Too Much or Too Little Faith in Success? Experimental Evidence from Colombian Entrepreneurs*

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Abstract

The high failure rate of new businesses in Colombia suggests a high entry rate among entrepreneurs with only low success potential. We test the hypothesis that this may be driven by the tendency to incorrectly estimate their success likelihoods. Specifically, we test the relative roles of ambiguity preferences, confidence, and optimism and whether there are heterogeneities in these biases with regard to the true underlying potential for success as an entrepreneur. We recruit current, past, and aspiring Colombian entrepreneurs to participate in an online experiment. As part of the study, we simulate the decision to become an entrepreneur by having participants make an "entry decision" about playing an entrepreneurship-related game for stakes or taking a certain payment. We vary the available information to disentangle the potential behavioral biases leading to over-entry. We find a high degree of entry at the baseline, with over 80% of participants choosing to play the game for stakes across the board that is statistically significantly higher than what risk preferences can account for combined with the expectation of 20% succeeding. Providing information about the average likelihood of success encourages the lower potential participants to enter *more*, closing the slight gap between them and their higher potential counterparts at baseline. Information about the individual-specific skill-based success likelihood discourages some lower potential individuals, in some circumstances, suggesting over-confidence. Sharing information about the role of luck may discourage the lower potential participants, providing evidence against high levels of optimism or risk-seeking in this group. Taken together, the findings show that overconfidence among the lower potential individuals generates over-entry in this group, but the resulting high failure rate does not deter high-potential individuals' entry.

Keywords: Entrepreneurship, Optimism, Confidence, Ambiguity, Entry decision, Lab-in-the-field.

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1 Introduction

It is an established fact that most businesses in developing countries do not succeed. In Colombia, only 23% of businesses survive for at least four years (Alfonso and Pardo Martínez, 2015), less than half the rate in the US[1]. The literature has extensively studied the causes of failures related to features of the environment in developing countries, such as capital and labor constraints and the political environment. But many features of the environment that constrain businesses are knowable ex-ante; for example, business loan requirements are publicly available. The knowable constraints raise the question, why do aspiring entrepreneurs choose to start businesses that are likely to fail?

Behavioral economics can provide an answer to the question above. This literature has shown, for example, that individuals often incorrectly estimate the likelihood of favorable outcomes in laboratory settings (Camerer and Lovallo, 1999; Heger and Papageorge, 2018). While these experiments precisely estimate how participants behave, they often rely on college students or online recruitment and use simple strategic games. Both of these choices present challenges for externally validity in order to describe how real entrepreneurs behave. In this paper, we address this challenge by studying the behavior of real Colombian entrepreneurs in a controlled environment which allows us to shed light on their decision process facing a new, uncertain entrepreneurial opportunity.

We study three specific behavioral traits that may bias how entrepreneurs estimate their likelihood of success. First, one may be uncertain about the difficulty of success in general, for example, when not many data points are available about the outcomes of similar endeavors. Second, one may be uncertain about one's skill level regarding the entrepreneurial task ahead. Third, one may be uncertain about the role of luck. We use an online experiment with Colombian entrepreneurs to test whether there is evidence of participants incorrectly estimating their success likelihood in an entrepreneurial game mimicking an entry decision. We do so by implementing informational treatments carefully designed to reduce them each potential bias. Furthermore, we investigate whether there is heterogeneity in these biases by underlying entrepreneurial potential as a potential mechanism explaining high failure rates due to higher over-entry among entrepreneurs less likely to succeed.

More precisely, the first behavioral trait we focus on relates to preferences over

[1]For comparison, in the US, the corresponding statistic was 56% in 2015 and has been within 5 percentage points of that value since 2007, according to the Bureau of Labor Statistics.

ambiguity. Following Maccheroni et al. (2006), we define ambiguity seeking behavior as decisions consistent with an increased perceived probability of the favored outcome when the source of uncertainty is an ambiguous event relative to an unambiguous one, such as the flip of a fair coin. This can also be understood as people having biased priors over the random process determining outcomes. We test whether there is evidence in favor of ambiguity preferences leading to biased decisions by studying behavior in the absence of information about average success rates in our entrepreneurial online game.

The second type of behavior we study involves over or under-*confidence*, (Camerer and Lovallo, 1999). Choices explained by this phenomena imply people holding incorrect beliefs about how their skills or preparedness translates into a higher likelihood of success. We test whether there is evidence over or under-confidence leading to biased decision-making among entrepreneurs by directly shocking their beliefs about how likely are they to succeed in the experimental entrepreneurial game based on their observable characteristics.

Finally, we also study optimism (conversely pessimism), which relates to an increased (decreased) perceived probability of a favored outcome relative to a neutral or non-favored one(Amore et al., 2021) . We test whether there is evidence for this trait leading to behavior change by modifying the amount of randomness or luck involved in the entrepreneurial game. When randomness increases, mechanically decreasing the role of skill in the game, an optimist entrepreneur would assign higher likelihood to favored outcomes and thus be more likely to "enter the market".

This paper studies these three potential sources of biased decisions through an online lab-in-the-field experiment. Our sample consists of aspiring entrepreneurs recruited through various entrepreneurial networks, including university alumni groups and the social media of an entrepreneurship and innovation-focused government agency. The fact that we work with real entrepreneurs, allows us to measure how their prepared as entrepreneurs relates to their behavior and the prevalence of decision-making biases. Therefore, our experimental design allows us to test the extent to which these biases contribute to *over-entry* among relatively low-potential entrepreneurs, and *under-entry* among relatively high-potential entrepreneurs.

The experiment consists of two parts. First, participants complete a survey where we collect some of their basic information and information about their previous experiences with entrepreneurship and related skills, their business idea, and their financial literacy. We use the latter three to calculate their "entrepreneurial preparedness" score ("EP score" thereafter, which we show is a good proxy for their entrepreneurial potential). Second, participants learn that they will play an entrepreneurship-related game and need to decide whether to play for stakes or not. If they "enter" (play for stakes), they win 20,000 Colombian Pesos ($\sim$ 5.3 USD) if they score higher than a certain threshold and otherwise win nothing. If they choose not to play for stakes, they receive a certain 5,000 COP regardless of their game performance. During the experiment, we implement additive information treatments related to their expected success likelihood in the game, addressing the above-mentioned three behavioral traits.

We first show that participants more often than not choose to enter and play for stakes, with very little information about the entrepreneurial game. The study is not designed to be able to make welfare claims about individual entry decisions. However, we consider whether, on average, the sorting of aspiring entrepreneurs could be improved by fewer low EP entries or more high EP entries. Even though there is a weak positive correlation between entry decisions and the continuous EP score, consistent with no relative under-entry among the higher EP individuals, we observe high entry rates across the board as even participants in the lower half of the EP score distribution enter 80.8% of the time at baseline. When we restrict the sample to the subset of participants for whom we measured their risk preferences, this number is 87.8%. We use their risk preferences to construct the maximum bound on their entry rate that would be consistent with their risk preferences. We estimate the maximum bound to be 63.7%, and conclude that the observed entry rate of the low EP individuals relatively large in magnitude.

We then use the additive informational treatments to investigate the role of the three behavioral traits in the over-entry among the low EP individuals. In addition to the baseline information, we implement three additive informational interventions targeting each of the biases. We randomize participants into making a decision under all four sets of information-availability or in only three of them, using the randomization and changes in their decisions for our identification strategy.

We first implement an information treatment about the average level of difficulty of winning. We share with participants that we expect 20% of the participants to score high enough to win the prize, based on our analysis of the first 80 participants' performance. This intervention allows us to test whether sharing information about the average difficulty matters and whether there is evidence of any bias in its absence. Importantly, this changes the random process associated to the entrepreneurial game by lifting the uncertainty in participants' choices and transforming them to a simpler decision under know risk. We also start with this information treatment because it is the most basic signal about the decision-making environment. It is unlikely that more complex information would be shared without first providing this information about the general difficulty of the game. Furthermore, if this relatively simple information proves helpful, that would have important implications for practitioners working with aspiring entrepreneurs as general stats about success-rates for entrepreneurs are generally available.

This average success information encourages some low EP individuals to enter. Their entry rate increases by 6.8 percentage points (p val < 0.1). This increase in entry is unexpected because we hypothesized that in the absence of information about average difficulty, ambiguity seeking or incorrect low priors about difficulty might be reasons for the over-entry observed at baseline. However, we find that the entry rates were high at baseline despite ambiguity avoiding preferences or priors consistent with over-estimating the task's difficulty. In the case of the high EP individuals, we find no statistically significant effect of sharing this information. This result provides evidence for heterogeneity by the underlying potential in the overall effect of ambiguity preferences and priors about the difficulty of success. Once the average difficulty of the game was revealed, the differences in entry between low and high EP became smaller, suggesting preferences over ambiguity or biased priors were actually favoring selection of better prepared entrepreneurs into entering the game.

The second piece of information we share addresses biased choices due to over or under-confidence. We share with participants the EP score we calculated for them, their percentile relative to the other participants, and the fact that the score is positively correlated with performance in the entrepreneurial game (based on pilot data). By studying the effect of this information, we can test whether sharing skill information matters and whether there is evidence of any over or under-confidence without it. This information is inspired by the literature on predicting entrepreneurial outcomes (for example, McKenzie and Sansone (2019) and Fafchamps and Woodruff (2017)) and that the EP score in our context is positively correlated with game outcomes. Sharing their EP score with the participants provides evidence for the hypothesis that some of the low EP individuals were entering because of over-confidence.

We find that learning about own EP score discourages entry, when shared after a first decision made with the average information available, reducing entry by 7.2 percentage points (p val < 0.05) for low EP participants. At the same time, we find no effect on the high EP individuals. Nonetheless, this result should be interpreted with caution as we find some indication of round or anchoring effects which might confound this finding.

The third piece of information we share with participants focuses on the role of randomness and luck. We share with participants how we expect them to score based on their EP score and how this is in turn affected by having good luck (defined as being in the top 10% luckiest) or bad luck (defined as being in the lowest 10% of luck). This information also includes a cross-randomization assigning participants to one of two versions of the game, one high randomness involved and one with low randomness. When the game involves more randomness and luck is more important, this translates into an information treatment with a wider range of scores for participants' expected outcome in the game (even conditional on skill). We first test whether being told that luck plays a greater or smaller role matters.

We find that it makes no statistically significant difference on neither low nor high EP participants. This is surprising because introducing a higher role for luck has a mechanical effect on participants' odds of success. For participants with skills below the level needed to "win" in this game when only skill matters (outside of the top 20% based on the average success information), the greater role of luck means greater upside and a higher probability of winning. For participants with high levels of skills, the effect is the opposite. The fact that we cannot reject a null effect on average when increasing the role of luck for both the lower and the higher EP individuals is not consistent with the participants responding to the expected, mechanical effect. Instead, results can only be rationalized by higher EP individuals being optimistic and expecting to be favored by luck, counteracting the mechanical effect; while the lower EP individuals displaying pessimism.

Taken together, our experimental findings suggest that overconfidence among low-potential entrepreneurs is driving over-entry among this group. Efforts to reduce over-entry by sharing average success probabilities increase entry suggesting high entry at baseline despite a perceived difficulty of success or ambiguity aversion. This is consistent with the failure rates remaining stable or even increasing over time, as knowing about them would not discourage the ones less likely to succeed. Sharing information about individual-specific skill discourages some of the lower EP individuals when shared after a first decision with the average information available, providing suggestive evidence for over-confidence in the absence of this information. Although sharing information about the role of luck may discourage some participants, this effect does not change with the amount of randomness involved. This means luck only has limited effects on behavior and therefore, over-entry appears not to be driven by optimism. Overall, we find evidence for the benefits of sharing individual-specific skill information with aspiring entrepreneurs and for sharing information about the average success rate with caution as it might encourage less prepared entrepreneurs.

This paper contributes to the development economics literature studying the causes of business failures and interventions to improve the success likelihoods of entrepreneurs. Previous work has studied the impact of lack of access to credit (De Mel et al., 2008; Banerjee et al., 2015; Karlan and Zinman, 2009) and the impact of the lack of managerial capital (Bruhn et al., 2010; Bloom et al., 2013; McKenzie and Woodruff, 2014). Additionally, past work has studied targeting interventions to spur enterprise growth, using business plan competitions (McKenzie, 2017; Fafchamps and Woodruff, 2017), personality tests (Badal, Badal; Olafsen and Cook, 2016), firm characteristics (Lussier, 1995; Brown et al., 2014; Moreno and Coad, 2015) and social networks (Hussam et al., 2022). Unlike the existing literature, this paper brings to light the entry decision for opportunity entrepreneurs and the biases that may affect their decision-making. We provide evidence that overconfidence of individuals with lower levels of preparedness may be a contributing factor of the high failure rates. Additionally, we provide suggestions for policymakers about how to help improve these decision processes to better support aspiring entrepreneurs.

There is also a growing literature on studying the heterogeneous impact of capital on firm outcomes (Beaman et al., 2021; Banerjee et al., 2019; Bryan et al., 2021; Meager, 2022). This paper is related to this growing literature by examining heterogeneity in belief formation about the odds of a risky entrepreneurial opportunity. It is plausible that the differences we observe by entrepreneurial preparedness are driving some of the findings of the above-mentioned papers. For example, Bryan et al. (2021) provide suggestive evidence for appearing broadly optimistic (meaning general faith in success) being a driver of their observed heterogeneous returns to capital. Our paper provides a complement by diving deeper into specific behavioral biases that could result in appearing broadly optimistic and correlation with underlying entrepreneurial potential. The decision between a high-risk and high-reward versus a (relatively) certain option is not unique to opportunity entrepreneurs deciding to start a business. Entrepreneurs who start a business out of necessity may have choices between what kind of a business to start. Similarly, already established entrepreneurs may have choices between what approach to take for expanding their businesses, as studied by Bryan et al. (2021). Thus, the findings of this paper and the role of behavioral biases affecting a decision between an entrepreneurial high-risk and reward versus a certain option may be relevant more broadly than the context studied by this paper.

This paper also contributes to the behavioral economics literature that has identified various forces that may lead to biased estimates of the likelihood of success. Previous literature has studied overconfidence (Koellinger et al., 2007; Gutierrez et al., 2020; Charness et al., 2018; Heger and Papageorge, 2018), overoptimism (Arabsheibani et al., 2000; Heger and Papageorge, 2018; Amore et al., 2021), ambiguity preferences (Gutierrez et al., 2020), decision weight distortion by the salience of payoffs (Bordalo et al., 2012), the tendency to overweight small probabilities (Camerer, 2004; DellaVigna, 2018). Furthermore, additional factors have been identified that could lead to over-entry into entrepreneurship, such as risk preferences (Elston et al., 2005), the joy of winning (Elston et al., 2005), and prospect theory (Kahneman and Tversky, 1979). Some of the existing literature is linked to entrepreneurial over/entry, either as motivation for lab experiments (Gutierrez et al., 2020; Heger and Papageorge, 2018) or by studying entrepreneurs directly (Amore et al., 2021). However, none of the existing papers study real entrepreneurs in lab experiments, to the best of our knowledge. We contribute to this literature by being the first paper (to our knowledge) studying *real entrepreneurs* in a lab experiment and by focusing on opportunity entrepreneurs in a developing country.

Furthermore, some existing studies have focused on disentangling some of the potentially overlapping causes of overestimating the likelihood of success (Gutierrez et al., 2020) and estimating the correlation between the underlying sources (Heger and Papageorge, 2018). However, no studies have examined the correlation between the tendency to over or under-estimate the probability of success and true underlying potentials for success to the best of our knowledge. This paper contributes to the existing literature by focusing on real entrepreneurs and studying the correlations between underlying entrepreneurial preparedness and various sources of biased estimates of success: confidence, luck, and ambiguity. Thus, our approach allows for heterogeneity in these biases by underlying the likelihood of success and tests whether some aspiring entrepreneurs overestimate their chances of success while others underestimate them.

The rest of the paper is organized as follows. Section 2 details the study context and the experimental approach. Section 3 provides the conceptual framework for our approach, including the hypotheses and identification strategy. Section 4 presents the results including descriptive statistics of the data, and Section 5 concludes the paper.

2 Background and Study Design

2.1 The Colombian Context

Colombia is a lower middle-income country in South America with a GDP per capita of $6,131 in 2021, according to the World Bank. The country has a high level of entrepreneurial intentions. According to the Global Entrepreneurship Monitor (GEM), Colombia had been among the leaders in Latin America in this metric from 2006 through 2018. In 2018, Colombia had one of the highest rate in the region, with almost 50% of its adult, 18-64 year old population intending to start a business within 3 years. For comparison, this number was less than 12.15% in the US. Table 1 below shows these trends in detail. The high rate of entrepreneurial intentions can also be documented by the high rate of total early-stage entrepreneurial activity relative to the rate of established business ownership (TER). According to data from the GEM, this ratio was over 3 in Colombia in 2018, and stayed among the highest ones in Latin America during the twelve year period before 2018.

	2018			Average for 2006 - 2017		
	Intentions	TER	TEAOPP	Intentions	TER	TEAOPP
Argentina	14.83%	1.01	71.14%	22.70%	1.48	67.02%
Brazil	26.05 %	0.88	62.21%	24.79%	1.11	63.47%
Chile	48.67%	2.93	75.81%	39.72%	2.56	75.63%
Colombia	**48.84%**	**3.26**	**87.56%**	**53.83%**	**2.44**	**70.38%**
Peru	39.7%	2.68	76.00%	39.71%	3.19	76.37%
United States	12.15%	1.98	90.47%	10.23%	1.53	82.01%

Table 1. Entrepreneurial Intentions, Early-Stage Entrepreneurial Activity and Opportunity as Motivation in Colombia and Elsewhere.

Note: This table shows data from the Global Entrepreneurship Monitor (GEM), and own calculations based on the GEM data (TER, TEAOPP, and the average values). *Intentions*, as defined by GEM, show "the percent of the adult, 18-64-year-old, population who intends to start a new business in the coming three years". *TER* show the ratio of the total early-stage entrepreneurial activity to the ("the percentage of 18-64 population who are either a nascent entrepreneur or owner-manager of a new business"(GEM)) to established business ownership ("the percentage of 18-64 population who are currently an owner-manager of an established business, i.e., owning and managing a running business that has paid salaries, wages, or any other payments to the owners for more than 42 months"(GEM)). *TEAOPP* show the percent of early-stage entrepreneurial activity that is motivated by seeing a business opportunity, as opposed to a necessity ("finding no other option for work"(GEM)).

In addition to the high level of entrepreneurial intentions and early-stage entrepreneurial activities, there are two additional important factors in the Colombian environment. One is that over 70% of new businesses were motivated by a market opportunity as opposed to necessity, according to GEM data during 2006-2017, and it even reached over 85% in 2018. These statistics are among the higher ones in Latin America. The other important statistic is the high rates of failure. In Colombia, only 23% of all businesses survive for at least four years (Alfonso and Pardo Martínez, 2015).

Based on these statistics, the overall picture of Colombia is a country where a high fraction of the population starts up short-lived businesses with the motivation of choosing to start as opposed to a necessity in the majority of cases. Given these characteristics, Colombia is well suited for studying the decision-making process about starting a business, focusing on evaluating the odds of success and the role of behavioral biases. If these biases play a role, Colombia is a great candidate for first identification in the field. Nevertheless, we hypothesize that the same behavioral factors are likely present in other countries as well, even if to a lower extent. Thus, we expect the study to have implications for other countries too.

2.2 Recruitment for the Study

We conducted a lab-in-the-field experiment with aspiring, current, and past opportunity entrepreneurs based in Colombia. During the first stage of the study, we recruited 80 entrepreneurs from a pool of attendees at the entrepreneurship and innovation-focused Heroes Fest in Bogotá, Colombia, in September 2019. For the second stage of the study, we recruited 357 participants. Because of the COVID-19 pandemic, the recruitment for the main study took place entirely online, relying on various university alum networks as well as the social media of INNpulsa, the largest governmental organization focused on innovation and entrepreneurship in Colombia, and other entrepreneurship networks.

Participants received an email invitation for participation. They first had to accept the consent form to be eligible to participate. Then, they had to pass an eligibility screening. The screening established residency in Colombia, being at least 18 years old, and having a strong connection to entrepreneurship: running an own business currently, or in the past, working on starting an own business currently or in the past, or planning on starting a business in the near future with an idea either about the sector or the problem that the business would solve.

The study took place online via the Qualtrics platform. The survey was designed to be completed between 25 and 35 minutes. The median time elapsed between starting and finishing the survey, including time spent away from the survey, was 51.4 minutes. The minimum payment received was COP 30,200, the maximum was COP 59,000, and the average was approximately COP 38,300 ($\sim$ \$10.9)[2]. Of this amount, COP 30,000 was the payment for participants' time for completion, while the remaining was the result of the incentives used. The payments were designed to be high enough to be reasonable for busy entrepreneurs to dedicate their time and attention to the survey.

Payments were paid out using the third-party application called Rappi. This application is widely used in Colombia as a "super-app" with a range of features from food delivery to paying other individuals. We relied on the fraud prevention mechanisms of this application to deter fraudulent intentions for trying to complete the survey multiple times for payment. Additionally, we used a combination of the information provided for payment, IP address, inconsistencies in survey answers, and time spent on specific survey pages to disqualify multiple survey-takers. The 437 total participants whose data is used passed these tests.

2.3 Experimental Design

The survey consisted of two main sections. The first section included basic demographic and other survey questions. Some of these questions, as detailed below, were used to calculate participants' entrepreneurial preparedness (EP) score, also referred to as the entrepreneurial potential score. The second section of the survey consisted of the entrepreneurial game and, prior to playing the game, the decision about the stakes. The sections below provide details on the decision process and the game itself.

2.3.1 The Entrepreneurial Preparedness Score

The construction of the entrepreneurial preparedness (EP) score is constructed using three types of variables. First, participants share their previous experiences with starting or running a business, being in a managerial role, and with skills invaluable for starting a business, such as marketing, business development, and experience in the relevant business sector. Second, participants share the level of development and their commitment to their business idea. Third, they answer financial literacy

[2]Participants had the option to participate without receiving a payment. Approximately 6.7% of them chose this option. They could share such intent at the beginning of the survey and could later change their mind at the end. In order to receive payment, they had to provide their full name, phone number, and email address and had to have a working Rappi account.

questions.

The score was designed to include factors that are linked to entrepreneurial success, and that can change over time. As a result, the score is not a judgment on the participants' affinity to entrepreneurship or a fixed potential, but instead, it is a snapshot of their preparedness at a specific point in time. The survey was designed to set this reference point in time to be the same for everyone or as close to it as possible. Participants who run a business currently or did so in the past were asked to think about the time just before they started making sales. Participants who are working on a business currently or did so in the past without having reached the stage of making sales were asked to think about the current point in time or the last point in time when they were still working on their business. Participants who are planning to start their businesses were also asked to think about the current point in time. With regards to the past experiences questions, for participants who have or had co-founders, the experience of the entire founding team was considered, not only their own.

The goal for designing the EP score was to be able to test the hypothesis that there is heterogeneity in behavioral biases that may affect one's perception of the odds of a new entrepreneurial opportunity. For the findings to be relevant outside of the experiment, the EP score was designed to be composed of variables that are clearly linked to entrepreneurial success, would be relevant outside of the experiment to their actual success, and that they could improve on. Additionally, the EP score is essential for testing the hypothesis about overconfidence. The key to being able to test this hypothesis is that the EP score is predictive of performance in the entrepreneurial game.

The above design of using the EP score information as a signal about skill in the game is based on two assumptions. The first is that organizations working with entrepreneurs could gather data predictive of their expected outcomes. Existing literature, for example, McKenzie and Sansone (2019) and Fafchamps and Woodruff (2017) show that precisely predicting entrepreneurial outcomes is hard, but useful insights are possible. They investigate various methods of creating predictive scores and find R-squared values ranging between 0.01 and 0.15 and 0.14 and 0.38, respectively. The second assumption is that this experiment can mimic this predictiveness, and the Entrepreneurial Preparedness (EP) score we calculate during the study is predictive of participants' outcomes in the entrepreneurial game. We found evidence for this relationship during the first stage of our study involving 80 participants. We estimated that, on average, a 1-point higher EP score results in 57.2 points higher score in the game[3]. The estimated coefficient has a p-value of 0.024, an R-squared of 0.12 (in the high role of luck version of the game), and is robust to various specifications. The positive and statistically significant held up for the full sample too.

2.3.2 The Entrepreneurship Game

The experiment is designed to mimic the decision of an aspiring entrepreneur between a certain, lower outcome and a new and unfamiliar option with a higher return potential with also a greater risk. The entrepreneurship game is designed to meet this criterion by being unfamiliar and entrepreneurial and being both entrepreneurship-related and entrepreneurship-themed. Because it is not feasible to mimic the entire experience of starting up a new business in a 5-10 minutes game, we picked one challenge that entrepreneurs have to face and created a game focused on it. The game follows a multi-armed-bandit style where participants have to weigh the opportunity of exploring options to learn more about them and the opportunity of exploring familiar options. It mimics the challenges of business development and finding the right product-market fit where repeated experimentation is needed until a great solution is found.

The game is also entrepreneurship-themed because the challenge for the participants is presented as needing to decide which of six sectors is the best one for developing a new service in. In each round of the game, participants pick between one of six sectors to develop in. Then, they observe customer turnout and corresponding profits (score). They play a total of 15 rounds. In addition to scores coming from customer turnout, they receive additional points for guessing correctly at the end which one was the best sector. Participants know that they may observe each of the possible customer turnouts in each of the sectors. They also know that the best sector is the most likely to have the highest customer turnouts, while the opposite is true for the worst one. They are also told that any one of the sectors might be the best as the order of sectors is randomly assigned for each participant's game session. Please refer to Appendix B, Figure B1, for an example of the screens participants saw during the game.

An additional important attribute of the game is that it is possible to change the role of luck. The role of luck was changed by varying the underlying likelihood of the

[3]The EP score ranges from 0 to 100 while the game score ranges from 0 to 10,000 with the necessary threshold for winning set at 6,600.

good versus bad customer turnouts for each sector. A good turnout is one with a high customer turnout regardless of how good the sector is or one that is informative in the sense that the customer turnout reflects how good the sector is on average. These two attributes were weighted to define how good each turnout was for a sector, given how good the sector ranks on average. In defining how lucky a participant got, the potential outcomes for all sectors in each round were considered to isolate the effect of luck from participants' learning and choices. In the high role of luck version of the game, in each round, one of the 24 possible sets of six potentials (one for each of the six sectors) was drawn randomly. In the low role of luck version of the game, restrictions were in place to limit the distribution of luck by narrowing the overall set of possible distributions of the sets of six outcomes drawn across the 15 rounds.

2.3.3 The Entry Decision and the Informational Interventions

Before playing the game, participants decide whether to play for stakes or without stakes. They are told that they will play an entrepreneurial game. If they choose to play for stakes and score above a pre-set threshold, they receive COP 20,000 ($\sim$ 5.7 USD) and nothing otherwise. (They are told the range of possible scores and the threshold they need to reach.) If they play without stakes, they receive COP 5,000 with certainty. In the baseline condition that is all the information that they know before making their decision.

Participants in the first stage of the study ($N = 80$) made only one decision about whether to play the game for stakes or not under the baseline condition. Participants in the main stage were told that they will make multiple decisions and one of them would be chosen at random to get actually implemented. These participants made three or four binary decisions about whether to play for stakes or not. After the baseline condition, three informational treatments were revealed, one at a time, corresponding to the three sources of uncertainty of interest: ambiguity about difficulty, confidence in one's skill, and optimism about the role of luck. The data of the first 80 participants were analyzed to create truthful information pieces that were shared with the second-stage participants. When the pieces of information were shared, they included the corresponding note that these are our expectations based on our analysis of the first 80 participants and the design of the game. We also noted that the first 80 participants were also Colombian entrepreneurs just like the participants who received the information. The details of these information pieces are discussed below and Appendix B has examples of the screens participants saw for each piece of information.

The first piece of information shared was about the *average level of difficulty* of scoring about the threshold. By sharing this information, we can test whether this information matters and whether there were any biases beforehand, in the absence of this information. The information shared was the following: "**We expect 20% of the game participants to score at least 6600 points,** which is needed for winning COP 20,000". The first part of this information was shared in bold and underlined font, as can be seen in Figure B2 in Appendix B. All the information from the previous page was also visible on the screen with this new information.

The second piece of information shared was the EP score that we calculated for the participants. We first asked participants what they believed their EP score was. When asking them about this, we also shared with them information about the distribution of the EP score. Then, we revealed their score along with information about how their score compared with the distribution of other participants' scores, based on information from the first 80 participants. Next, we checked their understanding of interpreting the information about the comparison to the distribution of scores of the others. Finally, we shared with them that the EP score is predictive of game performance, and if they perform in the game as we expect them based on their EP score, then how we expect them to perform relative to the distribution of others' performance. The information shared on the page asking for the decision about the game included the following pieces of information in addition to all the previously shared information, and its original version can be seen in Figure B3 in Appendix B.:

- As we shared with you earlier, we calculated your Entrepreneurial Preparedness score (EP). **This score is predictive of performance in the Entrepreneurial Game.**
- The EP score we calculated for you is X. Compared with other participants, Y% of them had an EP score at least as high as yours.
- This means that **if you perform in the Entrepreneurial Game as your EP score predicts, Y% of participants will have a score at least as good as yours.**
- Note: the above information is based on 80 previous participants of the Entrepreneurial game who were also Colombian (aspiring) entrepreneurs.

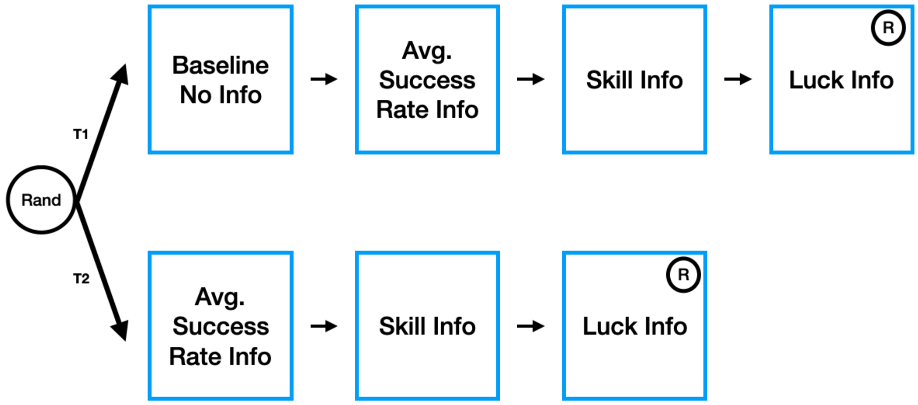
The third piece of additional information shared addressed the role of luck. We implemented this informational intervention to be able to test whether participants' behavior is consistent with the mechanical effect of the greater role of luck and whether there is evidence for optimism (over-weighting the probability of favorable outcomes) or pessimism. Participants were randomized into one of the two versions of the game where the role of luck either mattered more or less, and they received the corresponding information. The new information shared included the following in addition to previous information. (See Figure B4 in Appendix B for the original version, including formatting and graphics):

- This game also has an element of luck that affects the score. If you and everyone else had **average luck**, then, based on your EP score, we expect that **X% of the other participants will perform at least as well as you** in the game.
- However, if you are among the **10% of participants with the best luck**, we expect you to score such that **Y%** of the other participants or less will score at least as well as you.
- However, if you are among the **10% of participants with the worst luck**, we expect you to score such that **Z%** of the other participants or more will score at least as well as you.
- In summary:
  Good luck: **Y%** of the other participants or less scoring at least as well as you
  Bad luck: **Z%** of the other participants or more scoring at least as well as you
- Note: the above information is based on our analysis of the first 80 participants of the game, who were also (aspiring) Colombian entrepreneurs.

The order of the informational interventions shared was the same for all participants. We chose this order because it seemed unlikely that the latter, more complex pieces of information, would be shared without the context of the simpler pieces of information.

In addition to randomizing whether participants played the game version with the higher or, the lower role of luck, we also randomized participants into making three or four binary decisions about playing the game with stakes or not. As a result, some participants had already access to the Average Information for their first decision, while others decided on each of the four conditions, including the baseline. (Participants in the first stage of the experiment only had the baseline condition and the high-luck version of the game.) Figure 1 below summarizes the decisions of the participants in the second and main stage of the study.

Figure 1. Experimental Design: Order of the Information Treatments



Note: This Figure explains how participants in the experiment were randomized into either making 3 or 4 binary entry decisions and how these decisions progressed in terms of our information treatments. Additionally, the figure also shows that participants were cross-randomized into the high or low role of luck versions of the game (and corresponding information) when they arrive into the Luck Information stage.

2.3.4 Incentives

Participants were incentivized during their binary decisions about whether or not to play the game for stakes. They were told up front that one of their decisions will be implemented with equal probability. In addition to the incentivized "entry decisions" of interest, there were multiple other incentive-compatible decisions.

In addition to making the binary decisions about the stakes for the games, participants in the second, main stage of the experiment also made one additional decision about whether or not to play the game for stakes or not. This additional decision was implemented after all the information was revealed and the corresponding binary decisions were made. The final decision was in fact a list of choices between playing the game for stakes or getting paid based on a simple lottery where the prize was COP 20,000, just like in the case of scoring high enough when playing the game with stakes, or nothing. The choices from this list of choices resulted in the incentive-compatible elicitation of participants' beliefs about their probability of success in the game.

We also elicited additional beliefs from the participants in an incentive-compatible way. We elicited their risk preferences independent from (and prior to) the game. We first asked them about their EP score (and corresponding percentile), in an incentivized way, prior to revealing the score we calculated for them. Additionally, we also elicited their incentive-compatible belief about their game performance percentile relative to other participants after their EP score was revealed. Furthermore, participants knew that there was a small chance that regardless of their choices, their game performance would matter, so they were incentivized to do their best while playing the game[4].

3 Conceptual Framework

This paper tests whether there is evidence of behavioral biases due to various sources of uncertainty when evaluating new business opportunities. Furthermore, the paper tests whether there is any heterogeneity based on underlying potential. The goal of the experiment is to mimic the decision between a certain and a higher risk higher reward unfamiliar entrepreneurial opportunity in a lab setting. The experiment is designed to be able to control important aspects of the decision-making environment and so test the hypotheses. The sections below describe the conceptual framework we use, the details of the hypotheses, and the identification strategy.

3.1 The Model

The goal of the paper is to empirically test for the presence of certain behavioral biases that have been proposed in the behavioral economics literature and tested in other contexts. We rely on existing approaches to provide a model for guiding the thinking about the hypotheses we test.

We model the entry decision into starting a new business or choosing the higher risk higher return business options as follows. The decision maker has the choice between the lottery E (entry) and the certain outside option C. If they enter, they have a probability p_i to win prize P if they succeed and they receive a payoff of 0 otherwise. A risk-neutral decision maker with linear utility enters when $p_i \geq C/P = T$. In the case of a more complex decision maker, for example, without risk neutrality or linear utility, we can denote their individual specific compensations for the resulting difference in the needed threshold with m_i. As a result, they enter when p_i is greater than their individual specific threshold, $p_i \geq T + m_i = T_i$. As long as the values

[4]Participants in the first stage were told that there is a 1 in 50 chance that we reverse their choice. Participants in the main stage knew that one of the options in the list choice elicitation was not a choice but the option that they will play the game for stakes. The corresponding probability of being paid based on this single option that did not involve a choice was either 1 in 32 or 1 in 40, depending on the randomization.

of P and C and their m_i do not change, their threshold for entering remains the same. Throughout the experiment, P and C remain the same, and we assume that the interventions designed to affect only beliefs about p_i are successful in affecting only that and leaving m_i unchanged. Under these circumstances, we can learn about participants' belief formation about their probability of success, p_i.

Starting up a new business, pursuing a new entrepreneurial opportunity, or playing the game in this experiment are all not simple lotteries. In addition to luck, skill also matters. We define s_i to be the skill percentile of individual i relative to the pool of (aspiring) entrepreneurs. In the case of the game in the experiment, we denote the mapping from skill to score with $f(s_i)$. A similar mapping could also be used when mapping skills to profits, for example. In the case of the experiment, to win P when playing the game, one needs to score above a predefined threshold K in order to win. We assume that $f(s_i)$ increases in s_i. As a result, the exact functional form of $f(s_i i)$ does not matter, the only aspect of it that matters is the threshold of s, where $f(s_i) \geq K$ first holds. We call this value s_K.

Under the simplest, deterministic case with no uncertainty, p_i takes on only the degenerative values of 0 or 1. In this case, only skill plays a role in the outcome, luck or randomness plays no role. Additionally, the participants know exactly their own skill, as well as s_K. As a result, $p_i(s_i) = 0$ for all $s_i < s_K$, and $p_i(s_i) = 1$ for all $s_i \geq s_K$. In this paper, we study the effects of three sources of uncertainty decisions makers face:

- Uncertainty about the average level of difficulty of the game or in general about the mapping from skill to score, as captured by s_K.
- Uncertainty about their own skill s_i.
- Uncertainty due to the role played by luck or randomness on the scores (i.e. score is $f(s_i) + \varepsilon_i$ and people have beliefs over the random variable ε_i)

We hypothesize that these sources of uncertainty are present simultaneously in the absence of clear information about them. We first test in the entry decisions under the baseline condition whether there is evidence of particularly high entry rates among low EP or particularly low entry rates among the high EP individuals. We hypothesize that if such phenomena are present, these three sources of uncertainty might play a role. We test their impact one at a time by removing or reducing the sources of the uncertainties, one at time. We assume that their impacts are additive and we explain their implications below one by one.

3.1.1 Uncertainty About the Average Level of Difficulty

If the mapping from skill to score is not known, participants have to form a belief about the threshold of skill at which the game score is expected to be above the threshold in the absence of luck. Based on the values of P and C and their past experiences, participants form a belief about s_K, s_K^i. If they have a certain belief about this threshold that results in a certain belief $\hat{p}_i$ of 0 or 1 about their p_i, given their s_i. If they have an uncertain belief about s_K^i, then their believed probability of success, $\hat{p}_i$, will be a probability reflecting the likelihood of $\mathbb{P}(s_K^i \leq s_i)$.

We hypothesize that participants may form biased beliefs about the average level of difficulty because of their prior or their belief formation might be affected by ambiguity preferences. Following Maccheroni et al. (2006), we define ambiguity seeking as a decision consistent with an increased perceived probability of the favored outcome when the source of uncertainty is an ambiguous event relative to an unambiguous one, such as the flip of a fair coin. In this case, the average difficulty of the game is unknown in the baseline condition. While participants likely have priors based on their past experiences and the relative sizes of P and C, the average likelihood of winning P is ambiguous. Participants with ambiguity-seeking preferences act as if their odds were better than what is warranted based on their priors, such that $\hat{p}_i = \mathbb{P}(s_K^i \leq s_i + a_i)$, with a_i reflecting the bias due to ambiguity preferences. For participants with ambiguity-avoiding preferences, a_i is negative.

We test whether there is a systemic relationship between participants' potential, EP score, and the difference between participants' $\hat{p}_i$ and the true p_i given the difficulty level of the game. While we cannot test the effect of priors and of potential ambiguity preferences separately, we test for their overall effect. Once we share with participants the information about the expected percentage of participants who will score above K, we remove all the uncertainty about the average difficulty of the game. At that point, if participants knew their skill for sure and assumed that luck played no role, they would know exactly whether they would win or not. Comparing their entry decision before and after this information is revealed, we can test whether sharing this information matters and whether there are any biases in its absence. If low EP individuals are ambiguity-seeking or are optimistic about the task at hand being easy, then we would expect them to get discouraged when the average success rate is revealed. We can test to what extent the over-entry observed at baseline among the low EP participants can be attributed to the lack of information about the average difficulty of scoring high enough in the game. Additionally, we test whether the high and the low EP individuals react differently to this information.

3.1.2 Uncertainty About Their Own Skill

If participants are not sure about their entrepreneurial skill (preparedness), then they form a belief about their s_i, $\hat{s}_i$. This belief is based on their priors as well as any over- or under-confidence that could bias their belief. Based on this belief, they form the belief about their probability of success: $\hat{p}_i = \mathbb{P}(s_K \leq \hat{s}_i + c_i)$ where c_i is the factor of over- or under-confidence that is positive for overconfidence and negative for under-confidence. Based on previous work in the literature, we expect that individuals with a low EP score are more likely to be overconfident about their skill level than individuals with a high EP.

We test whether there is a systemic relationship between participants' potential, EP score, and confidence level. Once we share with participants the information about their EP score and that it is correlated with game performance, we provide a signal about their skill. At that point, if participants believed the information and assumed that luck played no role, they would have an exact prediction about whether they would win or not. Since the information we share is only predictive of skill in the game but not exact, an element of uncertainty still remains. However, we hypothesize that the information is relevant and can reduce previous confidence-related biases. Comparing their entry decision before and after this information is revealed, we can test whether sharing this information matters and whether there are any biases in its absence. If low EP individuals are over-confident, then we would expect them to get discouraged when information about their skill is shared. We can test to what extent the over-entry observed at baseline among the low EP participants can be attributed to possible overconfidence. Additionally, we test whether the high and the low EP individuals react differently to this information.

It is important to note that what we test here is whether an imperfect, yet informative signal about entrepreneurial skill, or preparedness, is relevant and whether it can correct for any confidence-related biases. The motivation for the paper is to test the potential role that behavioral biases might play in entrepreneurial entry decisions such that it could recommend strategies for addressing these biases in the field. The design of using the EP score information as a signal about skill in the game is based on two assumptions. The first is that organizations working with entrepreneurs could gather data predictive of their expected outcomes. Existing literature, for example, McKenzie and Sansone (2019) and Fafchamps and Woodruff

(2017) show that precisely predicting entrepreneurial outcomes is hard, but useful insights are possible. They investigate various methods of creating predictive scores and find R-squared values ranging between 0.01 and 0.15 and 0.14 and 0.38, respectively. The second assumption is that this experiment can mimic this predictiveness, and the Entrepreneurial Preparedness (EP) score we calculate during the study is predictive of participants' outcomes in the entrepreneurial game. We found evidence for this relationship during the first stage of our study involving 80 participants. We estimated that, on average, a 1-point higher EP score results in 57.2 points higher score in the game. The estimated coefficient has a p-value of 0.024, an R-squared of 0.12, and is robust to various specifications. The positive and statistically significant held up for the full sample too.

3.1.3 Uncertainty Due to the Role of Luck in Scores

If the score is not determined only by skill, but luck (or randomness) also plays a role, then the game score becomes $f(s_i) + \varepsilon_i$, assuming an additive relationship between the impact of randomness and skill, substitutability, in other words. Note that bad luck means a negative value of ε, while good luck means a positive value. When there is an element of randomness, knowing the average level of difficulty and one's skill is not enough to predict with certainty whether one will score above the threshold or not. One needs to form a belief about the range of possible values of luck, determine the minimum amount of luck needed for scoring above the threshold for a given skill level, and the likelihood of luck being at least as good as the minimum needed. The result of forming these beliefs is that one can form their belief about their perceived probability of success as follows: $\hat{p}_i = \mathbb{P}(K \leq f(s_i) + \varepsilon_i) = \mathbb{P}(s_K \leq s_i + g(\varepsilon_i))$

In addition to knowing (or having a belief about) the average level of difficulty of winning, participants must form a belief about the relative role of skill versus luck contributing to the game score. At one extreme, where only skill matters, knowing that 20% of participants are expected to score high enough to win P means that the top 20% of most skilled participants will score high enough. At the other extreme, if only luck matters, it is expected that each participant has a 20% chance of getting lucky and winning. Under the additive assumption between the impact of skill and luck, in between the two extremes, one has to form a belief about the relative role of luck versus skill: what is the maximum amount of game points that can come from luck? We assume that participants form a belief about the maximum possible role of luck based on their priors. Additionally, their belief might be affected by optimism, defined as the overestimation of the probability of favorable outcomes, or the opposite of it, pessimism. We can represent the effect of potential optimism or pessimism as follows: $\hat{p}_i = \mathbb{P}(s_K \leq s_i + g(\varepsilon_i) + o_i)$, where o_i is the effect of optimism when positive and the effect of pessimism when negative.

We test whether there is a systemic relationship between participants' potential, EP score, and the difference between participants' pi' before and after the luck information is revealed. To be able to tease out the effect of priors and optimism (or pessimism), we randomize participants into one of two versions of the game, where the role of luck is greater or lower. Then we compare the effects of sharing information about the role of luck across this randomization. It needs to be noted that increasing the role of luck has a mechanical effect on the odds of participants. Under no luck, participants in the top 20% of skill would win for sure. However, when only luck mattered, they would have only a 20% chance of winning, just like everyone else. As the role of luck increases, their odds move from the one extreme of winning with certainty towards having only a 20% chance. This is the mechanical effect of increasing the role of luck on the highly skilled participants. At the same time, for participants with lower levels of skill, the mechanical effect is the opposite, as the role of luck increases, their odds of winning increase towards the 20% chance. We test whether we see evidence of this mechanical effect of the role of luck or if, instead, we see evidence of optimism or pessimism mitigating these mechanical effects. Then, we can make inferences about participants' priors by comparing their behavior before and after the luck information was revealed.

We hypothesize that lower EP individuals are optimistic and over-enter at baseline because they believe that luck will be on their side. Combined with the mechanical effect of the greater role of luck, we expect to see significantly greater entry rates under the high versus the low luck condition in this group. We also test whether high EP individuals react as expected to the luck information and whether there is heterogeneity in the level of optimism by EP.

3.2 Hypotheses

The first two hypotheses we test are whether low EP individuals over-enter at baseline and whether high EP individuals under-enter. The study is not designed to be able to make welfare claims about individual entry decisions. However, we consider whether, on average, the sorting of aspiring entrepreneurs could be improved by fewer low EP entries or more high EP entries. First, we test whether high EP individuals enter more than low EP individuals. Second, we test whether low EP individuals enter more than the maximum entry rate justifiable based on the average success rate and the low EP individuals' risk preferences. The experiment is designed such that we expect approximately 20% of the participants to score high enough in the game to win the prize. We construct the theoretical maximum entry rate that would be consistent with participants, on average, holding a belief consistent with a 20% success rate and participants' risk preferences.

If all participants were risk-neutral, then believing that they have a 25% chance of winning would be the lowest sufficient probability leading to entry. If everyone had the same belief about their individual probabilities of success, consistent with the average success rate of 20%, then they would all believe that their probability of success is 20%, and no one would enter. This is the lowest bound on entry rates consistent with the average success probability and risk-neutral participants. However, to test whether there is over-entry among the low EP individuals, we need the upper bound. We need the maximum fraction of participants who can enter with the minimum belief about their success likelihood, 25%. If 80% of participants believe that their own success likelihood is 25% and the rest believe that their success likelihood is 0%, then, on average, their beliefs are consistent with the 20% average success rate. Thus, we could conclude that an overall entry rate of up to 80% could be the highest entry rate consistent with the average success rate shared and participants' risk-neutral preferences. While this fact may appear counter-intuitive, Benoît and Dubra (2011) discuss in detail the implications of possibly differing subjective beliefs within a group.

We use the actual risk preferences data of the low EP individuals that we elicit in the first part of the survey to be able to do the above calculations based on their actual risk preferences. We calculate the upper bound on entry rates consistent with rational decision-makers following their risk preferences while their average beliefs are still consistent with the overall 20% success rate and the most number of them entering. Then, we test whether the observed entry rate is statistically significantly greater than this upper bound. If the entry rate is greater, that would signal that there are other factors at play beyond risk preferences, warranting the study of behavioral biases due to the above sources of uncertainties.

Next, we test whether the three informational interventions result in statistically significant changes in entry decisions, signaling the presence of biased estimates of success likelihoods in their absence. In particular, we test whether resolving uncertainty about the average level of difficulty, providing a signal about individuals' skill, and sharing information about the role of luck can meaningfully change behavior, providing evidence of a bias in their absence. We test these hypotheses one at a time, corresponding to the three separate informational interventions. Additionally, in the case of each of them, we test for heterogeneity in their effects by entrepreneurial potential, as measured by the entrepreneurial preparedness score. Lastly, in the case of the role of luck, we also test the impact of having a version of the game with a greater or lower role of luck. We test whether we see evidence for the mechanical effect of the increased role of luck or if there is evidence of optimism or pessimism.

3.3 Identification Strategy

As discussed in section 2.3.3, participants in the second, main stage of the study make multiple decisions about whether to play the game for stakes or not. Before each subsequent decision, an informational intervention takes place where an additional, additive information piece is shared about the participant's odds of success in the game. To identify the effect of the informational pieces, we compare the changes in participants' decisions before and after the information was shared. We estimate the additional effect of each informational intervention using this within participant framework. It needs to be noted that since it is a lab experiment, the only other thing that changes other than the new information being available, is that the individual had already made a choice previously. Thus, the effects we find this way might contain round effects and are to be interpreted as additional effects conditional on the previously available series of information.

Additionally, participants were randomized to make an entry decision in all four conditions or only in three of them, skipping directly to the average information condition. We use this randomization to test for the presence of any order effects. If there are indeed no order effects, the within participant effect estimates will be the same whether the participants make three or four decisions. Additionally, we use the random assignment to supplement the above analysis with between participant estimates. First, we can test the effect of the availability of the average information prior to the first decision by comparing the first decisions made under either condition. Second, we can estimate the relative difference in the additional effects of providing the average information after the first decision under the baseline condition compared with providing the skill information after the first decision under the average information condition. Third, similarly, we can estimate the relative difference in the additional effects of providing the skill information after the second decision under the average information condition compared with providing the luck information after the second decision under the skill information condition. It needs to be noted that the latter to estimates may be affected by differential anchoring effects based on earlier pieces of information.

It needs to be noted that the order of the additional information pieces was fixed for all participants. The baseline condition was followed by the average information, then the skill information, and finally the luck information. The order was used because it seems unlikely that some of the more complex pieces of information could be shared without providing the more basic information for context, as participants would likely get confused. As a result of this design, the effects identified (for the skill and luck information) are additional effects, and they are conditional on knowing the previous pieces of information already.

Finally, we estimate the differential effects of the relatively high versus the low role of luck treatments. We use the random assignment into either versions of the game to compare the effects of the luck treatment between individuals. We estimate the difference by the assignment to the high or low luck treatments both in the within individual changes and in the between individual differences estimates described above. Additionally, we estimate the effect of the relatively high versus low role of luck on participants' incentive compatible beliefs about their likelihood of scoring high enough in the game to win the prize. After participants had all the information, we elicited their incentive compatible beliefs about their odds of winning. We test whether the random assignment to either luck versions had an effect on this.

4 Results

4.1 Description of the data

Table 2 shows the summary statistics of the data. The average age of participants is approximately 35. The sample is almost balanced in terms of gender with 51% being male. In terms of socio-economic status, the average level of the sample falls in the middle range. Colombia has a system of denoting socioeconomic status with an indicator ranging from 1 (lowest) to 6 (highest), with the average of the sample being 3.2. Almost half of the sample has an undergraduate degree or more education (45%). Approximately 30% of the sample is working exclusively on their own business, while the rest are a student (17.4%), employed elsewhere (42%), or looking for work (9.8%). In terms of the sector of their business (current, past, or planned), the tertiary sector is the most frequent (42%).

	Mean	Sd	Min	Max
Age	35.448	11.659	18.000	69.000
Male	0.513	0.501	0.000	1.000
SES	3.205	1.233	1.000	6.000
Highschool	0.140	0.348	0.000	1.000
Undergrad or more	0.451	0.498	0.000	1.000
Employed elsewhere	0.420	0.494	0.000	1.000
Unemployed	0.098	0.298	0.000	1.000
Student	0.174	0.379	0.000	1.000
Sector=Secondary	0.218	0.414	0.000	1.000
Sector=Tertiary	0.423	0.495	0.000	1.000
Sector=Quaternary	0.137	0.345	0.000	1.000

Table 2. Summary statistics of the main stage data (N = 357)

Note: This table shows the summary statistics for select variables. *SES* refers to socio-economics status that is measured in Colombia on a 1 (lowest) through 6 (highest) scale. *Employed elsewhere* means employment other than by own business.

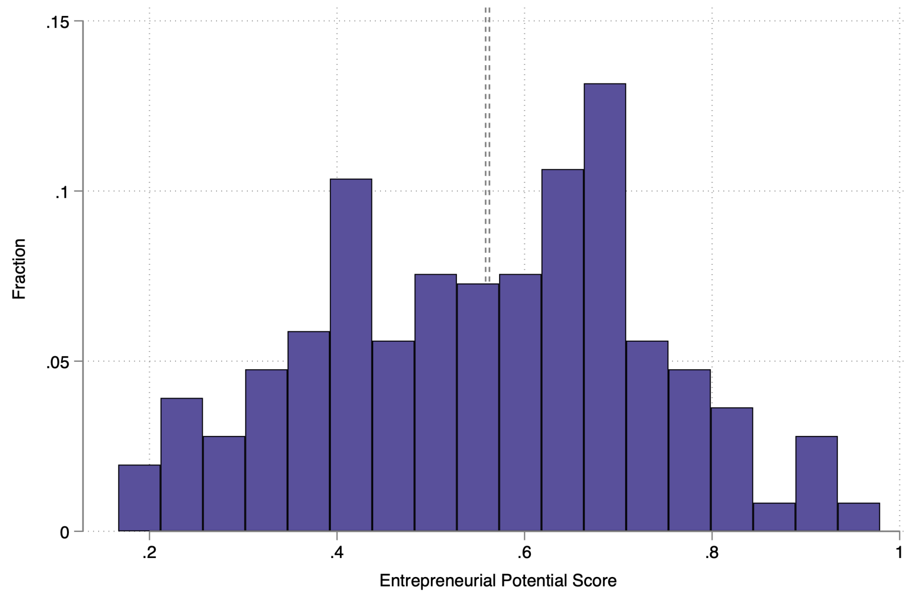
We test for the balance of these statistics in the randomization into the high or the low role of luck game versions and also into the three or four entry decisions. The F-Tests of joint significance of covariates explaining each assignment are not significant at the 5% level. The Table A1 in Appendix A shows the details of these balance tables.

Graph 2 shows the distribution of the EP scores. The distribution is symmetric with two peaks and the extreme values being the least frequent. The two dashed lines show the mean and the median values at 0.558 and 0.563, respectively.

4.2 Entry decision at baseline

We test whether the entry decision at baseline is positively correlated with the EP score. When looking at all the data from both stages that contain entry decisions under the baseline condition, 80.8% of participants with EP scores in the bottom half of the distribution choose to enter. Participants in the upper half of the EP score distribution have an entry rate of 87.2%, which is not statistically significantly greater at the 95% confidence level, only at the 90% level. Nevertheless, we do not find evidence in favor of lower entry rates among high EP than low EP individuals. If we regress the entry decision in the baseline condition on the continuous EP score,

Figure 2. The distribution of the Entrepreneurial Preparedness (Potential) score (EP)

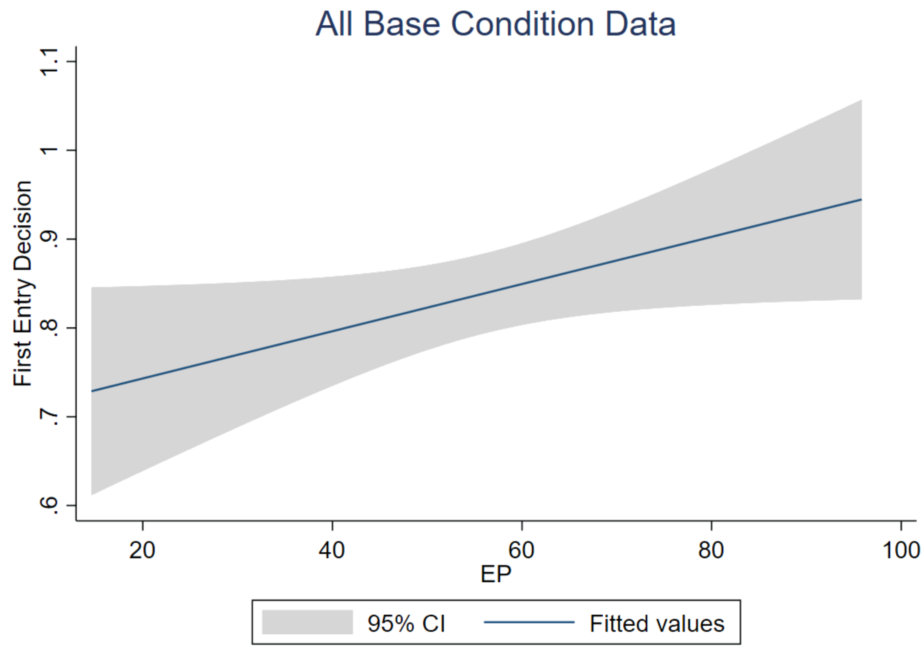


Note: This Figure shows the distribution of the EP score. The two dashed lines show the mean and the median at 0.558 and 0.563, respectively.

we detect a slight upward trend that is statistically significant. The plot shown in Figure 3 is the predicted likelihood of entry by EP scores using a linear fit and all baseline condition data from the two stages. While a declining or flat relationship can be rejected, the data shows a flat slope. Thus, we reject the hypothesis of under-entry among high EP individuals. Nevertheless, even participants with low EP scores enter at high rates.

Next, we analyze the risk preference data of the low EP individuals to construct the maximum bound on their entry rates that would be consistent with the 20% average success rate and their risk preferences. The risk preference question made participants choose between six lotteries. Based on their answers, we can group them into six groups, one risk-seeking, one risk neutral, and four groups with varying degrees of risk aversion. Assuming a CARA utility function, we can extrapolate from the lottery choices, with values ranging between COP 200 and COP 7,000, to their preferences between the certain payment of COP 5,000 and the winning prize of COP 20,000. The risk preference results highlight that even values lower than COP 5,000, such as COP 2,000, is significant for a large fraction of the participants, driving the high fraction of risk-averse individuals, suggesting that using different utility functions would still yield similar conclusions.

Figure 3. The relationship between EP score and entry decision for all baseline data



Note: This Figure shows best fit line and confidence interval when regressing entry decision on EP for all baseline data. The y axis shows the first entry decision made, that is, the one under the baseline condition. The figure is only based on data from participants who made their first decision under the baseline condition.

Table 3 shows the lottery choices used in the risk preference elicitations and the corresponding CARA utility functions $(1 - e^{-x*COP})$, using the lowest levels of risk preferences that would still mean choosing the given option as opposed to the next more risk-averse option. Additionally, the table also shows the needed minimum perceived probability of success in winning the prize in the entrepreneurial game in order to choose to enter as well as the number of individuals who chose the given option. In the case of the low EP individuals, the choices among the six options are nearly balanced, with the risk-seeking and the second most risky preferring risk-averse options being about 33% more popular and the two most risk-averse options being less popular by the same degree.

We can calculate the maximum bound on entry rates consistent with the below risk preferences and average success of 20% as follows. To have the maximum number of entries, we need the most risk-seeking individuals to be entering the most, with the lowest probability of success beliefs that would lead them to enter. For the most risk-seeking group, based on the risk preference question, we cannot put a minimum

	Low Prize	High Prize	Min x in U()	**Min $I\!P$**	N (LEPI)	N (HEPI)
Lottery 6	200	7,000	NA	ε%	39	55
Lottery 5	1,200	6,000	NA	**25.0%**	30	25
Lottery 4	1,600	5,200	0.165	**58.3%**	28	23
Lottery 3	2,000	4,400	0.234	**69.6%**	41	36
Lottery 2	2,400	3,600	0.387	**85.5%**	20	16
Lottery 1	2,800	2,800	1.203	**99.8%**	21	23

Table 3. Risk Preference Data

Note: This table shows the six lottery choices participants had with each of the two outcomes having an equal chance of occurring and both the Low and the High prizes denoting Colombian Pesos. *Min x in U()* refers to the minimum value of x in the CARA utility function $1 - e^{-x*COP}$ that would mean choosing this lottery option instead of the next, higher, more-risk averse, option. *Min $I\!P$* shows, given the CARA based on the previous column, what is the lowest probability of success such that a participant with the given level of risk preference would choose to enter as opposed to taking the certain COP 5,000. *N* show the number of low EP individuals (LEPI) and high EP individuals (HEPI), respectively, who selected the given option.

bound on the probability of success they need to be entering. So we use epsilon, in practice, 0% in the calculation. The maximum number of entries is the result of all individuals in the three most risk-seeking groups entering as well as (rounding up) 17 of the fourth most risk-seeking group entering, while the rest believe their probability of success to be 0% and they do not enter. In this case, we have 39 + 30 + 28 + 17 = 114 entries out of 179 participants, which is an entry rate of 63.69% [5].

The entry rate among these 179 participants at baseline is actually 87.8% with a 95% confidence interval of [80.6%, 95.0%], statistically significantly higher than the above-calculated 63.7%. While in the baseline condition, the average success rate of 20% is not known, using the benchmark as if this information was known, we can confirm over-entry among the low EP participants not explained by risk preferences. In the next section, we test whether sharing the average success rate moves participants closer to the above-calculated upper bound of 63.7%. If that were the case, we would conclude that seeming over-entry at baseline could be all driven by rational decision-makers who had the incorrect priors. If, however, we still observe an over-entry after sharing the average success rate, then it is warranted to test for the roles of behavioral biases such as over-confidence and over-optimism.

Figure 4 shows the proportion of entry at baseline (Panel A) alongside risk data among the 357 participants for whom we have risk preference information (Panel

[5] The average probability of success across all individuals, in this case, is (30*0.25 + 28*0.583 + 17*0.696 + 104*0)/179 = 0.2.

B). The two graphs show that only risk-neutral or risk-seeking preferences cannot account for all the entries at baseline. As discussed above, heterogeneous success probability beliefs among the participants, incorrect priors, the roles of uncertainties studied by the informational interventions, or other factors must be at play. In the following sections, we test whether the presence of biases due to the three sources of uncertainty we study might explain some of the gap, the over-entry of the low EP individuals.

4.3 The effect of sharing the average success information

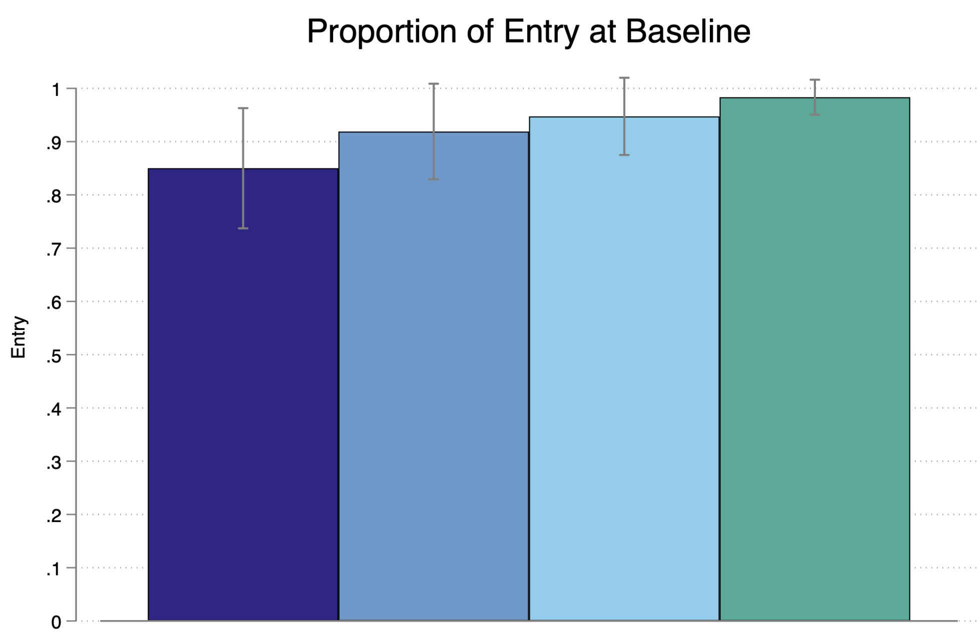
First, we use a between participants approach and rely on the random assignment into making the first decision under the baseline or the average information condition to estimate the effect of revealing this information. We regress the entry decision on the EP score, the dummy indicator of the average information being presented, and the interaction of these two, as well as demographic and business characteristics control variables. To increase power, we included the data from the first stage with the main data, including control for being in the first stage, where all participants decided under the baseline condition.

$$Entry_i = \alpha + \beta_1 * Avg_i + \beta_2 * EP_i + \beta_3 * EP_i * Avg_i + \gamma * X_i + \varepsilon_i$$

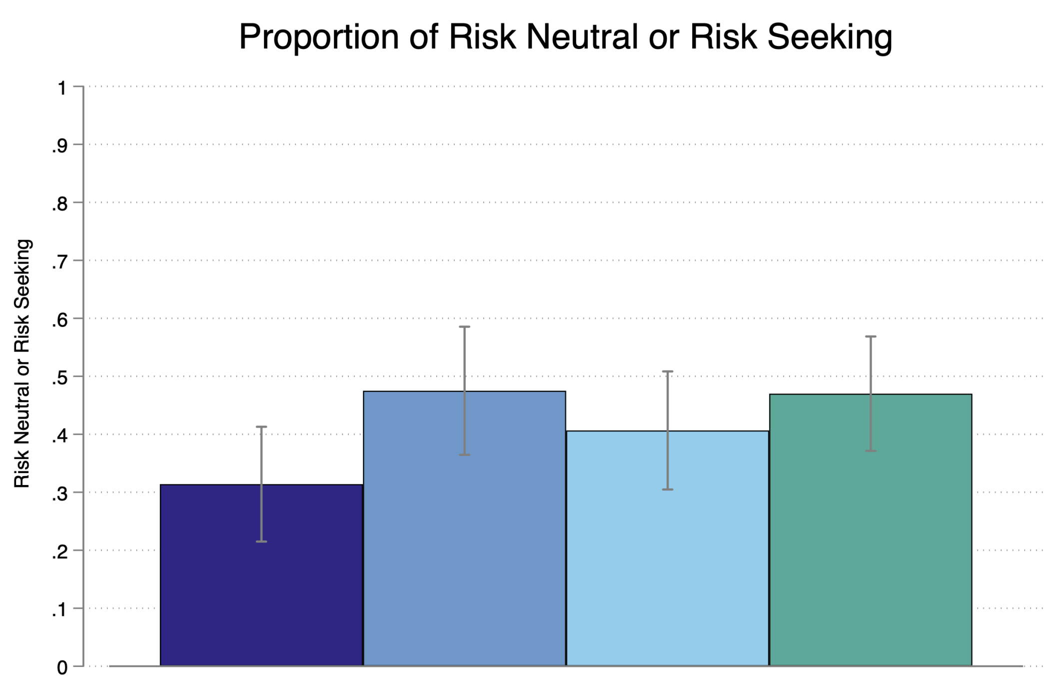
- The error term used is robust to heteroskedasticity.
- X_i includes the control variables.
- We estimate the above using either the continuous EP score variable, a dummy indicator of the EP score being higher than average, or a dummy indicator of the EP score being higher than the median.
- β_1 estimates the ATE of providing people with information about the game's difficulty for participants with very low EP. Also, β_3 estimates how this effect increases or decreases with EP.
  - Our hypothesis is that $\beta_1 < 0$ if people with low EP were over-entering in the absence of this information. On the other hand, we expect $\beta_3 \neq 0$ if this information affects high EP individuals differently than low EP individuals.

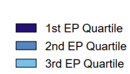
Figure 4. Proportion of baseline entry relative to risk seeking and risk neutral preferences

Panel A: Entry at Baseline



Panel B: Risk neutral or risk seeking participants

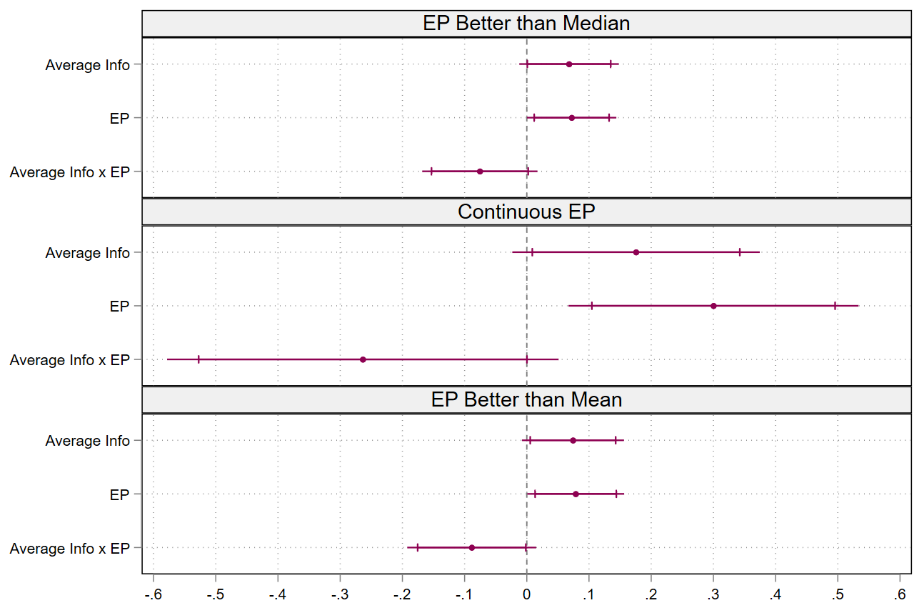




- β_2 estimates the effect of the EP score on entry in the baseline condition. If this coefficient is not positive, that would suggest that at the baseline, less prepared individuals enter more than standard economic theory would suggest.

The results of this regression are shown in Figure 5 including the estimated coefficients as well as the 90% and 95% confidence intervals for the main coefficients. The results show the estimates using the three approaches for the EP score: the continuous, the binary indicator of better than average, or the binary indicator of better than the median. Results for the full regression can be found in Appendix A in Table A2.

Figure 5. The effect of the average information on entry using different formulations of the EP



Note: This Figure shows the regression coefficient estimates of the equation from section 4.3. Each of the three panels show the coefficient on the average information treatment, the EP score, and the interaction term of these two. The three panes show the results using the three different versions of the EP score, high EP defined as greater than the median, or greater than the mean, as well as using the continuous EP score.

Sharing the average success rate information encourages the individuals in the lower half of the EP score distribution by 6.8 percentage points on average, which is statistically significant at the 90% level, as the top panel of Figure 5 shows. The interaction term between the average information treatment and having high EP is negative and comparable in magnitude, meaning that the treatment has a near-zero effect for this group. The positive and statistically significant coefficient on the high

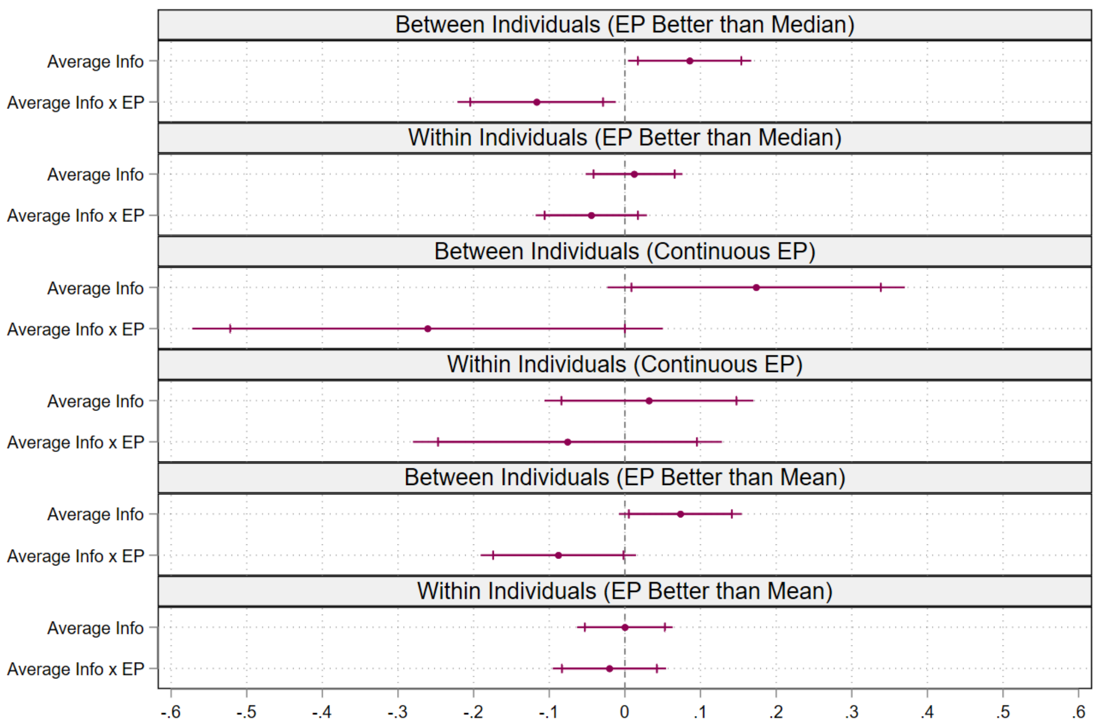
EP indicator means a small but significant difference between the baseline entry rates of these two groups. This result is slightly different from what is presented in section 4.2. because here, the sample is restricted to the second, main-stage participants only.

The results from the average treatment mean that we reject the hypothesis that lack of information about the average difficulty was contributing to the over-entry of the low EP individuals in the baseline condition. In fact, the results are the opposite of what we hypothesized, they were over-entering in the baseline condition despite ambiguity-aversion or an overestimation of the average difficulty. Sharing the average information reverses these rather pessimistic biases and encourages further entry. In the case of the high EP individuals, there is no effect of the information suggesting no evidence for bias in its absence. In other words, the differences in the entry rates by EP at baseline were due to differences in beliefs about the overall difficulty of success (and possibly differences in ambiguity preferences) as opposed to differences in beliefs about their own success probabilities.

The middle part of Figure 5 shows that the results are similar when using the continuous EP variable instead of the binary indicator of EP being greater than the median. The continuous EP variable has been scaled to range from 0 to 1 so that the effect magnitudes can be shown on the same scale. Indeed the effect sizes are comparable since the average effect at EP 0 is about twice as large as the effect size in the case of the binary indicator. Additionally, at about 0.75 EP the average information effect observed for 0 EP goes from positive to negative. In addition to the continuous EP results being similar, using the EP better than mean instead of median results are very similar too, as seen in the third section of Figure 5. The Appendix shows the regression table of the below results as well that the results are robust to controlling for risk preferences and for being the highest 20% of the EP score distribution.

Figure 6 compares the above results from the between individual estimates to those from the within individual estimates. It shows the change in individuals' entry decision between their decision under the baseline condition and when asked again after the average information was revealed. The estimates of the within individual changes in response to the average information are less for both groups than their between subjects estimates. For LEPI, the within estimate is 0.012 compared with 0.0679 and the differential effect for HEPI is also lower in magnitude, suggesting no difference for that group in both estimates. The lower point estimates of the within individual results for LEPI could suggest a negative second choice effect or an anchoring effect. Nevertheless, since the between individual estimates are the direct results from the random assignment during the first decision, we can conclude that providing the average information upfront resulted in the increased entry of the low EP individuals ($p < 0.1$), unlike what we hypothesized. Low EP individuals are over-entering at baseline despite of ambiguity avoiding preferences additionally or alternatively over-estimating the difficulty of task. However, additional study is needed for further evaluating potential round effect or anchoring effects as the impact of providing the information as an additional piece of information is potentially different than its impact when available right away.

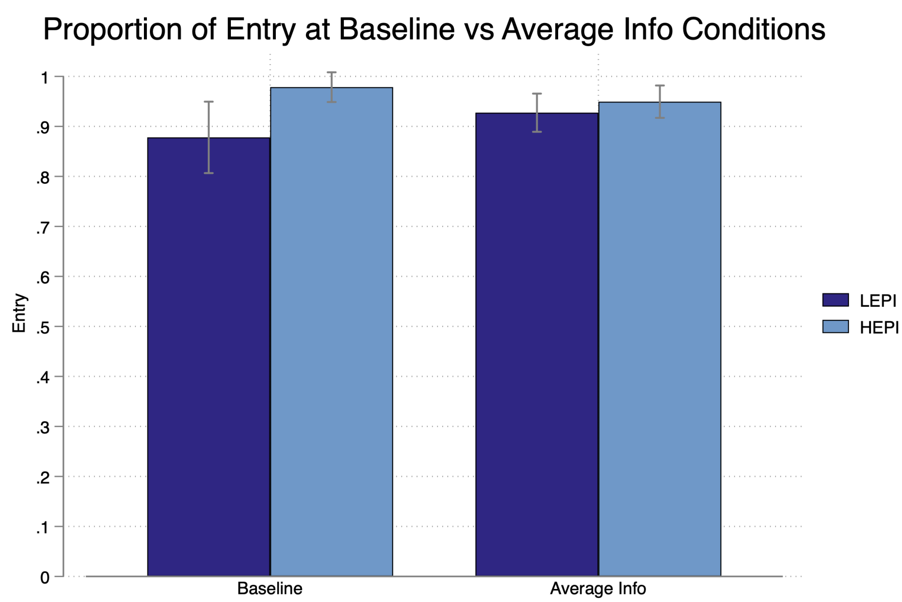
Figure 6. Comparison of the Within and the Between Individual Estimates of the Average Information Treatment versus the Baseline Information.



Note: This figure shows the coefficients when comparing the first decisions of individuals assigned to the average information versus the baseline condition (between individuals). Furthermore, it also shows the coefficients when estimating the effect of providing the average information for individuals who made their first decision under the baseline condition (within individuals).The between individual coefficients are the same as shown in Figure 5. The six panes show the results using the three different versions of the EP score, high EP defined as greater than the median, or greater than the mean, as well as using the continuous EP score. The confidence bars show both the 95% (line) and the 90 % (tick mark) confidence intervals.

Figure 7 includes all decisions made under the baseline or the average information condition by EP. It shows visually the encouraging effect of the average information on the lower EP individuals (LEPI). When the average information is shared, the entry rate of the low EP individuals is statistically significantly higher than the earlier calculated 63.7%, providing evidence for over-entry. As a result of the small increase in the entry for this group and the close to zero change in the case of the higher EP individuals (HEPI), the previous entry rate gap between the two groups closes. The lack of a statistically significant difference between the entry rates of the low versus high EP groups, once the average information is available, provides evidence of too much faith in success among the low EP group since their entry rates are indistinguishable from those of the high EP group. It appears that the low EP group is acting over-confident since the differences in the groups' skill levels do not appear to be taken into account. In the following sections, we investigate whether the uncertainties about skill and the role of luck can explain some of the gap.

Figure 7. The impact of the average information treatment on entry rates by EP.



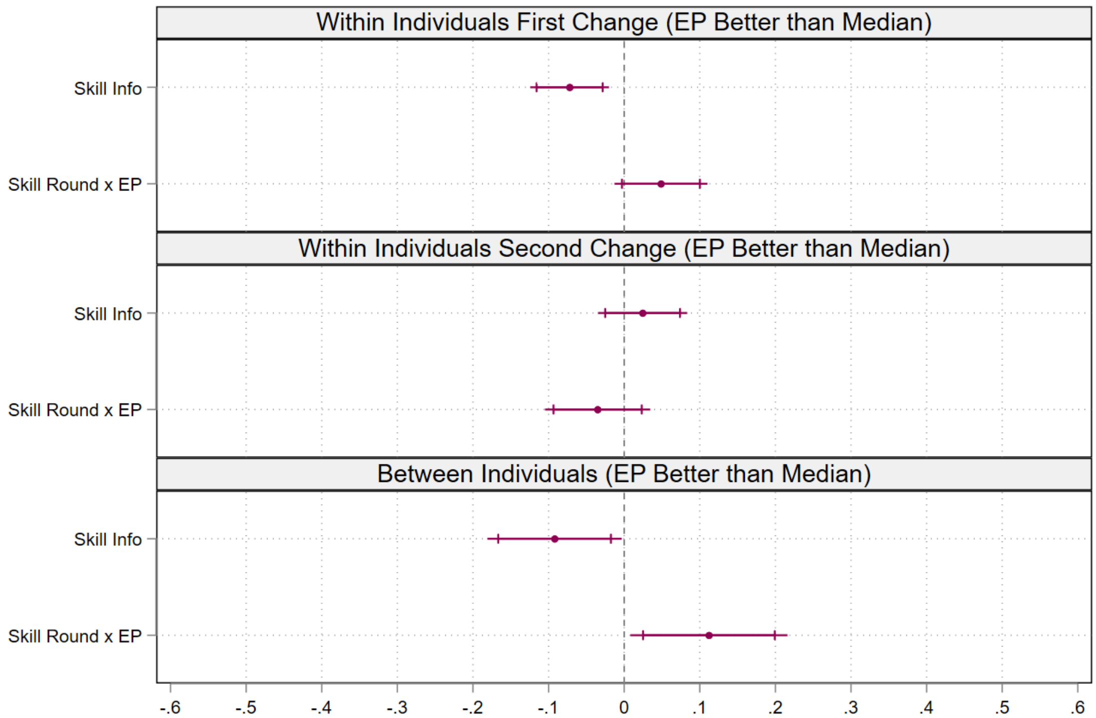
Note: This Figure shows the entry rates by EP under the baseline and average conditions. LEPI denotes the low EP individuals, whose EP score is not greater than the median value. HEPI denotes the high EP individuals, whose EP score is greater than the median value.

4.4 The additional effect of sharing skill information

We test the additional effect of sharing information about skill, the EP score, on the change in the entry decision. We start by estimating the within individual change when providing the skill information for individuals who made their first decision under the average information condition. This estimate is shown in the first pane of figure 8. The effect is negative for the low EP individuals, -0.072 ($p = 0.007$). The effect for high EP individuals, the sum of the two coefficients, is not statistically significant from zero. The second pane shows the same estimate for individuals who made their first decision under the baseline information and so for them the skill information is only introduced one round later, prior to their third decision, so the estimate is about the second potential change in their decision. Here, the estimate for the low EP individuals is 0.024 with 95% confidence interval of (-0.035, 0.0835). And once again, the effect for high EP individuals is not statistically significant from zero. The difference between the two estimates for LEPI highlight a potential round effect or anchoring effect based on the initial assignment. We hypothesized that round effects would not matter, however, the results suggest otherwise.

The third pane shows the results when comparing the changes between individuals first and second decisions across the two treatment arms. So in this case there is no difference in round effects and the result needs to be interpreted as the relative difference between the impact of sharing the average information after a first decision in the baseline condition and sharing the skill information after a first decision under the average information condition. The result is similar to that in the first pane. Sharing the skill information discourages the low EP individuals more than sharing the average information, by 0.092 percentage points ($p = 0.042$). And once again the relative difference for high EP individuals is not statistically significant from zero. Figures A1 and A2 in the Appendix show similar results when using the other two EP variables. Overall, the results suggest that sharing the skill information can be discouraging for the low EP individuals, at least when it is shared after a first decision under the average information condition. However, the impact is likely susceptible to the number of prior choices made or to potential anchoring during those choices. Thus, further study is needed.

Figure 8. Comparison of the Within and the Between Individual Estimates of the Additional Effect of the Skill Information (EP Higher than Median).



Note: This figure shows the coefficients when comparing the change in the decisions of individuals before and after the skill information is shared. The first pane shows the change within individuals decisions who were assigned to the average information treatment for their first decision. The second pane shows this change for individuals who were assigned to the baseline information for their first decision, so for them, the analysis is about the second possibility for changing their decision. The third pane shows the results from using the random assignment into the average versus the baseline condition for the first decision. This pane compares the changes between the first and second decisions of individuals in the two conditions, so it is to be interpreted as the relative difference between the average information's and the skill information's additional effects (between individuals). The confidence bars show both the 95% (line) and the 90 % (tick mark) confidence intervals.

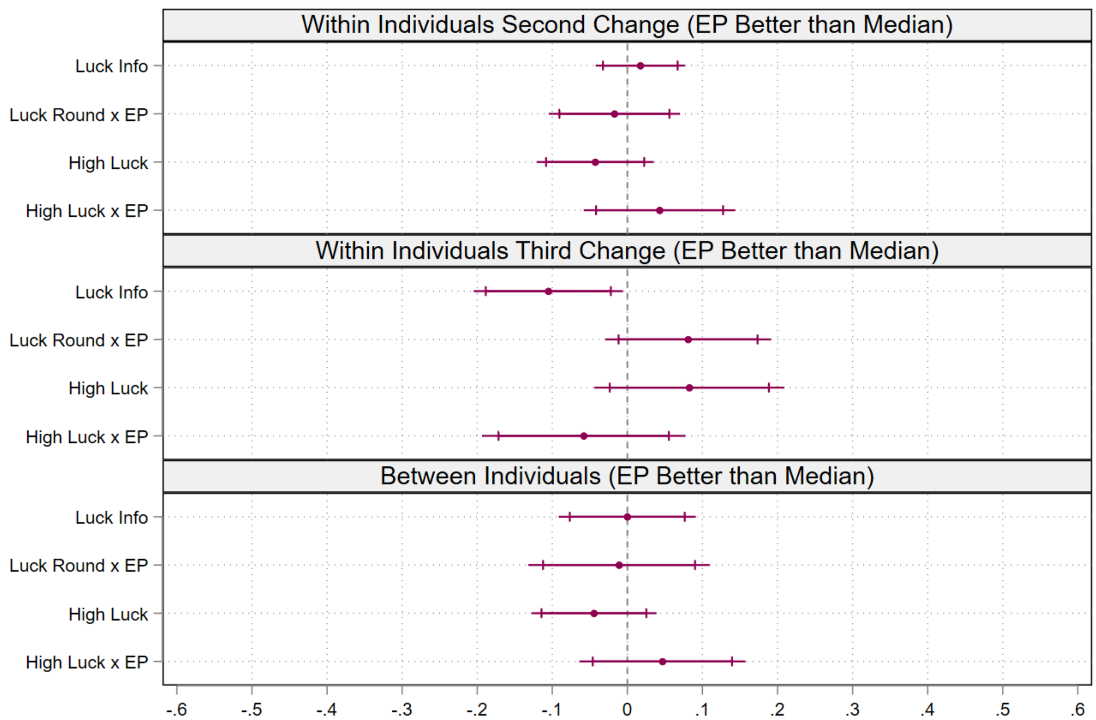
4.5 The additional effect of sharing luck information

We test the additional effect of sharing information about luck on the change in the entry decision similar to the above approach for estimating the additional effect of skill. We start by estimating the within individual change when providing the luck information for individuals who made their first decision under the average information condition and second decision under the skill information condition. This estimate is shown in the first pane of figure 9. The effect of sharing luck information when the role of luck is less for the low EP individuals is 0.017 (p = 0.568). When the role of luck is high, that means an additional effect of -0.043 (p = 0.279). The effects for high EP individuals, the sum of the two coefficients each under low and high luck conditions, are not statistically significant from zero. The second pane shows the same estimate for individuals who made their first decision under the baseline information and so for them the luck information is only introduced one round later, prior to their fourth decision, so the estimate is about the third potential change in their decision. Here, the estimate for the low EP individuals when the role of luck is less is -0.105 (p = 0.038) with 95% confidence interval of (-0.205, -0.006). When the role of luck is high, it results in the additional effect of 0.083 (p = 0.2). The effects for high EP individuals are once again not statistically significant from zero. The difference between the estimates for LEPI again highlight a potential round effect or anchoring effect based on the initial assignment. We hypothesized that round effects would not matter, however, the results suggest otherwise.

The third pane shows the results when comparing the changes between individuals second and third decisions across the two treatment arms. So in this case there is no difference in round effects and the result needs to be interpreted as the relative difference between the impact of sharing the skill information after a second decision with the average information available and sharing the luck information after a second decision under the skill information condition. The result is similar to that in the first pane. Sharing the luck information has no differential effect on the low EP individuals than sharing the skill information. The high luck treatment has a (not significant) negative effect, -0.045 (p = 0.294), and the effects for the high EP individuals are not statistically significantly different from zero. Figures A1 and A2 in the Appendix show similar results when using the other two EP variables. Overall, the results are ambiguoug about the effects of the luck information. If the skill information is discouraging and the relative effect of the luck information is the same, that would suggest that sharing the luck information can be discouraging for the low EP individuals, at least when it is shared after a second decision under the skill information condition. However, the impact is likely susceptible to the number of prior choices made or to potential anchoring during those choices.

The no or negative effect on the high luck coefficient is unexpected because we hypothesized that the mechanical effect of the increased role of luck would be observed. For both the low and the high EP individuals, there is no difference in sharing the luck information about the high or the low role of luck version of the game. Thus, the results suggest that the low EP individuals are pessimistic since otherwise, we should have detected the positive effect of the high role of luck game version. At the same time, the results are the opposite for the high EP individuals and suggest that they are optimistic since otherwise, we would have detected the negative effect of the high role of luck.However, the results are somewhat uncertain, and so, further study is needed.

Figure 9. Comparison of the Within and the Between Individual Estimates of the Additional Effect of the Luck Information (EP Higher than Median).



Note: This figure shows the coefficients when comparing the change in the decisions of individuals before and after the luck information is shared. The first pane shows the change within individuals decisions who were assigned to the average information treatment for their first decision. The second pane shows this change for individuals who were assigned to the baseline information for their first decision, so for them, the analysis is about the third possibility for changing their decision. The third pane shows the results from using the random assignment into the average versus the baseline condition for the first decision. This pane compares the changes between the second and third decisions of individuals in the two conditions, so it is to be interpreted as the relative difference between the luck information's and the skill information's additional effects (between individuals). The confidence bars show both the 95% (line) and the 90 % (tick mark) confidence intervals.

4.6 Additional results

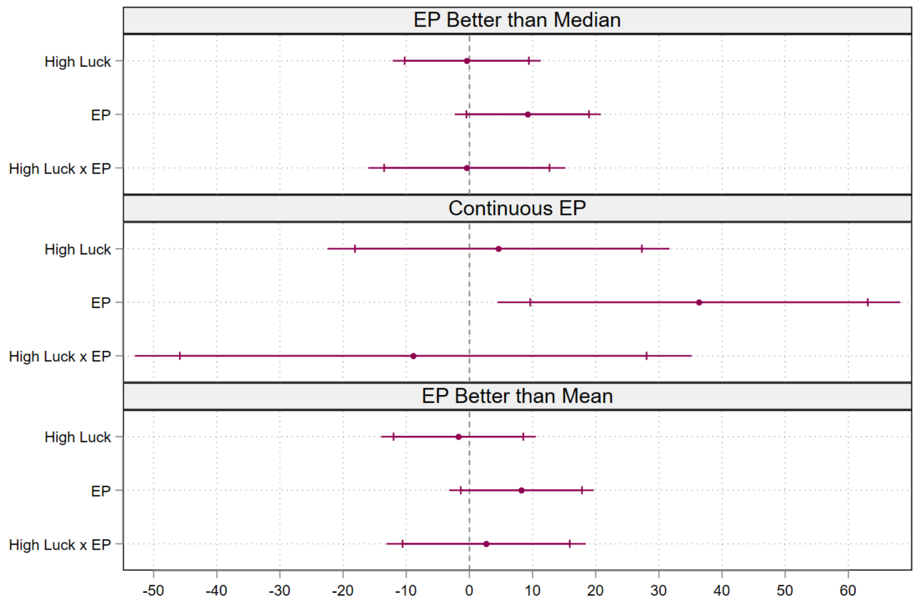
We conduct an additional test of the effect of the high versus the low role of luck. We regress the incentive-compatible belief about the own likelihood of success (elicited once all the information had been revealed) on the dummy indicator of the high (versus low) luck condition, the EP score, the interaction of the two, and control variables. We estimate the following:

$$\mathbb{P}(Succes_i) = \alpha + \beta_1 * HighLuck_i + \beta_2 * EP_i + \beta_3 * EP_i * HighLuck_i + \gamma * X_i + \varepsilon_i$$

- The error term used is robust to heteroskedasticity.
- X_i includes the control variables.
- We estimate the above using either the continuous EP score variable, or a dummy indicator of the EP score being higher than average, or a dummy indicator of the EP score being higher than the median.
- β_1 estimates the ATE of assigning people to the high-luck version of the game and provides information about it for people with very low EP. Also, β_3 estimates how this effect increases or decreases with EP.
- β_2 estimates the effect of the EP score on beliefs about own success likelihood.

Figure 10 shows the results of this estimation. The coefficients of the high luck version as well as its interaction with the EP score are both almost exactly zero in the top section of the figure. These results mean that the expected mechanical effects of the high role of luck cannot be observed, just like above in the case of the entry decision itself. The results in the middle and lower sections of the graph, using the continuous and the EP greater than average binary indicators, are similar. The coefficients on the EP score are positive in all three versions and significant when using the continuous EP score. The magnitude of the coefficient is approximately 10 percentage points when using the binary EP versions. These results are similar to the above observations about the correlation between EP scores and baseline entry decisions being positively correlated with a rather flat slope. In Appendix A, Table A4 shows similar results controlling for risk preferences and for being the highest 20% of the EP score distribution.

Figure 10. The effect of high role of luck on the incentive compatible success beliefs, $\hat{p}_i$ by EP

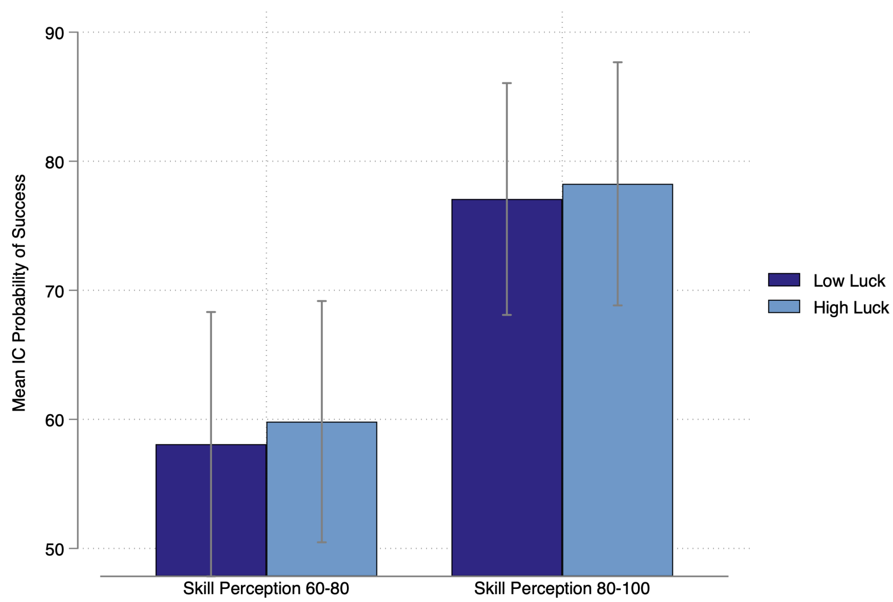


Note: This Figure shows the regression coefficient estimates of the equation from earlier this section. Each of the three panels shows the coefficient on the version of the game with the high role of luck, the EP score, and the interaction of the two. The three panes show the results using the three different versions of the EP score, high EP defined as greater than the median, or greater than the mean, as well as using the continuous EP score.

The results of Figure 10 show that instead of seeing the impact of the mechanical effect of the greater role of luck, we see a zero effect, suggesting pessimism among the lower EP individuals and optimism among the higher EP ones. To provide additional evidence for this conclusion, the graph below shows the average perceived probability of success against perceived incentive-compatible game skill percentiles just below the 80th percentile and for the ones above it under the two versions of luck. (Note, individuals who fall exactly on the 80th percentile have been dropped).

Figure 11 shows a slight, not statistically significant increase in the perceived probability of success for individuals in the second fifth, the 60-80th percentile, of the perceived skill percentile distribution when the role of luck increases. While this result may be consistent with the mechanical effect of the increased role of luck, the results are suggestive of no optimism among this group. If there was both optimism and the mechanical effect, we would expect to be able to detect the increase in the perceived probability of success. In the case of the top fifth, 80th, and above percentile, of the perceived skill percentile distribution, we expect to see a decrease in the perceived probability of success when the role of luck is increased. However, we see a slight, not statistically significant increase instead. This result is suggestive of optimism in this group counter-acting the mechanical effect. Overall, these results also suggest that optimism and perceived skill percentile are correlated, similar to the results in section 4.5.

Figure 11. Average incentive compatible beliefs of success probability, $\hat{p}_i$ by luck and perceived skill.



Note: This Figure shows the average incentive-compatible success rate beliefs, $\hat{p}_i$ by incentive-compatible skill beliefs under the two luck versions of the game. The beliefs about $\hat{p}_i$ were elicited after all the information was shared. The luck information participants saw reflected whether they were assigned to the lower or higher role of luck versions of the game. As discussed in section 3.1.3, there is a mechanical effect of the increased role of luck that affects the odds of the lower EP individuals positively while the odds of the higher EP individuals negatively. The graph shows the realized effects of the high role of luck for the individuals with skill beliefs in the second fifth of the distribution, greater than or equal to 60% and less than 80%, and for the individuals in the top fifth of the distribution, greater than 80%. Note that individuals who believe to be exactly at the 80% were excluded.

4.7 Robustness checks

To test the robustness of the above-presented results, we conduct various robustness checks. As mentioned above, for each of the analyses we use three different formulations of the EP score. Two of these variables are binary indicators of having a high EP score, greater than the median or greater than the mean. The third variable used is the continuous EP score itself.

In addition to using these three different formulations, we also conduct an additional estimation strategy, combining the various between subject approaches into a single regression, as shown below.

In this approach, we utilize the randomization into three versus four entry decisions to identify causal effects by comparing across the randomization. We use a first differences approach and regress the change in entry decision on dummy indicators of the intervention messages, and the dummy indicators interacted with the EP score. We also control for potential differentials in the round effects between the second and the third, as well as between the third and the fourth decisions. Since it is a first differences approach, it means that any unobservables that do not have effects varying over time are differenced away and cannot bias the estimation. The equation we estimate is the following:

$$\Delta Entry_{it} = \alpha + \delta_3 + \delta_4 + \beta_1 * Skill_{it} + \beta_2 * Luck_{it} + \beta_3 * HighLuck_{it}$$

$$+\gamma_1 * EP_i * Skill_{it} + \gamma_2 * EP_i * Luck_{it} + \gamma_3 * EP_i * HighLuck_{it} + \varepsilon_{it}$$

- The error term is clustered at the individual level.
- β_1 estimates the ATE of providing people with additional information about their skill relative to providing additional information about the average difficulty for their second decision for low EP people. Also, γ_1 estimates how this effect increases or decreases with EP.
  - Our hypothesis is that people with low EP are overconfident, and then correcting this implies $\beta_1 < 0$. If people with high EP are, on the contrary, under-confident and do not know their place in the skill distribution, then $\gamma_1 > 0$.
- β_2 estimates the effect of making luck salient and making people realize that luck is somewhat important to explain success in this game, relative to sharing the average information for people with very low EP. Also, $gamma_2$ estimates how this effect changes with EP.
- β_3 estimates the effect of making luck salient and making people realize that luck is very important to explain success in this game for people with very low EP. Also, γ_3 estimates how this effect changes with EP.
  - If the mechanical effects of the increased role of luck are observable, then low EP individuals enter more when the role of luck is greater such that

$\beta_3 > 0$. At the same time, for people with high EP the effect is expected to be the opposite, so $\gamma_3 < 0$.

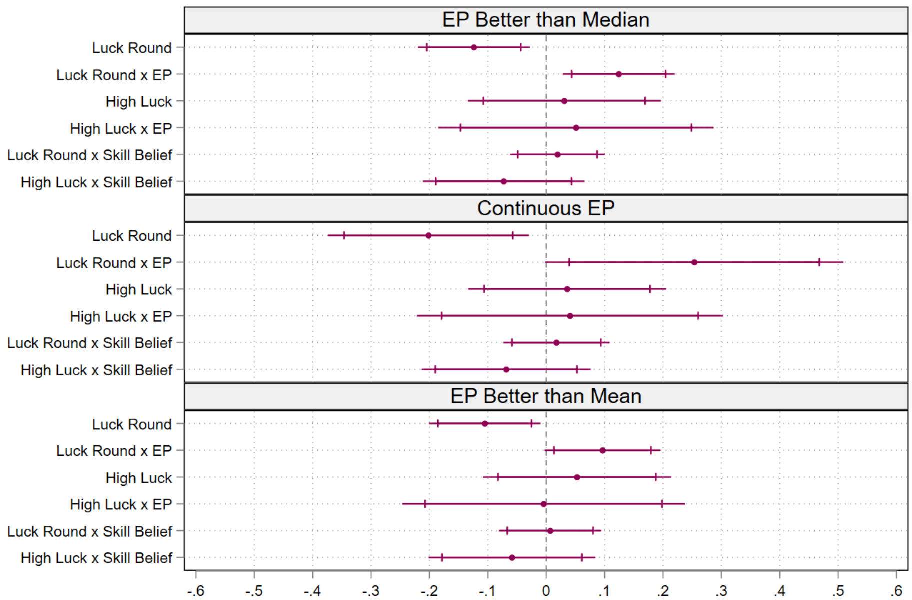
- We estimate the above using either the continuous EP score variable, or a dummy indicator of the EP score being higher than average, or a dummy indicator of the EP score being higher than the median.
- We estimate the above also using the additional control terms of interacting the decision order dummies with the EP score. We do this because we found evidence that low EP individuals are more susceptible to order effects.
- The estimated effects are interpreted as the additive effects of providing these additional pieces of information.

The results of this regression are shown in the Appendix. The results are similar to the between subject results shown earlier. We also run the same regression controlling for risk preferences and for an additional binary indicator of the EP score being particularly high, in the top 20%.

In the case of the analyses about the role of luck, we undertake a couple of additional robustness checks. The first one of them is shown in this section, Figure 12, while the rest are in the Appendix with similar results. We include controls for participants' beliefs about their skill percentile in the game or the difference between this value and their measured EP. Additionally, we estimate the same regression from section 4.6 but using the beliefs about their skill percentile in the game instead of their EP values. Figure 12 shows the results when controlling for skill beliefs.

Figure 12 shows that when controlling for participants' incentive-compatible beliefs about their skill in the game, the main results remain similar to the ones presented in section 4.5. Looking at the first section of the figure shows that the effect of sharing the luck information is negative and statistically significant for the low EP individuals and zero for the high EP individuals since the two coefficients cancel each other out. The effect of the high luck version of the game is close to zero, slightly positive in this case for the low EP individuals and slightly higher for the high EP individuals as the two coefficients do not cancel each other out in this case. At the same time, the coefficient on the interaction of the skill belief and the high luck indicator is negative and not statistically significant although it has the largest magnitude after the luck and the luck interaction with EP coefficients.

Figure 12. The additional effect of the luck information controlling for beliefs about skill in the game



Note: This Figure shows the regression coefficient estimates of the luck coefficients of the equation from section **??** with added controls for perceived game skill beliefs' interactions with the luck information and the high luck coefficients. The three panes show the results using the three different versions of the EP score, high EP defined as greater than the median, or greater than the mean, as well as using the continuous EP score.

This result provides suggestive evidence that participants' beliefs react to the higher role of luck consistently with the mechanical effects expected, while the actual skill reacts the opposite way. Since the coefficient is rather noisy, this conclusion is just a conjecture. Based on the results it seems that individuals who believe in having high skill in the game but were told that their EP is low get discouraged when luck plays a greater role, consistent with its expected mechanical effect on the high EP individuals which they believe themselves to be. At the same time, individuals who believe in having high skill in the game and were told that their EP is high do not get discouraged by when luck plays a greater role, consistent with optimism balancing out the expected mechanical effect. As a result, we conjecture that it seems that the individuals who believe in having high skill in the game have a limited amount of faith in uncertainties of various kinds favoring them: the ones who believe that they are more skilled than their EP score suggests become cautious when larger variation in luck could hurt them. At the same time, the ones who simply believe their high EP score are optimistic about good luck favoring them when the larger variation in luck could hurt them. We provide an additional check for this pattern in Table C1 with similar conclusions when we split the sample into four groups instead of two: high EP who believe in having high skill, high EP who believe in having low skill, low EP who believe in having high skill, and low EP who believe in having low skill.

5 Conclusion

We find evidence that when presented with an uncertain and new high-risk high return entrepreneurial opportunity, at baseline, a large fraction, over 80% of individuals choose to take the opportunity instead of the certain outside option. We also find a weak positive association between EP score and entry decision. As a result of the relatively high entry rate of the lower EP individuals and that risk preferences cannot explain this, we conclude that the results provide evidence for over-entry among the low EP individuals at baseline. At the same time, there is no evidence of under-entry among the high EP individuals.

We set out to test the role of behavioral biases due to three sources of uncertainty in explaining the over-entry of the low EP individuals at baseline. We also tested whether there are any heterogeneities in these effects in terms of affecting high and low EP individuals differentially. We found the unexpected result that when sharing information about the average level of difficulty, it encourages the low EP individuals but not the high EP individuals to close the gap between their entry rates in the baseline. Sharing the individual-specific skill information and information about the role of luck both discourage low EP but not high EP individuals. We found evidence of a discouraging effect of the skill information when provided after a first decision with the average information available, providing evidence consistent with over-confidence among some of the low EP individuals in the absence of this information. Furthermore, having a greater role of luck in the game score has no differential effect for either group, providing suggestive evidence for pessimism among the low EP and optimism among the high EP individuals. However, we found evidence for round effects or anchoring effects, so further study is needed.

Overall, the results show suggestive evidence for some of the treatments appearing promising in reducing the over-entry of the low EP individuals: sharing skill information with information about the average level of difficulty, as well as sharing information about the role of luck. However, sharing only the average level of difficulty might encourage their entry, as it did in the case of this study. Additionally, we find evidence for heterogeneities in the impact of the treatments tested by entrepreneurial potential. Unlike the low EP individuals, the high EP individuals' decisions were not affected by any of the treatments suggesting that none of the biases tested are present in their case (or cannot be detected by the treatments used here). Furthermore, we found significant round effects or anchoring effects among the less prepared individuals which means that further study is needed - to better understand these effects in difference contexts.

While we found evidence for some of the interventions being able to discourage the entry of the low EP individuals, the magnitudes of these effects were relatively low. Thus, it is an open question of what other factors or biases might explain the gap between the entry rates of the low EP individuals and their risk preferences and odds for success. Additionally, we found evidence for the luck information treatment having no differential effects when the role of luck is higher versus lower which is unexpected. Future studies should examine in more detail how individuals perceive the role of luck and form beliefs about their success likelihoods in the face of it. Our results suggest that optimism positively correlates with underlying skill could explain this pattern. However, additional study is needed to confirm this and to rule out other possible explanations.

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A Appendix 1: Tables and Figures

	Mean by choices				Mean by luck	
	3 choices	4 choices	pval Δ	High	Low	pval Δ
Age	34.330	36.611	0.064	35.448	35.449	0.999
Male	0.495	0.531	0.487	0.508	0.517	0.869
SES	3.111	3.302	0.146	3.206	3.203	0.987
Highschool	0.137	0.143	0.882	0.133	0.148	0.681
Undergrad	0.407	0.497	0.086	0.453	0.449	0.937
Employed	0.379	0.463	0.110	0.436	0.403	0.528
Unemployed	0.093	0.103	0.765	0.072	0.125	0.092
Student	0.198	0.149	0.221	0.160	0.188	0.498
Secondary	0.220	0.217	0.952	0.243	0.193	0.255
Terciary	0.396	0.451	0.287	0.403	0.443	0.447
Quaternary	0.121	0.154	0.361	0.133	0.142	0.796

Appendix Table A1. Summary statistics of the main stage data (N = 357)

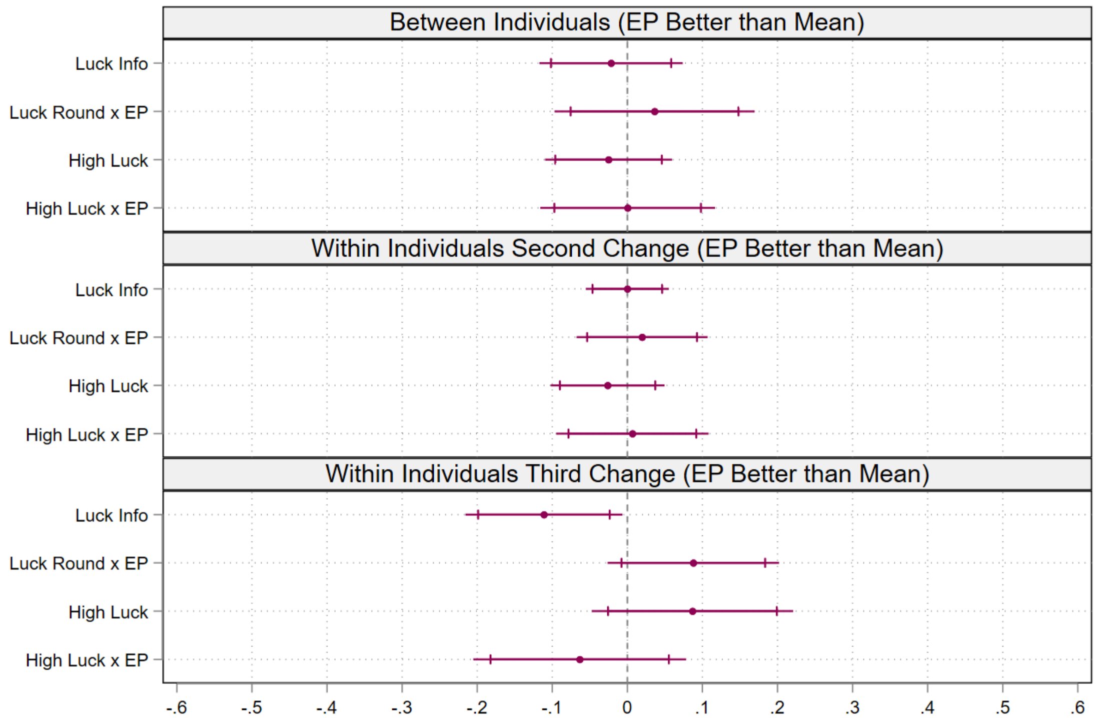
Note: This table shows the balance of key covariates across the two randomizations.
The F-Tests of joint significance of covariates explaining each assignment are not significant at the 5% level.
SES refers to socio-economics status that is measured in Colombia on a 1 (lowest) through 6 (highest) scale.
Employed elsewhere means employment other than by own business.

Appendix Table A2. The effect of the average information on entry

VARIABLES	(1) Entry	(2) Entry	(3) Entry
Avg. Info	0.176*	0.0742*	0.0679*
	(0.101)	(0.0416)	(0.0407)
EP	0.300**		
	(0.119)		
Avg. Info * EP	-0.264		
	(0.160)		
EP>Mean		0.0787**	
		(0.0396)	
Avg. Info * EP>Mean		-0.0885*	
		(0.0527)	
EP>Median			0.0721**
			(0.0365)
Avg. Info * EP>Median			-0.0755
			(0.0471)
Observations	351	351	351
R-squared	0.120	0.111	0.111

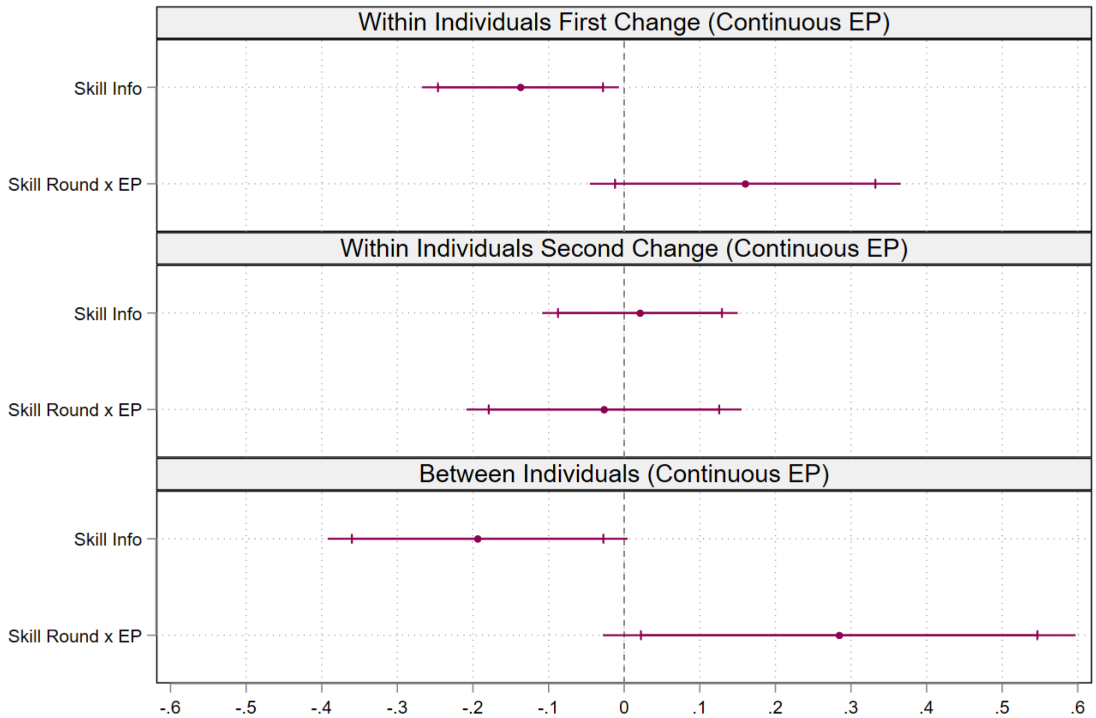
Robust standard errors in parentheses. Regression includes demographic controls and is restricted to first entry decision of all participants. *** p<0.01, ** p<0.05, * p<0.1

Appendix Figure A1. Comparison of the Within and the Between Individual Estimates of the Additional Effect of the Skill Information (EP Higher than Mean).



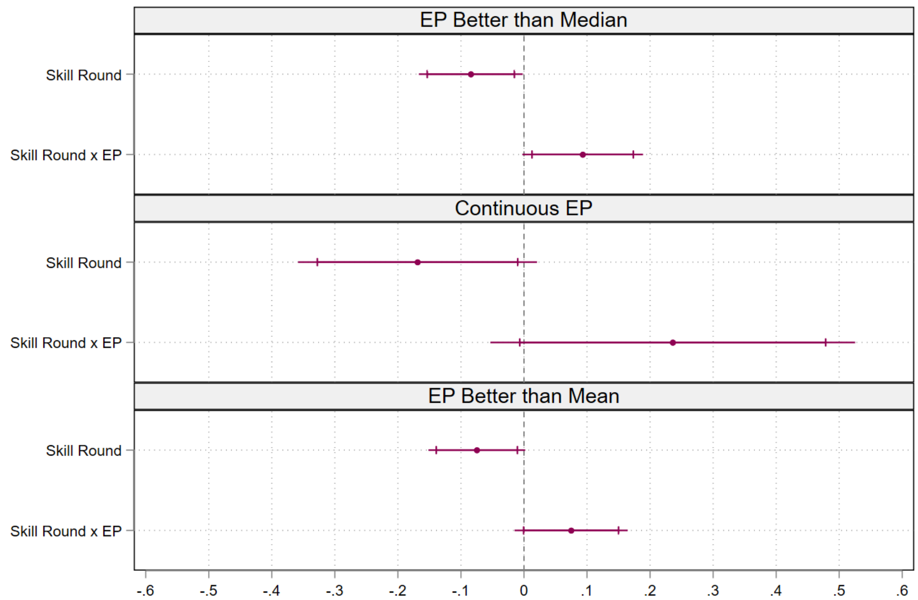
Note: This figure shows the coefficients when comparing the change in the decisions of individuals before and after the skill information is shared. The first pane shows the change within individuals decisions who were assigned to the average information treatment for their first decision. The second pane shows this change for individuals who were assigned to the baseline information for their first decision, so for them, the analysis is about the second possibility for changing their decision. The third pane shows the results from using the random assignment into the average versus the baseline condition for the first decision. This pane compares the changes between the first and second decisions of individuals in the two conditions, so it is to be interpreted as the relative difference between the average information's and the skill information's additional effects (between individuals). The confidence bars show both the 95% (line) and the 90 % (tick mark) confidence intervals.

Appendix Figure A2. Comparison of the Within and the Between Individual Estimates of the Additional Effect of the Skill Information (Continuous EP).



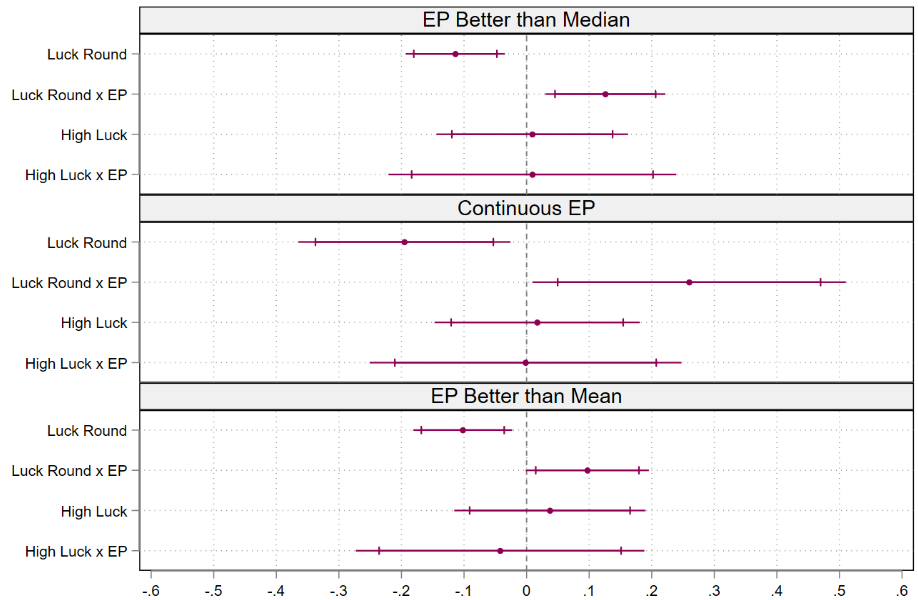
Note: This figure shows the coefficients when comparing the change in the decisions of individuals before and after the skill information is shared. The first pane shows the change within individuals decisions who were assigned to the average information treatment for their first decision. The second pane shows this change for individuals who were assigned to the baseline information for their first decision, so for them, the analysis is about the second possibility for changing their decision. The third pane shows the results from using the random assignment into the average versus the baseline condition for the first decision. This pane compares the changes between the first and second decisions of individuals in the two conditions, so it is to be interpreted as the relative difference between the average information's and the skill information's additional effects (between individuals). The confidence bars show both the 95% (line) and the 90 % (tick mark) confidence intervals.

Appendix Figure A3. The additional effect of the skill information on change in entry using different formulations of the EP



Note: This Figure shows the regression coefficient estimates of the skill coefficients of equation from section **??**. Each of the three panels shows the coefficient on the skill information treatment and its interaction term with the EP score. The three panes show the results using the three different versions of the EP score, high EP defined as greater than the median, or greater than the mean, as well as using the continuous EP score.

Appendix Figure A4. The additional effect of the luck information on change in entry using different formulations of the EP



Note: This Figure shows the regression coefficient estimates of the luck coefficients of equation from section **??**. Each of the three panels shows the coefficient on the luck information treatment and its interaction term with the EP score, as well as the effect of the game version with high role of luck and its interaction term with EP. The three panes show the results using the three different versions of the EP score, high EP defined as greater than the median, or greater than the mean, as well as using the continuous EP score.

Appendix Table A3. The additional effect of the skill information on change in entry

VARIABLES	(1) ΔEntry	(2) ΔEntry	(3) ΔEntry
Skill Info	-0.169*	-0.0562	-0.0844**
	(0.0964)	(0.0404)	(0.0419)
EP	-0.0759		
	(0.104)		
Skill Info * EP	0.236		
	(0.147)		
EP>Mean		-0.0204	
[		(0.0380)	
Skill Info * EP>Mean		0.0336	
		(0.0500)	
EP>Median			-0.0445
			(0.0374)
Skill Info * EP>Median			0.0931*
			(0.0487)
Observations	889	889	889
R-squared	0.017	0.016	0.018

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses. Regression includes round fixed effects and variables related to effects of luck, also interacted with EP variable. Outcome variable is the change in entry decision relative to the previous round. *** p<0.01, ** p<0.05, * p<0.1

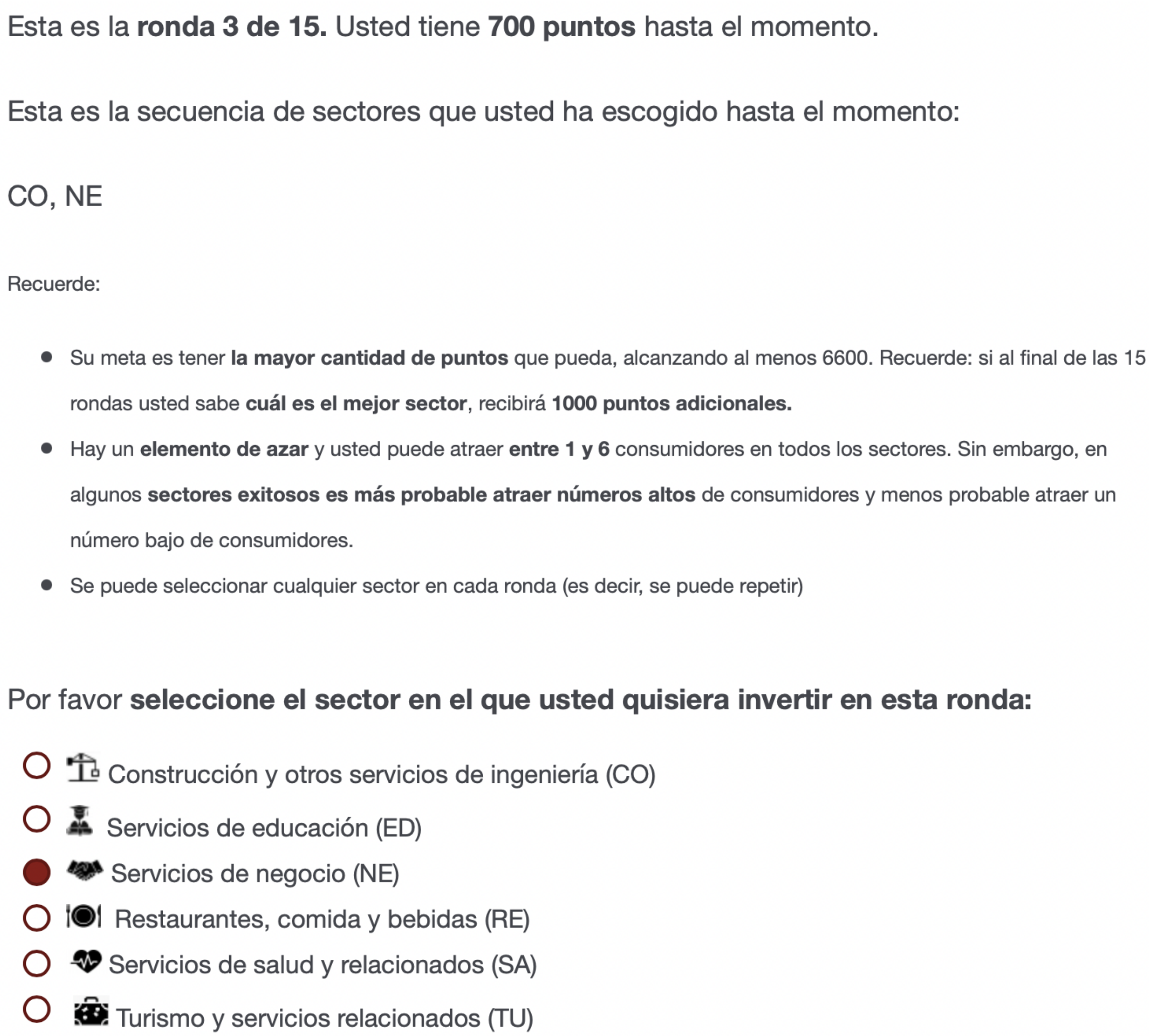
Appendix Table A4. The additional effect of the luck information on change in entry

VARIABLES	(1) ΔEntry	(2) ΔEntry	(3) ΔEntry
Luck Info	-0.195**	-0.105**	-0.115***
	(0.0862)	(0.0415)	(0.0416)
High Luck	0.0169	0.0266	0.0156
	(0.0834)	(0.0379)	(0.0368)
EP	-0.0759		
	(0.104)		
Luck Info * EP	0.260**		
	(0.127)		
High Luck * EP	-0.00168		
	(0.127)		
EP>Mean		-0.0204	
		(0.0380)	
Luck Info * EP>Mean		0.102*	
		(0.0527)	
High Luck * EP>Mean		-0.0243	
		(0.0431)	
EP>Median			-0.0445
			(0.0374)
Luck Info * EP>Median			0.128**
			(0.0517)
High Luck * EP>Median			-0.00296
			(0.0419)
Observations	889	889	889
R-squared	0.017	0.016	0.018

Note: Robust standard errors in parentheses. Regression includes round fixed effects and variables related to effects of skill, also interacted with EP variable. Outcome variable is the change in entry decision relative to the previous round. *** p<0.01, ** p<0.05, * p<0.1

B Appendix 2: Online Survey

Appendix Figure B1. Screenshot of the Game



Esta es la **ronda 3 de 15.** Usted tiene **700 puntos** hasta el momento.

Esta es la secuencia de sectores que usted ha escogido hasta el momento:

CO, NE

Recuerde:

- Su meta es tener **la mayor cantidad de puntos** que pueda, alcanzando al menos 6600. Recuerde: si al final de las 15 rondas usted sabe **cuál es el mejor sector**, recibirá **1000 puntos adicionales.**
- Hay un **elemento de azar** y usted puede atraer **entre 1 y 6** consumidores en todos los sectores. Sin embargo, en algunos **sectores exitosos es más probable atraer números altos** de consumidores y menos probable atraer un número bajo de consumidores.
- Se puede seleccionar cualquier sector en cada ronda (es decir, se puede repetir)

Por favor **seleccione el sector en el que usted quisiera invertir en esta ronda:**

- Construcción y otros servicios de ingeniería (CO)
- Servicios de educación (ED)
- Servicios de negocio (NE)
- Restaurantes, comida y bebidas (RE)
- Servicios de salud y relacionados (SA)
- Turismo y servicios relacionados (TU)

Note: This Figure shows and example of the game screen participants saw. They see the number of the current round (out of 15), the sequence of their past sector choices, their points so far, and a summary of the game mechanics and goals. They pick one of the six sectors as their choice for the current round.

Appendix Figure B2. Screenshot of the Average Information

Se espera que el 20% de los participantes de este juego (1 de cada 5) obtengan 6600 puntos o más, que es lo necesario para ganarse los 20 mil pesos adicionales.

Nota: Esta información viene de nuestro análisis de 80 participantes que ya jugaron el Juego de Emprendimiento. Todos fueron colombianos y son emprendedores o aspiran serlo.

Note: This Figure shows the Average Information treatment shared with the participants. They saw the recap of the same information from the previous page as well.

Appendix Figure B3. Screenshot of the Skill Information

Nos gustaría preguntarle de nuevo si quiere jugar por el premio o no. Antes de que tomé la decisión, queremos compartir con usted información adicional sobre el juego.

Como le contamos anteriormente, hemos calculado su puntaje de Preparación para Emprender (PE). **Este puntaje es predictivo de su desempeño en el Juego de Emprendimiento.**

Este puntaje (PE) que hemos calculado para usted es 12.5. En comparación con otros participantes, exactamente 57.5% de ellos obtuvo un puntaje igual o mayor que usted (57.5 de cada 100).

Esto significa, **si usted se desempeña en el juego como su puntaje PE predice, exactamente 57.5% de los participantes tendrán un puntaje igual o mayor que usted**.

Nota: La información anterior viene de nuestro análisis de 80 participantes que ya jugaron el Juego de Emprendimiento. Todos fueron colombianos y son emprendedores o aspiran serlo.

Note: This Figure shows an example of the Skill Information treatment shared with the participants. The exact information depended on the EP score calculated for the participant. They saw the recap of the same information from the previous pages as well.

Appendix Figure B4. Screenshot of the Luck Information

Nos gustaría preguntarle de nuevo si quiere jugar por el premio o no. Antes de que tomé la decisión, queremos compartir con usted información adicional sobre el juego.

Este juego tiene un elemento de suerte que afecta el puntaje final. Si usted y el resto de personas tuvieran la misma **suerte promedio**, con base en su puntaje PE, se espera que **57.5% de los participantes obtengan un puntaje mayor o igual que usted** en el juego.

No obstante, puede que usted no tenga suerte promedio:

- Si usted está dentro del **10% con mejor suerte** en el juego, se espera que **13%** de los participantes o menos tengan un puntaje igual o mayor que usted.
- Si usted está dentro del **10% con peor suerte** en el juego, se espera que **90%** de los participantes o más tengan un puntaje igual o mayor que usted.

En resumen:

Buena suerte

13% de los participantes o menos tendrán un puntaje igual o mayor que usted

Mala suerte

90% de los participantes o más tendrán un puntaje igual o mayor que usted

Note: This Figure shows an example of the Luck Information treatment shared with the participants. The actual numbers were based on the participant's EP score and their assignment to the game version of the high or low role of luck. They saw the recap of the same information from the previous pages as well.

C Appendix 3: Robustness checks

Appendix Table C1. The additional effect of the luck information on change in entry by EP and beliefs

VARIABLES	(1) ΔEntry	(2) ΔEntry
Luck Info	-0.0918**	-0.156**
	(0.0433)	(0.0613)
High Luck	0.0179	0.0623
	(0.0365)	(0.0506)
High EP	-0.0445	
	(0.0373)	
Luck Info * High EP	0.106**	
	(0.0502)	
High Luck * High EP	-0.00519	
	(0.0416)	
Low EP&High Beliefs		-0.0742
		(0.0583)
High EP&Low Beliefs		-0.0945
		(0.0726)
High EP&High Beliefs		-0.0620
		(0.0478)
Luck Info * Low EP&High Beliefs		0.192***
		(0.0711)
Luck Info * High EP&Low Beliefs		0.183**
		(0.0924)
Luck Info * High EP&High Beliefs		0.166**
		(0.0666)
High Luck * Low EP&High Beliefs		-0.122*
		(0.0678)
High Luck * High EP&Low Beliefs		-0.0471
		(0.0685)
High Luck * High EP&High Beliefs		-0.0457
		(0.0533)
Observations	889	889
R-squared	0.018	0.030

Robust standard errors in parentheses. Regression includes round fixed effects and variables related to effects of skill, also interacted with the EP and beliefs variables. EP and beliefs classifications into high and low are relative to the mean. Outcome variable is the change in entry decision relative to the previous round. *** $p<0.01$, ** $p<0.05$, * $p<0.1$