	66	4.48	0.73	4.53	4.43	0.604
Helping other people does not improve my mood	66	2.68	1.43	2.75	2.60	0.674
I do not consider it my duty to act disinterestedly	66	2.76	1.28	2.92	2.57	0.271
I feel a duty to help others whenever possible	66	4.12	0.85	4.11	4.13	0.917
Risk taker (staircase)	66	12.18	6.59	12.06	12.33	0.866
Use mouse	66	0.44	0.50	0.56	0.30	0.038
Use laptop	66	0.83	0.38	0.83	0.83	1.000
Panel B. Non-student sample						
Female	145	0.63	0.48	0.62	0.65	0.676
Age (years)	145	30.50	5.68	29.99	31.06	0.258
Education level						0.588
Primary	145	0.01	0.12	0.01	0.01	
Bachelor	145	0.06	0.23	0.03	0.09	
Technical	145	0.21	0.41	0.20	0.22	
University or higher	145	0.65	0.48	0.68	0.61	
Occupation						0.182
Unemployed	145	0.14	0.35	0.14	0.13	
Full-time worker	145	0.44	0.50	0.41	0.46	
Part-time worker	145	0.10	0.31	0.16	0.04	
Self-employed	145	0.22	0.42	0.21	0.23	
Unpaid worker	145	0.01	0.12	0.00	0.03	
Other	145	0.09	0.27	0.05	0.10	
Social protection	145	0.19	0.40	0.20	0.19	0.892
Retirement plan	145	0.58	0.50	0.58	0.58	0.993
Trust [1-4 scale]						
Government	145	1.95	0.90	1.97	1.93	0.759
Ministerio de Salud y Protección Social	145	2.23	0.81	2.21	2.25	0.792
ADRES	145	2.30	0.84	2.29	2.30	0.916
Colpensiones	145	2.70	0.87	2.62	2.78	0.257
Altruism [1-5 scale]						
I felt great afterwards helping others	145	4.59	0.71	4.58	4.61	0.803
Helping other people does not improve my mood	145	2.57	1.48	2.61	2.52	0.735
I do not consider it my duty to act disinterestedly	145	2.57	1.42	2.63	2.49	0.558
I feel a duty to help others whenever possible	145	4.32	0.90	4.26	4.38	0.447
Risk taker (staircase)	145	14.23	9.03	14.39	14.06	0.823
Use mouse	145	0.56	0.50	0.58	0.54	0.608
Use laptop	145	0.80	0.40	0.80	0.80	0.934

Notes: For balance checks, we employ $t-$tests for comparing means of continuous and binary variables. For other categorical variables we employ a Chi-squared test.

Table A2: OLS model explaining the treatment effect on market selection (Excluding groups with bots)

	Selection of *Market C*		
Market Info	0.050*	0.050	0.057*
	(0.030)	(0.031)	(0.031)
Female			-0.033
			(0.033)
Student			-0.115**
			(0.048)
Mean of Dep. Var (Baseline)	0.65	0.65	0.65
Observations	955	955	955
R-squared	0.009	0.031	0.058
Round FE	Yes	Yes	Yes
Group FE	No	Yes	Yes
Individual Controls	No	No	Yes

Notes: Model 3 includes the following non-significant covariates: age, individual's risk parameter, and device controls (use of mouse and laptop). Round fixed effects included. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A3: OLS model explaining the treatment effect on market selection by samples

	Selection of *Market C*	
	Non-student	Student
Market Info	0.048	0.092*
	(0.034)	(0.055)
Mean of Dep. Var (Baseline)	0.69	0.55
Observations	725	330
R-squared	0.084	0.149
Round FE	Yes	Yes
Group FE	Yes	Yes
Individual Controls	Yes	Yes

Notes: Models include the following covariates: age, sex, individual's risk parameter, and device controls (use of mouse and laptop). Round fixed effects included. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A4: OLS model for accuracy of beliefs about market selection.

	Absolute accuracy of beliefs	
Market Info	-0.189***	-0.187**
	(0.073)	(0.073)
Round 1	-0.157	-0.157
	(0.128)	(0.129)
Market Info × Round 1	0.258*	0.258*
	(0.153)	(0.154)
Test for linear combination		
Market Info + Market Info × Round 1	0.068	0.072
	(0.134)	(0.135)
Mean of Dep. Var (Baseline)	1.24	1.24
Observations	1,055	1,055
R-squared	0.032	0.033
Round FE	Yes	Yes
Group FE	Yes	Yes
Individual Controls	No	Yes

Notes: Model 2 includes as additional non-significant covariates: age, sex, the individual risk parameters, a dummy capturing whether the participant is a student, and device controls (use of mouse and laptop). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: OLS regression coefficients for Figure 3 involving the differences on market selection by treatment groups and beliefs.

	Selection of *Market C*	
Market Info	0.337*	(0.187)
Belief = 1	0.289***	(0.099)
Belief = 2	0.345***	(0.082)
Belief = 3	0.601***	(0.073)
Belief = 4	0.640***	(0.072)
Belief = 5	0.780***	(0.075)
Belief =1 x Market Information= 1	-0.387	(0.242)
Belief =2 x Market Information= 1	-0.398*	(0.204)
Belief =3 x Market Information= 1	-0.359*	(0.195)
Belief =4 x Market Information= 1	-0.292	(0.195)
Belief =5 x Market Information= 1	-0.291	(0.194)
Mean of Dep. Var Baseline	0.64	
Observations	1,055	
R-squared	0.210	
Round FE	Yes	
Group FE	Yes	
Individual Controls	Yes	

Notes: Control variables include age, sex of the participant, a dummy if the participant is a student, the individual risk aversion parameter and device controls (use of mouse and laptop). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6: OLS regression coefficients for Figure 4 involving the differences in productivity by market and beliefs.

	Productivity	
Market Info	0.137	(0.122)
Belief = 1	0.037	(0.475)
Belief = 2	-0.289	(0.466)
Belief = 3	-0.718	(0.450)
Belief = 4	-0.860*	(0.477)
Belief = 5	-1.069**	(0.509)
Market C	-0.623	(0.736)
Belief =1 $\times$ Market C= 1	-0.112	(0.955)
Belief =2 $\times$ Market C= 1	0.626	(0.814)
Belief =3 $\times$ Market C= 1	0.695	(0.771)
Belief =4 $\times$ Market C= 1	0.959	(0.796)
Belief =5 $\times$ Market C= 1	1.031	(0.800)
Female	-0.258**	(0.128)
Age (years)	-0.069***	(0.013)
Student	0.815***	(0.186)
Mean of Dep.Var Base-Info	7.68	
Observations	1,055	
R-squared	0.235	
Round FE	Yes	
Group FE	Yes	
Individual Controls	Yes	

Notes: Control variables include age, sex of the participant, a dummy if the participant is a student, the individual risk aversion parameter, and device controls (use of mouse and laptop). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.