Income Risk, Precautionary Saving, and Loss Aversion – An Empirical Test*

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This paper empirically examines Kőszegi and Rabin's (2009) hypothesis that uncertainty about future income triggers precautionary savings among loss-averse individuals. We extend their theoretical analysis and empirically study the relation between income risk, loss aversion and precautionary savings among a sample of the low-income population subject to substantial income risk. We find that savings are higher for individuals who face higher income risk (unemployment). The results confirm the theoretical prediction and individuals who are more loss-averse save more.

JEL-classification: D11, D14, D15, D81, D90, G40, J65, O16

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1. Introduction

Income shocks, such as unemployment, diseases, or natural disasters, are pervasive (World Bank, 2013) and have serious negative impacts on the population (e.g., their mental health and suicide rates; see Christian et al., 2018; Clark et al., 2016). Due to limitations in access to credit markets and weak social protection systems in many developing countries, savings are one of the few alternatives that households have to mitigate the effect of income shocks (Dercon, 2010; Tovar and Urrutia, 2017). Paradoxically, saving rates are quite low (World Bank, 2014). Using household surveys in ten Latin American countries, Bebczuk et al. (2015) find that the mean saving rate as a proportion of disposable income is only 13 percent and about half of the population (45 percent) has negative saving rates. This paper examines empirically the relation between uncertainty, loss aversion, and savings.

Our conceptual framework is based on Kőszegi and Rabin's (2009) reference-dependent model of inter-temporal consumption. Risk-averse individuals with stochastic wealth decide in the first period how to split wealth, while uncertainty is resolved in the second period. Deviations in consumption from initial expectations induce a gain-loss sensation. When individuals are loss-averse, bad news about consumption changes are more unpleasant than good news are pleasant. The prospective loss from lowering expected future consumption generates a precautionary savings motive. Individuals who are loss-averse are predicted to save to minimize the impact that future wealth shocks could have on reducing consumption below the expected level. The larger the frequency and magnitude of the shocks and the larger the degree of loss aversion, the more individuals are predicted to save.

We examine the relation between savings, loss aversion and income risk, focusing on the low-income population in Bogotá, Colombia. Similar to comparable population groups in other developing countries, this population is exposed to substantial income uncertainty (Loayza et al., 2009; Stampini et al., 2016). The unemployment rate is relatively high

(10.4%), and a large share of the employed population depends on informal employment (52%) or are underemployed (30.1%). Hence, this population group presents a good case study to test the theory.

In 2013, we launched an independent study on the financial situation of low-income households. The study entitled 'Savings for old age in Colombia' comprised a survey and complementary experimental incentivized measures of loss aversion, risk preferences, and time preferences. The analysis focuses on the relation between survey measures of the total value of assets and the incentivized measures of risk and loss aversion. We measure income uncertainty using different objective measures.

In line with the precautionary savings motive predicted by the reference-dependent model of inter-temporal consumption by Kőszegi and Rabin (2009), we find that loss-averse individuals increase savings when they are exposed to greater uncertainty. This finding is robust to different measures of loss aversion and income uncertainty, to the inclusion of controls on a large set of socioeconomic characteristics, and to different econometric specifications. The novelty of this result is that it demonstrates that the relationship between loss aversion and savings is more complex than previously proposed. While previous studies have considered loss aversion as creating an obstacle to savings (e.g., Thaler and Benartzi, 2004), our study shows that, in the presence of uncertainty, loss aversion promotes precautionary savings. The larger the degree of loss aversion, the larger is the increase in savings.

The closely related model of Bowman et al. (1999) predicts that because of loss aversion there is an asymmetric response to news about income shocks on savings. Good news regarding future income leads to an immediate upward adjustment in consumption, while bad news results in less than proportional adjustments of consumption. Empirical evidence supports this hypothesis using macrodata (Bowman et al., 1999; Shea, 1995) and microdata (Fisher and Montalto, 2011; Lee, 2014). In this paper, we focus instead on the effect of uncertainty of future income shocks on savings.

Similar to the classical precautionary savings theory (Leland, 1968), the Kőszegi and Rabin precautionary savings model (2009) incorporates prudence, i.e., a positive third derivative of the utility function. The classical theory, that does not account for loss aversion, has been studied extensively; see Guiso et al. (1992), Dynan (1993), or also Christelis et al. (2019) for a more recent example.

We make various contributions to the literature on loss aversion, uncertainty and savings. First, while previous papers have examined the relation between reference-dependent expectations and consumption decisions, these papers do not focus on future income risk (Herweg and Mierendorff, 2013; Karle et al., 2015; Marzilli Ericson and Fuster, 2011). Second, unlike previous studies, we use a direct and incentivized measure of loss aversion at the individual level. Hence, we contribute to the research by explicitly considering the impact of loss aversion on savings. Last, we consider various measures to capture uncertainty about future income, which allows us to test the robustness of the results.

The closest to our study is Hwang (2017), who tests whether loss aversion depresses insurance demand and promotes precautionary savings. Loss-averse individuals might perceive the insurance premium as a loss when negative shocks are not realized. Hence, they would rather prefer to save as a precaution against future income shocks. Consistent with this theory, they find that loss-averse individuals are less likely to own term-life insurance and are more likely to own whole-life insurance and hold a higher level of wealth. We explicitly investigate the relation between uncertainty about future income and savings, which is a distinctive question.

Previously, Benartzi and Thaler (1995) showed that loss aversion can explain the equity premium puzzle and affects participation in equity markets. There is also empirical evidence linking (expectation based) loss aversion and labor markets (Abeler et al., 2011; Camerer et al., 1997; Daido and Murooka, 2016; Farber, 2008; Fehr and Goette, 2007; Imas et al., 2016; Wenner, 2015), purchase decisions (Herweg and Mierendorff, 2013; Karle et al., 2015; Marzilli Ericson and Fuster, 2011), sports (Allen et al., 2016; Bartling et al., 2015; Markle et al., 2018; Pope and Schweitzer, 2011), innovation (Rosokha and Younge, 2019) and domestic violence (Card and Dahl, 2011), among others. We contribute to this line of research by focusing on the relation between loss aversion and savings.

Our paper also connects to the literature considering behavioral approaches to increase the savings rate among the poor (for a comprehensive overview of the research on savings among the poor, see Karlan et al., 2014). In particular, a couple of interventions have considered the effect of loss aversion on savings. One of the best-known interventions is Thaler and Benartzi's (2004) 'SMarT (Save More Tomorrow™) Program'. They propose that loss-averse individuals perceive saving a portion of their current income as a loss, and show that decisions on future savings can increase savings. Karlan et al. (2016) compare the effectiveness of reminders that are framed as a loss ("your dreams won't come true") versus as a gain ("your dreams will come true") and find no significant effects of the frame on a household's savings rate. However, they do not consider heterogeneous effects of the degree of loss aversion. We consider this aspect further by exploring the relationship between uncertainty, loss aversion, and savings. This research could suggest alternative interventions to increase savings.

The paper is structured as follows. The next section presents the model of intertemporal consumption by Kőszegi and Rabin (2009), from which the hypotheses of the study are derived. Section 3 explains the empirical strategy used to test the predictions of this model, and Section 4 explains how the different measures were obtained. Results are presented in Section 5, and the approaches and findings of the paper are discussed in Section 6. Section 7 concludes.

2. Theoretical Framework

The conceptual framework that we use in the analysis is based on the reference-dependent utility model of inter-temporal consumption by Kőszegi and Rabin (2009). First, we introduce this model and derive the precautionary motive for saving as presented in their paper. In a second step, we extend the analysis to derive hypotheses relating the strength of the precautionary savings motive with the degree of loss aversion.

The model considers a two-period consumption-savings decision problem where individuals face uncertainty regarding their future wealth. Here, we present the model for the case in which wealth, W, is a binary random variable and uncertainty is resolved in the second period. In Appendix A.1, we present the two-period model for a more general case where W is non-binary random wealth.

We assume that with equal probabilities, wealth takes two possible values: $W_0 + s$ and $W_0 - s$, where W_0 is deterministic income and $s > 0$ a scalar, reflecting income risk.[1] An individual has to divide wealth W between consumption c_t in two periods, $t = 1, 2$, maximizing the sum of instantaneous utility in the first period and the expected instantaneous utility in t=2:

$$U = u_1(c_1) + \mathbb{E}[u_2(c_2)],$$

subject to the budget constraint $c_1 + c_2 = W$.

In the first period, there is no uncertainty on income and instantaneous utility is given by:

$$u_1(c_1) = m(c_1),$$

where m is the utility of consumption that is assumed to be three times differentiable, increasing and strictly concave.[2]

[1] Results generalize to non-binary random income; see the corresponding Proposition 8 in Kőszegi and Rabin (2009), as well as Proposition 1 and its Corollary in this study, for more general results.

[2] We abstract from overconsumption and assume that a deviation in Period 1 from the ex-ante optimal plan cannot increase the assessment of the overall utility in Period 1; see Proposition 5 in Kőszegi and Rabin (2009).

The expected instantaneous utility in the second period, $\mathbb{E}[u_2(c_2)]$, depends on the expected utility of consumption in that period, m, and on the so-called 'gain-loss utility'. Before the first period starts, it is assumed that agents choose their favorite credible consumption plan, which specifies possibly stochastic consumption levels for each period. This plan is called the Personal Preferred Equilibrium (PPE).[3]

When uncertainty is resolved in the second period and consumption decisions are implemented, plans are updated and lead to new beliefs. Changes in beliefs induce a gain or a loss in utility through 'gain-loss utility' depending on whether new beliefs imply a higher or lower consumption level than previously believed. Following Kahneman and Tversky (1979), it is assumed that individuals weight utility losses different than utility gains by using a factor $\lambda > 0$ that captures the degree of loss aversion. For an individual who is loss-averse, we have $\lambda > 1$, whereas for a gain-seeking individual we have $\lambda < 1$.

If income is high (i.e., if $W = W_0 + s$), which occurs with probability 1/2, there is a gain in utility from changes in beliefs, as the individual had planned a lower consumption level (c_2^-) with probability 1/2. This change is weighted by $\eta > 0$, which captures the weight attached to gain-loss utility. Conversely, if income is low, there is a loss in utility since the agent had planned a higher consumption level (c_2^+), again with probability 1/2; this change is weighted by $\eta > 0$ and $\lambda > 0$ to account for loss-averse ($\lambda > 1$) or gain-seeking ($\lambda < 1$) behavior.[4]

[3]Details on this concept are given in Appendix A.2 or in Kőszegi and Rabin (2009).

[4]The assumption of putting a higher weight on utility below the reference point, hence assuming loss aversion (i.e., $\lambda > 1$), is common in reference-dependent models. Kőszegi and Rabin (2009) call it the "clearly correct assumption", although empirical studies could not exclusively validate this assumption (e.g., Schmidt and Traub, 2002). Therefore, we only assume $\lambda > 0$ and allow for 'gain-seeking' behavior. See Appendix A.1 for further details.

Summarizing, the expected instantaneous utility in the second period is given by:

$$\mathbb{E}[u_2(c_2)] = \frac{1}{2}\left(m(c_2^+) + \frac{1}{2}\eta\left(m(c_2^+) - m(c_2^-)\right)\right) \\ + \frac{1}{2}\left(m(c_2^-) - \frac{1}{2}\lambda\eta\left(m(c_2^+) - m(c_2^-)\right)\right),$$

where m is the utility of consumption as defined above, $c_2^+ = W_0 - c_1 + s$ and $c_2^- = W_0 - c_1 - s$.

As shown by Kőszegi and Rabin (2009), for an interior solution, the optimal consumption path satisfies:

$$m'(c_1) = \frac{1}{2}m'(c_2^+) + \frac{1}{2}m'(c_2^-) + \frac{1}{4}\eta(\lambda - 1)[m'(c_2^-) - m'(c_2^+)]. \tag{1}$$

To see whether increases in risk, s, increase $m'(c_1)$ (then c_1 decreases if m is strictly concave), we apply a Taylor approximation of the right-hand side of (1) around $s = 0$ to obtain:[5]

$$m'(c_1) \approx m'(c_2) + \frac{1}{2}m'''(c_2)s^2 + \frac{1}{2}\eta(\lambda - 1)(-m''(c_2))s. \tag{2}$$

From this derivation, we see that, for a loss-averse individual (i.e., when $\lambda > 1$), uncertainty causes an increase in savings as consumption decreases in period 1 when $m''' > 0$ or when the last term dominates the second term in (2). The first condition corresponds to the classical theory of precautionary savings, as initiated by Leland (1968), where 'prudence', which can be defined as the preference for allocating a zero-mean risk to a state of higher wealth instead of to a state of lower wealth, causes the individual to save.

Following the assumption of Kőszegi and Rabin (2009) that m is a global utility function, small risks in the model might still be substantial in "practical terms", and thus the last term dominates the second term in (2).[6]

[5] See Equation (11) in Kőszegi and Rabin (2009).

[6] Their assumption is needed, since technically, this is true only for small s; see their comment in Footnote 25 in Kőszegi and Rabin (2009).

Generalizing to the case where second-period income has more than just two realizations and where people might overconsume in the first period leads to the first hypothesis from this model.[7]

Hypothesis 1. *For loss-averse agents, uncertainty increases savings.*

We now extend the analysis of Kőszegi and Rabin (2009) to consider how the degree of loss aversion affects the precautionary savings motive. From both (1) and (2), we see that savings increase in the degree of loss aversion.[8] This finding can be generalized to non-binary income risk and individuals overconsuming in the first period: Suppose wealth is now equal to $W_0 + sy$, where y is a non-deterministic mean-zero lottery that is resolved in Period 2. Overconsumption is linked to a parameter $\gamma \geq 0$ in this more general framework (Appendix A.1), which captures the importance attached in Period 1 to a change of beliefs regarding consumption in Period 2. As shown in Kőszegi and Rabin (2009), an individual increases consumption in the first period relative to the ex-ante optimal level if $\gamma < 1/\lambda$; see Appendix A.1 for further details.

Proposition 1. *For any increasing, strictly concave, three times differentiable consumption utility function m, any $\eta > 0, \lambda > 0, \gamma \geq 0$, and s small and positive, the personal preferred equilibrium consumption rule satisfies $dc_1/d\lambda < 0$.*

The proof of Proposition 1 is in Appendix A.3. From this proposition, we derive the following hypothesis:

Hypothesis 2. *With income uncertainty that is resolved in the future, the effect of the degree of loss aversion on savings is unambiguously positive. This also includes coefficients of loss aversion $\lambda \leq 1$.*

[7] See Proposition 8 in Kőszegi and Rabin (2009).

[8] Although this effect is independent of the amount of risk s on the right-hand side of (2), we have to keep in mind that this expression is a Taylor approximation around $s = 0$. Thus, it is a good approximation only for small amounts of risk. Although the first-order condition (1) holds independently of the risk level, for large amounts of risk it cannot technically be said for sure whether this condition yields a utility maximum. For small amounts of risk, however, the second-order condition for a utility maximum is satisfied.

Irrespectively of Hypotheses 1 and 2 being true (i.e., the degree of loss aversion or uncertainty for loss-averse individuals having a positive effect on savings), from (1) and (2) we see that the effect of loss aversion on savings increases in uncertainty and that the effect of uncertainty on savings increases in loss aversion. As expected, this result generalizes to non-binary income lotteries and individuals overconsuming in the first period:

Corollary 1. *For any increasing, strictly concave, three times differentiable consumption utility function m and any $\eta > 0$, $\lambda > 0$, $\gamma \geq 0$, the personal preferred equilibrium consumption rule satisfies $d^2c_1/(dsd\lambda)|_{s=0} < 0$.*

From Corollary 1 and following the interpretation of small risks in the model by Kőszegi and Rabin (2009), we can derive the third hypothesis:

Hypothesis 3. *The effect of the degree of loss aversion on savings is an increasing function of uncertainty. Equivalently, the effect of uncertainty on savings is an increasing function of the degree of loss aversion. As in Hypothesis 2, this also includes coefficients of loss aversion $\lambda \leq 1$.*

3. Empirical Strategy

We want to test the previous hypotheses derived from Kőszegi and Rabin's (2009) model and investigate the relationship between income risk, loss aversion on the individual level and savings. In the analysis, we use individual measures of savings, income risk, and loss aversion.

To test Hypothesis 1, if the effect of income uncertainty on the saving decision for loss-averse individuals is unambiguously positive, we run the following regression:

$$\text{Savings}_i = \beta_1 s_i + \zeta X_i + \beta_0 + \varepsilon_i, \qquad \text{(Model 1)}$$

where Savings_i is the first-period income minus c_1 (first-period consumption), s_i is the individual's income uncertainty, X_i is a vector of socioeconomic characteristics for individual i, and ε_i is the error term; β_1 and ζ are regression coefficients estimating the relation between savings and income uncertainty and socioeconomic characteristics, respectively, and β_0 is the intercept of this model. The data would support Hypothesis 1 if $\beta_1 > 0$.

To test the second hypothesis, postulating that the higher the loss aversion is, the higher the savings are when facing income risk, we run the following regression:

$$\text{Savings}_i = \beta_2\lambda_i + \zeta X_i + \beta_0 + \varepsilon_i, \qquad \text{(Model 2)}$$

where λ_i is the degree of loss aversion of individual i with corresponding regression coefficient β_2. We run this regression for the complete sample considering that this population group is highly exposed to income uncertainty. A positive β_2 would support Hypothesis 2.

Finally, we test Hypothesis 3, claiming that the effect of uncertainty on savings is an increasing function of the degree of loss aversion by estimating the following equation:

$$\text{Savings}_i = \beta_3(s_i \times \lambda_i) + \beta_1 s_i + \beta_2\lambda_i + \zeta X_i + \beta_0 + \varepsilon_i, \qquad \text{(Model 3)}$$

where β_3 is the regression coefficient of the interaction term of individual loss aversion λ_i and individual income uncertainty s_i. Hypothesis 3 is supported if $\beta_3 > 0$.

Note that we center income risk measures around mean values and loss aversion around 1. Hence, β_1 is the main effect of uncertainty for a loss-neutral individual, while β_2 is the main effect of loss aversion estimated at a mean level of income uncertainty. The theoretical model does not provide definitive predictions on savings for loss-neutral individuals facing income risk. We report marginal estimations following from this regression for the effects of loss aversion and income uncertainty at different levels of income uncertainty and loss aversion, respectively, which allows these results to be interpreted within the contexts of Hypotheses 1 and 2.

The next section presents the definitions of loss aversion, savings, and income risk, as well as the methods used to estimate them.

4. Data and Definition of Variables

The data used in the study were collected between October and November 2013 as part of the project 'Savings for the Old Age'. The study comprised an extensive survey of the financial situation of the households and incentivized economic experiments on risk and time preferences.

We conducted a two-step sampling process. First, low-income neighborhoods were identified by assessing the proportion of people belonging to the two lowest socioeconomic strata. Neighborhoods with a larger proportion of low-income population, and which were assessed as safe for the team to visit, were eligible for the study. Participants for the study were then selected from a list of households in the area in 2010. The criterion for selecting participants was that they should be beneficiaries of the social health insurance, SISBEN. This condition would guarantee that the participants were from low socioeconomic strata.

In total, 640 participants completed the survey and the experiment. The survey lasted around 90 minutes. The experiment was completed at a different location a few days later and took about 20 minutes.

Below, we define the measures used and explain how the variables were calculated.

4.1. Savings

We measure savings as the total value of an individual's assets. This includes total savings in checking accounts, certificates of deposit, mutual funds, savings in cash or in other currencies, the value deposited in savings plans (i.e., money to buy a house or to pay for the education of their children), and the net value of loans given. We use the sum of those categories, since in cases of emergency it is possible to withdraw money from all of these savings devices.

4.2. Income Risk

In the analysis, income risk is measured by the unemployment rate aggregated at the locality level and the (self-reported) risk of becoming unemployed aggregated at the level of a local planning unit.[9] We use these measures since unemployment is one of the main sources of income risk with which our population group is confronted. In addition, unemployment is quite high in Colombia. DANE estimated the unemployment rate at 8.64 percent in Bogotá for 2013.

The advantage of this measure is that it can be considered to be exogenous for a single individual who cannot affect the unemployment rate or risk. The assumption that we use is that individuals observe when neighbors lose employment. This makes their subjective individual risk of income loss salient. Objectively, in big cities like Bogotá, where housing is segregated and to a certain degree informal in many areas, it can be assumed that individuals living in the same (poor) neighborhood work on similar job markets and are constrained in relocating for a job, and thus face similar unemployment risks (cf. the spatial mismatch hypothesis going back to Kain (1968), who documented that housing segregation of nonwhite workers in Detroit and Chicago affected their employment outcomes – among them unemployment risk –, and see for example Andersson et al. (2018) for recent empirical support of the now broader question "whether a worker with locally inferior access to jobs is likely to have worse labor market outcomes"). As detailed below, we find support for this conjecture in our data.

In the analysis, we use two different sources of information to compute unemployment figures, as explained in greater detail below.

Income Risk Based on Data from DANE This measure corresponds to the unemployment rate aggregated at the locality level (*localidad* in Spanish). We use the multipurpose survey from Bogotá (*Encuesta Multipropósito para Bogotá*) for the source of information to

[9]There are 20 localities in Bogotá aggregating more than 110 local planning units and 5100 neighborhoods or "barrios".

construct the unemployment data at the level of locality, which was conducted by Colombia's Statistical Department (DANE) and the District Planning Department (SDP). The figures correspond to the 2011 unemployment rate published in *'Índices de Ciudad'* by the *Secretaría de Planeación, Alcaldía Mayor de Bogotá.* The unemployment rate ranged from 6.86 percent in the *localidad 'Suba'* to 11.31 percent in *'San Cristóbal'*.[10]

Average Unemployment Risk Based on Survey Data All individuals who took part in the experiment and who were working at the time of the interview answered the question "What is the probability that you will lose your job next year". All those stating a positive probability where asked to also answer the question "If you lose your job, what is the probability of finding a new one next year?" Since the vast majority were confident of being able to find a new job within a year in the case of unemployment, and since this new job could potentially be better paid than the last one, we interpret the unemployment risk as income risk and not just as the risk of a negative income shock.

In order to reduce problems of endogeneity associated with this measure, we use the average probability at the local planning unit, *UPZ*. This measure has lower aggregation than the measure based on *localidad*, but a larger degree of aggregation than *barrios*.[11] Typically, a *localidad* consists of several *UPZ*; for example, the *localidad Suba* consists of 12 *UPZs*.

Using the average unemployment risk has two practical advantages. First, self-employed individuals cannot lose their job, but they can be exposed to income risk. By using averages, we can assign a level of income risk that is likely to be close to the reality of those individuals. Furthermore, the income risk an individual is exposed to might not only be driven by his or her own income risk, but also by the income risk their partner is exposed to as an example.

[10] The figure coming closest to what is commonly referred to as 'unemployment' is the *'Tasa de Desocupados'*, the rate of unoccupied persons.

[11] *UPZs* with fewer than 25 observations were grouped with their neighboring *UPZ(s)*.

As mentioned above, unemployment figures vary accross Bogotá: Official unemployment rates range from 6.9 percent (*localidad* Suba) to 11.3 percent (*localidad* San Cristóbal) and self-reported unemployment risk ranges from 15.2 percent in the *UPZ* Corabastos (*localidad* Kennedy) to 36.5 in Comuneros/Alfonso López (Usme). Comparing unaggregated, individual self-reported unemployment risk between these two UPZs shows significant differences, both in the mean and in the distribution, using a two-sided t test ($p<0.03$) and an exact Kolmogorov-Smirnov test ($p<0.1$), respectively. This suggests that labor markets differ for inhabitants of different neighborhoods, in line with the spatial mismatch hypothesis.

4.3. Loss Aversion

For the experimental elicitation of loss aversion, we used the non-parametric method introduced by Abdellaoui et al. (2007). This method is based on simple lottery choices where individuals compare two lotteries over a series of decision tasks that vary payoffs and probabilities of good and bad states of the world. Hence, it is cognitively equally demanding as other methods (e.g., Holt and Laury, 2005). The method applied corrects for the misperception of probability. In addition, using these choices, it estimates the utility points iteratively over a large range of values. The utility points can be connected to yield a utility function over the gain and loss domain.

The advantage of this method is that it is very flexible as it does not require any parametric assumptions over a utility function or probability weighting. Competing methods mostly focus on the elicitation of preferences at just one or a few (arbitrarily) selected points in the interval of interest (e.g., Binswanger, 1980; Eckel and Grossman, 2002; Holt and Laury, 2005).

The definitions of loss aversion we apply build on utility functions. Following Abdellaoui et al. (2007), we use five different definitions of loss aversion, since so far there is no agreement on a definition of loss aversion, and measures differ considerably. We also follow Abdellaoui et al. (2007) in the operationalization of these measures.

Kahneman-Tversky (KT) Kahneman and Tversky (1979) define an individual as loss-averse, if for all amounts of money x the utility μ of receiving this amount is lower than the disutility of losing that same amount, i.e., if $\forall\ x > 0: -\mu(-x) > \mu(x)$. A natural coefficient of loss aversion emerging from this definition is $-\mu(-x)/\mu(x)$ for every elicited amount $x > 0$. If $\mu(-x)$ for any of these eight elicited amounts of money $x > 0$ was not elicited, it was linearly interpolated. As the coefficient of loss aversion, we took the median of the computed coefficients.

Neilson (N) Neilson (2002) proposes computing the ratio of 'relative steepness', which is the utility value $\mu(x)$ divided by the corresponding x-value. This figure incorporates information about steep parts of the utility function at any point of the interval of interest – even in flat regions. If the relative steepness of the utility function over the loss domain is bigger than the one on the gain domain at any point, the individual is classified as loss averse, i.e., $\mu(-x)/x \geq \mu(y)/y$, $\forall\ x, y > 0$. For this definition, we computed the coefficient of loss aversion as the ratio of the infinum of $\mu(-x)/(-x)$ over the supremum of $\mu(y)/y$.

The remaining definitions rely on the steepness of the utility function as expressed by the derivative of the latter on both domains.

Wakker-Tversky (WT) Wakker and Tversky (1993) suggest applying the concept of Kahneman and Tversky (1979) to the derivative of utility, i.e., to compare the value of the derivative of the utility function for gains and losses 'point-wise' at certain absolute values: $\mu'(-x) > \mu'(x)$, $\forall\ x > 0$. At every elicited utility point $x > 0$ on the gain domain, the derivative $\mu'(x)$ was operationalized as the mean of the two connecting slopes to the left-hand side and to the right-hand side. $\mu'(-x)$ was operationalized as the slope of the linearly interpolated utility function at the point $-x$. Similar to the case for the definition by Kahneman and Tversky (1979), a natural coefficient emerging from the definition $\mu'(-x) > \mu'(x)$, $\forall\ x > 0$, is $\mu'(-x)/\mu'(x)$ for $x > 0$. In this case, we also took the median of the coefficients thus computed.

Bowman (B) Bowman et al. (1999) propose performing this comparison 'domain-wise', that is, $\mu'(-x) > \mu'(y)$, $\forall\ x, y > 0$. As in the case for the definition by Neilson (2002), the definition $\mu'(-x) > \mu'(y),\ \ \forall\ x, y > 0$ can be transformed into a coefficient of loss aversion by computing $\inf \mu'(-x)/\sup \mu'(y)$ for $x, y > 0$, where the derivatives where operationalized as just described.

Köbberling-Wakker (KW) Finally, Köbberling and Wakker (2005) define an individual as loss-averse if the slope of the utility function on the left-hand side of the reference point is steeper than the slope of the utility function on the right-hand side of the reference point: $\mu'(0_-)/\mu'(0_+)$. The definition of loss aversion $\mu'(0_-)/\mu'(0_+)$ was transformed into a coefficent of loss aversion by computing the ratio of slopes connecting 0 with the elicited utility points that are closest to 0 on both domains.

Meta-Measures To incorporate the different definitions of loss aversion, and to ensure that our results are independent of the exact definition of loss aversion, we compute different meta-measures of loss aversion based on data availability. The first meta-measure is the geometric mean of the coefficients resulting from the definitions by Neilson (2002) and Köbberling and Wakker (2005), available for all individuals. The second meta-measure additionally includes the coefficient based on the definition by Kahneman and Tversky (1979), which we can compute for 579 participants of the experiment, as this involves derivatives; see Section 5 for details. Finally, we compute a measure relying on all five definitions, available for 509 participants. We apply the geometric instead of the arithmetic mean, since all coefficients are ratios, thus centered around 1, where it is desirable that coefficients of .5 and 2 have a mean of 1 instead of 1.25. Additionally, the geometric mean is the adequate choice when ranges of single components differ, which is the case for the loss aversion coefficients resulting from the different definitions.

4.4. Risk Preferences

The experimental data were also used to estimate risk preferences corresponding to the curvature of consumption utility m and probability weighting that we may use as control variables. Although in the theoretical model m is assumed to be a concave function, for empirical elicitation of curvature we relax this assumption. We use similar procedures as Abdellaoui et al. (2007). First, we rescaled monetary amounts x to lie in the interval $[-1, 1]$. Second, we rescaled the utility function such that $m(-1) = -1$, $m(0) = 0$ and $m(1) = .5$, consistent with the elicitation method. Taking into account the rescaling of monetary amounts and the utility, in the third step we estimate the curvature of utility, estimating the following power utility function for the gain and loss domains:

$$m(x) = \begin{cases} -(-x)^a & \text{for } a > 0,\ -1 \leq x < 0 \\ 0.5 \cdot (x)^b & \text{for } b > 0,\ 0 \leq x \leq 1. \end{cases}$$

Finally, the estimated parameters, referred to as coefficients of risk aversion in expected utility (EU) theory, are used to classify utility curvature. For $x > 0$, the utility function is strictly concave if $0 < b < 1$, linear if $b = 1$, and strictly convex if $b > 1$. For $x < 0$, we have that the function is strictly concave if $a > 1$, linear if $a = 1$, and strictly convex if $0 < a < 1$. For more details, see Appendix B.1.

The experimental method proposed by Abdellaoui et al. (2007) also allows a non-parametric estimation of subjective probabilities. Using this method, we estimate the objective probability corresponding to a subjective probability of 50 percent.

4.5. Time Preferences

To elicit the near future impatience or interest rate, which we also use as control variables, we followed the experimental design by Andersen et al. (2008). People were asked whether they would prefer to receive an amount x in 30 days or an amount $x(1+r/12)$ with $r > 0$ in 60 days. This question was asked for different and increasing values of r and people normally switched from choosing x in 30 days to $x(1+r/12)$ in 60 days for a sufficiently high r. This switching point allows the calculation of a lower and an upper bound of the interest rate, but since people are making choices dealing with the concept of receiving money, interpreting the results as impatience is likely more accurate.

In addition, we let participants perform the same task with a more distant time-framing. In that setting, participants had to choose between receiving the lower amount in 180 days or receiving the higher amount in 210 days. This allows us to consider consistency in intertemporal choice. We compute the difference between interest rates or impatience for the two time frames. If people behaved consistently, we would expect impatience with regard to receiving a monetary amount 30 days earlier to be unaffected by the time distance in the future. If people became more patient, impatience in the more distant future should be lower.

4.6. Other Control Variables

In the empirical analysis, we also control for other covariates that have been found to affect the likelihood of saving or the amount of savings:

- Age has been found to affect savings positively (e.g., Conley and Ryvicker, 2004; Finke et al., 2006), but also negatively (Devaney et al., 2007).

- Female-headed households tend to accumulate less wealth (Conley and Ryvicker, 2004) and are less likely to have longer term saving motives such as retirement savings, instead of short term saving motives such as emergency savings (Devaney et al., 2007). Therefore, we control for being head of household and gender.

- The number of children in a household decreases the likelihood of holding assets (Fisher and Montalto, 2011; Sanders and Porterfield, 2010) and also the amount of wealth accumulated (Conley and Ryvicker, 2004), but not necessarily the amount of conditional investment in assets (Sanders and Porterfield, 2010). Thus, we include the number of adolescent household members in our regressions.

- Family size has been found to increase the likelihood of saving for safety and security reasons, such as emergencies or retirement, instead of saving for basic needs and safety reasons, respectively, in a hierarchy model of saving motives (Devaney et al., 2007). Therefore, we control for the number of adult household members.

- Inheritance has been reported to affect wealth positively (e.g., Conley and Ryvicker, 2004), which we capture by variables indicating whether or not father and mother of the respondent are still alive.

- Homeownership increases the odds of saving and the amount of savings (Finke et al., 2006; Fisher and Montalto, 2011). Therefore we control for the estimated market price of the family's home.

- Education and income are positively associated with higher wealth (Conley and Ryvicker, 2004; Finke et al., 2006; Fisher and Montalto, 2011) or the likelihood to save without additionally having credit card debt (Gorbachev and Luengo-Prado, 2019).

- Van Rooij et al. (2012) report a positive effect of financial literacy on accumulated savings and Gorbachev and Luengo-Prado (2019) find that the group of people that save and at the same time have credit card debt have lower financial literacy than those that are just saving. In the survey, we asked 18 questions on financial literacy related to topics such as interest rate, asset classes, basic math, and financial math. The variable included in the regression contains the number of correctly answered questions.

- Health status has been reported to have a positive influence on the likelihood of saving (Fisher and Montalto, 2010, 2011). We capture the health status by the BMI as well as by the regularity of exercising.

- Short-term planning and saving horizons, sometimes referred to as time preferences for the present, have been found to have a negative effect on the likelihood of saving, but also on net wealth (Devaney et al., 2007; Fisher and Montalto, 2010, 2011).

- The size of the safety net, or number of individuals available to provide financial help in case of need, increases the possibilities of households to cope with income shocks. We expect that, as more individuals have access to a safety net, they would decrease their savings rate.

Table 1: Summary Statistics

	Mean	s.d.	Min	Max	Obs.
Individual Information					
Age	49.0	13.4	24	87	640
Male (=1)	0.28	0.45	0	1	640
Relationship to head of HH					
Head of household (=1)	0.64	0.48	0	1	640
Partner (=1)	0.23	0.42	0	1	640
Son/Daughter or their partner (=1)	0.07	0.25	0	1	640
Other (=1)	0.06	0.24	0	1	640
Household Characteristics					
Number of adult household members	2.8	1.4	1	12	640
Number of adolescent household members	1.2	1.3	0	7	640
Father still alive (=1)	0.31	0.46	0	1	640
Mother still alive (=1)	0.51	0.50	0	1	640
Exercising					
Every day (=1)	0.17	0.37	0	1	640
At least once a week (=1)	0.18	0.38	0	1	640
At least once a month (=1)	0.09	0.28	0	1	640
Never or hardly ever (=1)	0.57	0.50	0	1	640
Other Health Indicators					
BMI	25.7	4.3	12.9	43.0	640
Education					
Highest year passed	5.8	3.3	0	11	640
Financial Literacy Score (max. 18)	9.3	3.4	0	16	640
Financial Situation of the Household					
SISBEN Level 2 (=1)	0.50	0.50	0	1	640
Size of Safety Net (# persons)	2.5	3.5	0	60	640
Monthly HH income per capita[a]	3.19	2.26	0.01	18.00	640
Market Price of House[a]	180.10	408.86	0.00	3000.00	640
Debt[a]	17.24	65.68	0.00	588.04	640
Savings[a]	2.56	13.91	0.00	200.00	640
Engaging in saving (=1)	0.15	0.35	0	1	640
Conditional Savings[a]	17.61	32.82	0.20	200.00	93
Planning Horizon					
Day to day (=1)	0.74	0.44	0	1	640
Next months (=1)	0.18	0.38	0	1	640
Next year (=1)	0.05	0.21	0	1	640
Next two to five years (=1)	0.02	0.14	0	1	640
Next five to ten years (=1)	0.01	0.11	0	1	640

Note: [a] Figures reported in 100,000 COP.

5. Results

5.1. Descriptive Statistics

Summary statistics are reported in Table 1. Participants in the study were between the ages of 24 to 87, with a mean age of 49 years. Our sample consists of roughly 70 percent women. The education level of the sample was quite low, even in the context of a developing country. On average, the highest educational attainment was passing the sixth year of school. Financial literacy was also relatively low: The average individual was able to answer roughly only half of the 18 questions concerning, for example, simple math or interest-rate topics correctly.

The mean monthly income in an average household was 319,000 COP, which at that time was roughly 170 USD. The poverty line at the date of the interview was approximately 155 USD. Half of the sample was assigned to the lowest socioeconomic strata according to the SISBEN classification.

Around 85 percent of the sample does not engage in savings and the overall mean of savings is 256,000 COP – approximately 130 USD –, thus less than the average per-capita household income per month. The mean savings of those who were actually saving was around 1,761,000 COP, which corresponds to roughly 900 USD. Those reporting non-zero savings save exclusively in cash (27 percent), in a savings account (20 percent), or exclusively for housing (34 percent). The majority of the sample (74 percent) reported carrying out their financial planning on a day-by-day basis, and more than half of the sample never, or hardly ever, exercises, which is reflected in a mean BMI of 25.7, corresponding to an overweight person.

Summary statistics on income risk are reported in Table 2. Secondary data reveal an average unemployment rate of 8.5%. This is substantially lower than the mean perceived risk of unemployment based on subjective data (25%). This difference can be due to a high degree of pessimism for the future or simply the commonly observed overweight-

Table 2: Summary Statistics of Income Risk Measures

	Mean	s.d.	Min	Max	Obs.
Regional Unemployment Rate (in pc)	8.5	1.7	6.9	11.3	640
Regional Unemployment Risk (in pc)	24.7	6.0	15.2	36.5	640

Note: The regional unemployment rate is measured at the *localidad* level and relies on secondary data provided by DANE; unemployment risk is self-reported and aggregated at the *UPZ* level; see Section 4.2 for details.

ing of small probabilities. The Pearson's correlation coefficient for the two measures of unemployment is $r = 0.505$ ($p < .0001$), which indicates a positive and large correlation according to Cohen's classification (see, e.g., Cohen, 1992). Since the number of *localidades* is limited, one could interpret the regional unemployment rate as an ordinal variable. In that case, the more appropriate Spearman's rank correlation coefficient is $r_s = 0.4886$ ($p < .0001$).

Experimental measures of the time and risk preferences are reported in Table 3. The measure of time preference indicates the mean annual interest rate r demanded to receive an amount $x \cdot (1 + r/12)$ in 60 days instead of an amount x in 30 days. This mean annual interest rate is valued at 29.6 percent.

On average, the interest rate, or mean impatience, stays approximately constant when the timing of receiving the monetary amounts changes from 180 to 210 days, as indicated by the increase in patience over time, expressed in percentage points. The observed impatience is in line with estimates from recent experiments that used the general population in Denmark (Harrison et al., 2002).

In Prospect Theory, the attitude towards risk can be expressed by the curvature of the utility function and probability weighting. The reported measure of utility curvature corresponds to the parameter of a power utility function, as explained in Section 4.4. On the gain domain, the median subject exhibits a concave utility curvature, indicated by a median curvature parameter of 0.7, which corresponds to risk aversion in expected utility theory settings. On the loss domain, the median curvature parameter is 1.1 and again

Table 3: Summary Statistics of Experimental Measures

	Mean	s.d.	Median	IQR	Obs.
Single Measures of Loss Aversion					
Bowman (B)	0.1	0.2	0.0	0.0, 0.0	564
Kahneman-Tversky (KT)	1.1	2.7	0.4	0.1, 1.1	579
Köbberling-Wakker (KW)	10.9	76.6	0.2	0.0, 1.0	640
Neilson (N)	0.2	0.5	0.0	0.0, 0.1	640
Wakker-Tversky (WT)	12.3	110.9	0.1	0.0, 0.3	564
Meta Measures of Loss Aversion					
Meta Measure 1 (KW, N)	1.1	4.6	0.1	0.0, 0.4	640
Meta Measure 2 (KT, KW, N)	1.0	3.1	0.1	0.0, 0.6	579
Meta Measure 3 (all)	0.3	1.0	0.1	0.0, 0.2	509
Impatience					
Near future impatience	29.6	15.2	22.0	16.0, 50.0	640
Increase in patience over time	0.3	16.3	0.9	-2.9, 0.9	640
Risk Preferences					
Utility Curvature: Gain Domain	6.0	29.9	0.7	0.2, 2.5	640
Utility Curvature: Loss Domain	8.0	16.0	1.1	0.5, 3.5	640
Probability Weighting: Gain Domain	41.5	32.9	40.6	9.4, 71.9	640
Probability Weighting: Loss Domain	68.5	28.5	78.1	46.9, 96.9	640

Note: The measures and meta-measures of loss aversion are described in Section 4.3; near future impatience is the mean annual interest rate, see Section 4.5. Utility curvature is the parameter of a power utility function and probability weighting is the probability that is perceived as 50%; see Section 4.4 for details.

indicates concave utility curvature, which corresponds to slightly risk-averse behavior in an expected utility framework. For gains, subjects tend to overweight probabilities around 40%, as reflected by a median value of $p_g = 40.6\%$ s.th. $w^+(p_g) = 1/2$. In lotteries involving losses, probabilities around $p_l = 80\%$ are underweighted by the median individual in our sample, since $w^-(p_l) = 1/2$.

It has generally been found that large probabilities are underweighted, whereas smaller probabilities, up to around 33%, are overweighted, which results in an S-shaped probability-weighting function (e.g., Abdellaoui, 2000; Camerer and Ho, 1994; Gonzalez and Wu, 1999; Tversky and Kahneman, 1992). Probability weighting in our study, however, seems to be more pronounced than what has been found in the literature with comparable methodology (e.g., Abdellaoui, 2000): Probabilities around 40% for the gain domain are still overweighted in our study. Similarly, probabilities of about 80% for the loss domain are more underweighted than, for example, in the study by Abdellaoui (2000), who find $w^-(78\%) = 2/3$. These probabilities were elicited for the larger outcome in a lottery in absolute terms; therefore, these findings could be due to the optimism of the Colombian people. With regard to utility curvature, our findings are in the range of previous results: For the gain domain, Abdellaoui et al. (2007) report a median coefficient of utility curvature of 0.71, although less heterogeneity. Others have found less pronounced curvature (Booij and van de Kuilen, 2009; Schunk and Betsch, 2006). Etchart-Vincent (2004) report a median coefficient of 0.97 for the loss domain, although most reported coefficients are lower (e.g., Abdellaoui et al., 2007; Booij and van de Kuilen, 2009; Schunk and Betsch, 2006).

Table 3 shows summary statistics for the different measures of loss aversion applied in this study. For all individuals, we can compute loss aversion coefficients based on the definitions by Neilson (2002) and Köbberling and Wakker (2005). Other definitions are more difficult to operationalize, in particular the ones relying on derivatives. Because some choice tasks involved stochastic dominant options for some individuals, which was a result from the iterative characteristic of the protocol, the number of available utility points differs. We exclude choices resulting from such choice tasks from the analysis, following e.g., Bleichrodt and Pinto (2000), who elicit probability-weighting functions non-parametrically with a comparable protocol. As a result, this hinders the operationalization of the loss aversion coefficients in some cases.

Putting the coefficients of loss aversion resulting from our experiment into context with other experimental results is less straightforward, since few studies use the same definition of loss aversion with the exception of Abdellaoui et al. (2007). They find higher mean and median values for all definitions.[12] Other studies focusing on monetary or health outcomes have found mean or median values between 1.43 and 4.8, relying on different definitions of loss aversion (e.g., Bleichrodt and Pinto, 2002; Booij and van de Kuilen, 2009; Fishburn and Kochenberger, 1979; Pennings and Smidts, 2003; Schmidt and Traub, 2002; Tversky and Kahneman, 1992).

In sum, the coefficients of loss aversion in this study are considerably lower than in other studies. This can be explained by a lower share of loss aversion and a higher share of gain-seeking behavior in our experiment. We elaborate on these characteristics in Section 6 and discuss how this could affect our results.

[12] Loss aversion coefficients based on the definitions by Bowman et al. (1999) and Neilson (2002) have the lowest mean (0.74 and 1.07) and median values (0.74 and 0.43) in their study, where the latter is even below 1 for both definitions. The highest value for the mean and median they obtain for loss aversion, as defined by Köbberling and Wakker (2005), with a mean of 8.27 and a standard deviation of 15. This indicates that the loss aversion coefficients below 1 are not just the result of our sample, but are observed in other studies as well. Furthermore, and also in our experiment, the lowest mean and median values for the loss aversion coefficients are based on the definitions by Neilson (2002) and Bowman et al. (1999); and similarly, the mean and median values of the coefficients based on the definition of loss aversion by Köbberling and Wakker (2005) are amongst the highest in our experiment.

5.2. Econometric Model

The outcome variable used in our analysis – savings (in 100,000 COP) – does not include negative values and is therefore a limited dependent variable according to the definition in Wooldridge (2013, Chapter 17). Furthermore, the empirical frequency of zeros in the distribution of the amount of savings in our sample exceeds the frequency of zeros according to any commonly used theoretical distribution in such cases (e.g., the Poisson distribution or the Negative Binomial distribution). This is to be expected, since not everybody actually engages in saving. Thus, the outcome variable is a so-called Corner Solution Response.[13]

The distribution of the value of saving in our sample is skewed, and values are reported repeatedly and are usually divisible by 100,000 COP. Therefore, we should assume a discrete rather than a continuous dependent variable. Given these characteristics of the outcome variable, we apply a Negative Binomial Hurdle model to study the relationship between income risk, loss aversion, and savings. The Poisson Hurdle model is nested in the Negative Binomial Hurdle model we fit and differences between the log-likelihoods of both models mostly exceed 100 by far. This indicates that a likelihood ratio test (conservatively assuming the test statistic to follow a chi-square distribution with one degree of freedom) would reject the hypothesis of no overdispersion.

This model is a so-called two-part model, where the probability of engaging in savings and the amount of savings is estimated separately by different models. For the Hurdle models applied here, the likelihood of both equations can be calculated separately. Using a logit-model, the probability 'that the hurdle is passed' and that a person engages in savings is estimated. The second model estimates the amount of savings once the hurdle

[13] The options to deny the response or to indicate that they did not know about the amount of savings were allowed and treated separately. Four respondents denied answering and five respondents did not know the amount of savings they held at the time of the interview. Together, this corresponds to about 1% of the respondents whose savings amount we could not observe. These cases were excluded from the analysis.

is passed, using a Truncated Negative Binomial model. In Appendix C.1, we discuss alternative models and their suitability in this context.

Following Grogger and Carson (1991), we compute marginal effects of loss aversion and income risk on the predicted amount of unconditional savings using the estimates resulting from fitting Model 3 with a Negative Binomial Hurdle model. Denoting savings for individual i with Y_i, the overall marginal effect of X_{ih}, i.e., of covariate h for individual i, on his or her predicted savings can be computed as:

$$\frac{\partial \mathbb{E}(Y_i|X_i)}{\partial X_{ih}} = \frac{\partial}{\partial X_{ih}}[\mathbb{E}(Y_i|X_i, Y_i > 0)][1 - F(0)] + \mathbb{E}(Y_i|X_i, Y_i > 0)\frac{\partial}{\partial X_{ih}}[1 - F(0)], \quad (3)$$

where $1 - F(0)$ is the share of the population for which we observe $Y_i > 0$. This means the overall effect can be decomposed into two effects: The effect on those who are saving, weighted by the probability of saving, plus the effect on the proportion that 'passes the hurdle' and is saving, weighted by the mean amount of savings in the saving population. We compute marginal effects using mean values of covariates, unless otherwise indicated.

5.3. Empirical Results

To test our hypotheses, we run three different models, as explained with detail in Section 3. Table 4 presents the estimated coefficients. The columns labeled 'DANE' present the results for the measure of income risk based on secondary information obtained from DANE, while the columns labeled 'Survey' present the results for the measure that uses survey data. Given that Model 2 is estimated without controlling for the degree of income risk, this column has no label indicating a measure of income risk. We present the results separately by the likelihood to save and the amount of savings, given that an individual is actually saving (i.e., the intensive margin of savings or conditional saving).

Estimation results of a direct test of Hypothesis 1 are presented below 'Model (1)' and 'Model (1b)' in Table 4. The first two columns present the results for the entire sample, while the columns labeled 'Model (1b)' present the results for the subpopulation of loss-averse individuals in the sample. All models control for main socioeconomic variables affecting savings, region and occupation. We find that the results partly support Hypothesis 1. Consistently with the predictions, we find that income risk is positively related with the amount of savings, given that an individual is actually saving. This result holds both for the complete sample and for the sub-population of loss-averse individuals. Yet, contrary to the predictions, the likelihood to save is negatively related with income risk for the loss-averse population in one of the two estimated models. Thus, we come back to Hypothesis 1 with a more detailed analysis below.

Estimation results of a direct test of Hypothesis 2 are reported in 'Model 2' of Table 4. In this specification, we do not include a measure of income risk, since it may be assumed that the entire sample is exposed to income risk due to a lack of a social protection system (see Section 3). From the results, we deduce that an increase in loss aversion is associated with an increase in both the likelihood to save and the amount of conditional savings. We summarize our findings with respect to Hypothesis 2:

Result 1. *An increase in loss aversion is associated with an increase in savings.*

Model 3 allows us to test Hypothesis 3, but we may also use these insights to evaluate Hypothesis 1 – in addition to the results from the direct test (Model 1 and Model 1b). We find that the likelihood to save is not correlated with income risk. Yet, supporting the theoretical model and in line with the results from Model 1 and Model 1b, we find that conditional savings are positively associated with income risk, and statistically significant when using the survey measure for unemployment risk. As the coefficient of loss aversion is centered around one, the coefficient of income risk shows the relation between income risk and the likelihood to save or savings for a loss-neutral agent.

Hence, we find support for Hypothesis 1:

Result 2. *An increase in income risk is associated with an increase in savings.*

The coefficients of the interaction terms between loss aversion and income risk are positive and significantly different from zero for the two measures of income risk that we use in the analysis. This indicates that the increase in savings due to income risk is increasing with the degree of loss aversion. Hence, this result supports Hypothesis 3.

Result 3. *The relationship between income risk and savings is an increasing function of the degree of loss aversion. Equivalently, the relationship between loss aversion and savings is an increasing function of the degree of income risk. This result strongly supports Hypothesis 3.*

To assess magnitudes of the overall relation, we compute the marginal effects (at mean values) on the predicted amount of (unconditional) savings, resulting from estimating Model 3. We first compute these marginal effects of income risk for gain-seeking to loss-neutral behavior ($\lambda = 1$), moderate loss aversion ($\lambda = 1.5$) and high loss aversion ($\lambda = 2$).

Figure 1 displays the corresponding marginal effects of income risk on predicted total savings.[14] We find that an increase in income risk is always associated with an increase in total savings – independent of the degree of loss aversion and the level of income risk. Furthermore, we find that the increase associated with an increase in income risk is larger, the higher the income risk and the higher the degree of loss aversion are. Hence, these results also provide supporting evidence for Hypothesis 3. This result holds for both measures of income risk. This effect is mainly driven by an increase in conditional savings rather than by changes in the likelihood to save (see Figure 4 in Appendix D).

In terms of the magnitude of the relation, the result depends on the source of data. The estimations for the secondary data imply that, when the average regional unemployment rate rises from 8.5 to 9.5 percent, for a moderately loss-averse sample, there is an increase in the average total savings of about 10,000 COP, or roughly 5 USD. This corresponds to a relatively small increase in savings of 4 percent, which is due to the small proportion of individuals engaging in saving. However, when the model is estimated using survey data

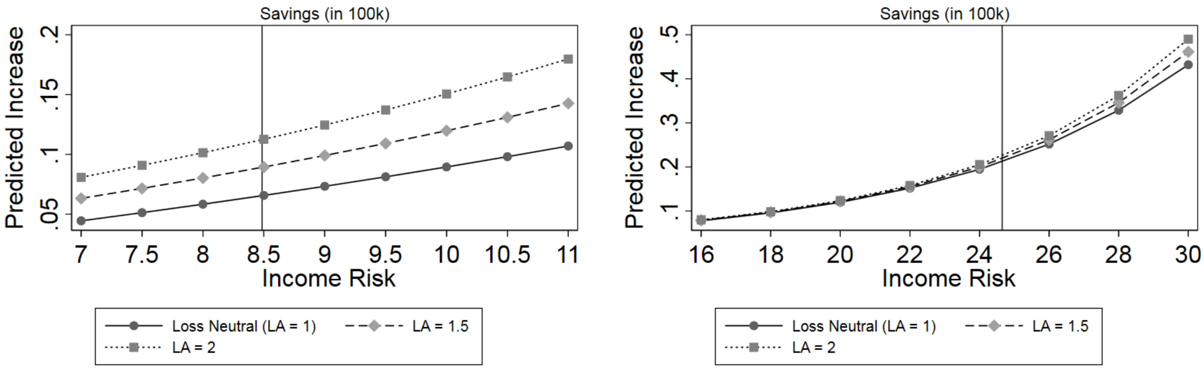
[14]The marginal effects on the intensive and extensive margin with confidence intervals are printed in Appendix D; see Figure 4.

Table 4: Results from Estimating Model 1, Model 2, and Model 3 Using a Negative Binomial Hurdle Model and Different Measures of Income Risk

	Model (1)		Model (1b)		Model (2)	Model (3)	
	DANE	Survey	DANE	Survey		DANE	Survey
Likelihood of Saving							
Income Risk	-0.052	-0.004	-0.395⋆	-0.001		-0.041	0.025
	(-0.72)	(-0.18)	(-1.93)	(-0.01)		(-0.55)	(0.66)
Loss Aversion					0.041⋆	0.035⋆	0.032
					(1.68)	(1.76)	(1.15)
Loss Aversion						0.008	0.012
× Income Risk						(0.83)	(1.55)
Amount of Savings							
Income Risk	0.196⋆	0.057⋆⋆	0.883⋆⋆⋆	0.130⋆⋆⋆		0.096	0.150⋆⋆⋆
	(1.89)	(1.96)	(3.37)	(6.02)		(1.12)	(3.35)
Loss Aversion					0.058⋆⋆	-0.038	-0.177⋆⋆⋆
					(2.55)	(-0.88)	(-3.25)
Loss Aversion						0.031⋆⋆	0.022⋆⋆⋆
× Income Risk						(2.12)	(4.47)
AIC	1232	1231	194	195	1244	1240	1225
Controls	25	25	6	6	25	25	25
Region	No	Yes	No	No	Yes	No	Yes
Occupation	Yes	Yes	No	No	Yes	Yes	Yes
Observations	640	640	97	97	640	640	640

⋆ $p < 0.1$, ⋆⋆ $p < 0.05$, ⋆⋆⋆ $p < 0.01$. t-values in parentheses.

Note: The dependent variable is the sum of all self-reported savings data in various savings devices, see Section 4.1. In this Negative Binomial Hurdle model, the participation equation estimates the likelihood to engage in savings, while the second equation estimates conditional savings – the amount of savings, given that a person is saving. The coefficient of loss aversion is centered at one and measured by a continuous and experimentally elicited meta-measure, based on the definitions of loss aversion by Neilson (2002) and Köbberling and Wakker (2005), see Section 4.3. Income risk is centered at the mean and is based on different measures, partly building on secondary data; see Section 4.2 for details. We control for variables listed in Tables 1 and 3. Furthermore, we control for regional and occupational sector at the *localidad* level and for the working sectors according to the ISIC classification of economic activities, if indicated. We account for potential heteroskedasticity by using robust standard errors.



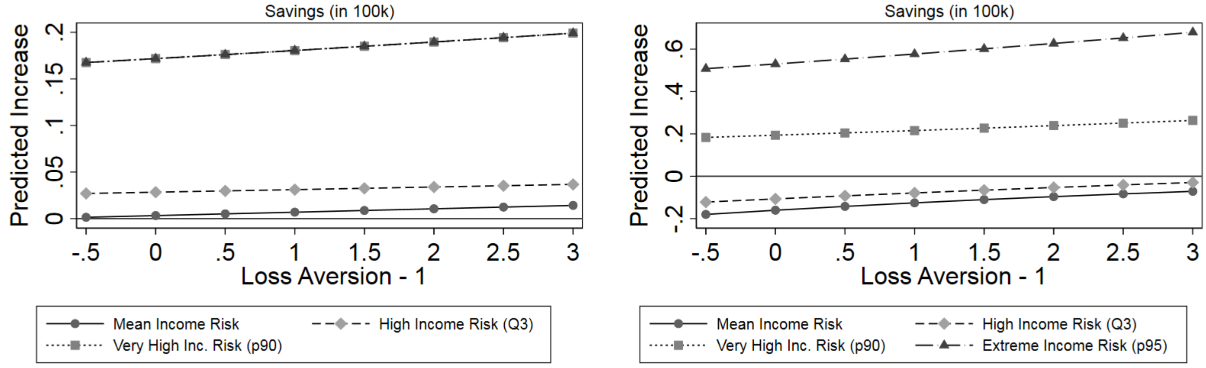
(a) Regional Unemployment Rate (DANE) (b) Regional Unemployment Risk (Survey)

Figure 1: Conditional Marginal Effect of Income Risk on Predicted Savings for Different Degrees of Loss Aversion

Note: Marginal effects computed according to (3) using mean values for remaining covariates and estimates from fitting Model 3; see Table 4 for the corresponding coefficients and Figure 4 for the marginal effects with confidence intervals for the intensive and extensive margins. Vertical lines indicate the mean values of the corresponding measure of income risk. Income risk is expressed in percent and the predicted increase in savings in 100,000 COP.

on the average personal perception of unemployment risk, the relation of income risk and savings is nearly twice as large.

We now turn to the predicted magnitude of the relation between loss aversion and savings. When controlling for the degree of income risk, including an interaction term between loss aversion and income risk (see column 'Model 3'), we see that Result 2 is driven by those facing a high level of income risk. The coefficient of loss aversion in the equation for the likelihood to save is positive, and so is the coefficient of the interaction term. However, in the equation for conditional savings, the coefficient of loss aversion is negative and significant for the survey measure. Yet, the interaction terms are both positive and significant. The coefficients of loss aversion correspond to an average level of income risk, as income risk measures are centered around the mean. For an individual who is exposed to a high income risk, loss aversion is positively associated with savings, as marginal effects in Figure 2 show (marginal effects on the intensive and extensive margin with confidence intervals are printed in Figure 5 in the Appendix). We consider different levels of income risk: The average level of income risk, a high level of income risk, defined



(a) Regional Unemployment Rate (DANE) (b) Regional Unemployment Risk (Survey)

Figure 2: Conditional Marginal Effect of Loss Aversion on Predicted Savings for Different Levels of Income Risk

Note: Marginal effects computed according to Equation (3) using mean values for remaining covariates and estimates from fitting Model 3; see Table 4 for the corresponding coefficients and Figure 5 for marginal effects with confidence intervals for the intensive and extensive margins. The predicted increase in savings is expressed in 100,000 COP.

as the third quartile of the distribution of income risk, a very high, and an extremely high income risk, corresponding to the 90% and 95% quantile of the income risk distribution. The marginal plot relying on the secondary DANE data (Figure 2(a)) indicates a positive effect of loss aversion on predicted savings even for average levels of income risk. Yet for the survey data (Figure 2(b)) the relation is negative even at a high level of income risk. For very high levels of income risk (i.e., 32.3%, corresponding to the 90% quantile of the income risk distribution, which is slightly more than a standard deviation above the average unemployment risk), the overall relation is positive.

5.4. Robustness Tests

In the literature, various definitions of loss aversion have been proposed. Yet, it is unclear which definition of loss aversion is best and should be considered standard (Abdellaoui et al., 2007). To address this issue, we have constructed different meta-measures of loss aversion combining two or more definitions. Our results are robust to using any of the different meta-measures of loss aversion for both Model 2, and Model 3.[15] This increases the validity of our results in comparison to using a single measure.

[15]We report results of the robustness tests in Table 5 and Table 6 in Appendix D.

6. Discussion

Our empirical results support the predictions formulated by Kőszegi and Rabin (2009), as well as those derived in our paper. We find that, among individuals exposed to income risk, savings are larger for loss-averse individuals. This finding, however, does not unambiguously establish causality. Our intention here was to explore if asset accumulation provides supportive evidence of the predictions of this model. Future work should, for example, focus on establishing causal relationships through the use of panel data.

Kőszegi and Rabin's (2009) model considers that the chance of falling behind expectations induces a precautionary savings motive among loss-averse individuals. In our empirical approach, we use measures of loss aversion that are derived from decisions about risky outcomes. Therefore, our measure does not correspond exactly to the measure in the model. While Gächter et al. (2007) show that there is a high correlation between experimentally elicited measures of loss aversion in riskless and risky choices, we are not aware of studies eliciting the correlation between loss aversion with regard to expected outcomes and loss aversion with regard to risky choices.

The measure for loss aversion that we use in this study is, on average, lower than that estimated by Abdellaoui et al. (2007) using a similar approach. However, other studies also find considerably lower shares of loss aversion at the individual level. For example, Schmidt and Traub (2002) and Bleichrodt and Pinto (2002) report that between 33 percent and 5 to 30 percent of their participants could be classified as loss-averse, respectively. In addition, Schmidt and Traub (2002) report that 24 percent of their participants exhibit gain-seeking behavior at the individual level. Against this background, our findings do not seem unrealistic and even less so when we consider that our experiment was conducted with a non-student sample in a development setting, where the mean household per-capita income lies near the poverty level and the prospect of losing money might be very familiar and not frightening enough to make an effort to avoid these losses at the price of forgoing gains.

We observe considerable heterogeneity in our measures of loss aversion, as expressed in standard deviations (see Table 3), which is to be expected in field settings. Would our sample be more loss-averse in reality than our measures indicate, we should expect a higher coefficient of loss aversion for every individual in the sample. This would not affect our results with regard to Hypothesis 3, as they are independent of the absolute value of the coefficient of loss aversion. Furthermore, as our results regarding Hypothesis 1 based on marginal effects also hold for what we label loss-neutral individuals and slightly gain-seeking individuals, we also consider the results regarding Hypothesis 1 to be unaffected by a possible miscalibration of our measures of loss aversion. Lastly, for the direct test of Hypothesis 2, we can assert that the results are unaffected by such a transformation. Given similar findings in other studies, however, we are quite confident in our measures of loss aversion.

In this study, we use the official regional unemployment rate and the perceived regional unemployment risk as a measure of income risk. These measures can be interpreted as exogenous, as one single individual cannot affect the labor market. Unfortunately, they are average measures and one of the measures relies on self-reported data. Therefore, they are likely to contain errors – be it because of their coarse nature or their incorrect assessment of unemployment risk. Therefore, the precautionary savings motive might be imperfectly captured in our data. Another potential limitation of this measure is that the labor market is usually considered as integrated, since individuals in urban areas can commute to other *localidades* to find employment. On the other hand, consistent with the spatial mismatch hypothesis (Kain, 1968), we find substantial variability in unemployment levels for the different units of analysis, which suggests that the labor market is fragmented. While unemployment risk is an important source of income risk for our population group, future work should also explore other sources of income risk affecting households, such as health risk and price changes.

Although the theory in Section 2 focuses on future income uncertainty, contemporaneous unemployment figures are a good prediction of future unemployment rates and thus future income risk. In addition, a higher unemployment rate in the past is likely to induce a certain feeling of riskiness about future income. Lastly, labor income risk affects overall income risk, because retirement income depends on savings built up during an individual's working years or the income of family members in the absence of a formal social security system. The latter, however, can be assumed to be limited if the household has been in monetary need during their education years, reducing the priority of education and increasing the priority of earning money.

All of our results are based on one particular sample: People from low-income households in Bogotá and approximately two-thirds are female. It would therefore be of great interest to validate this study's findings with other data from other countries which have other sociodemographic characteristics.

Despite the limitations, this study is to be considered as a first step in determining the role of loss aversion in financial decisions of the poor.

7. Conclusion

In this paper, we have tested whether the theoretical predictions of the intertemporal model of consumption and saving by Kőszegi and Rabin (2009) can be empirically supported. More specifically, we have tested whether loss-averse individuals who face income risk hold higher savings, which would be consistent with a precautionary savings motive based on loss aversion (Hypothesis 1). Our results support this hypothesis. A one-percent increase in income risk is associated with an increase in 4 to 8 percent of total savings. Secondly, we have tested whether individuals who exhibit a higher degree of loss aversion hold more savings than individuals with a lower degree of loss aversion, given that they face income risk (Hypothesis 2). Our results support this hypothesis, on average, and a detailed analysis shows that this is driven by individuals facing a high level of income risk. Lastly, we have investigated whether the increase in savings associated with an increase in income risk is larger, the higher the degree of loss aversion is (Hypothesis 3). For this last hypothesis, we find very strong support.

These findings can be used to inform policy-makers. Savings and pension campaigns could stress the uncertainty of future income to boost savings. Moreover, if future income is uncertain, a higher degree of loss aversion can be expected to induce an additional savings motive compared to a lower degree of loss aversion, so people should be reminded that it is unlikely that they will be able to maintain their current standard of living when their income drops.

In the analysis, we consider expectations of future income and consider how loss aversion affected savings. Following Pagel (2017), the analysis could be extended to consider how savings vary across the life-cycle. Future work could consider explicitly individuals' expectations by varying the priming and making individuals aware of future income uncertainty (Marzilli Ericson and Fuster, 2011). Another extension could consider how loss aversion affects reference points and probability weights. For example, Chen (2013) proposes that loss-averse individuals select the reference points to balance felicity of optimistic anticipation and future disappointment of the realization. On the other hand, Aizenman (1998) proposes that, in the presence of uncertainty of income, disappointment-averse individuals overweight the probability of low payments, which generates an incentive to accumulate higher buffer stocks.

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A. Theoretical Framework: Details (For Online Publication)

A.1. General Version of the Two-period Model by Kőszegi and Rabin (2009)

As in Section 2, we assume that an individual has to distribute wealth, W, for consumption across two periods such that $W = c_1 + c_2$, where c_t denotes consumption in period t for $t = 1, 2$. As in the main text, we consider the case in which wealth is stochastic and uncertainty is resolved in the second period.

Consumption in the first period (and thus saving) is determined by maximizing the expectation of the sum of instantaneous utilities u_t in both periods, where no discounting is assumed, i.e.,

$$U = u_1(c_1) + \mathbb{E}[u_2(c_2)]. \tag{4}$$

As in the simplified version of the model introduced in the main text, individuals are assumed to choose their favorite credible consumption plan before the first period starts (i.e., in period $t = 0$). Credible means that they anticipate whether or not they would be able to stick to the plan, and only consider those plans where they do not see an incentive to deviate from later on.[16] Favourite means that there are possibly several such credible plans, and the decision-maker chooses his or her preferred one according to the maximization principle. This plan is called preferred personal equilibrium (PPE) by Kőszegi and Rabin (2009) and at the time of planning in period $t = 0$, it leads to possibly stochastic 'rational beliefs' $F_{0,1}$ and $F_{0,2}$ about consumption in Period 1 and Period 2. Mathematically, these beliefs are simply probability distributions assigning a probability to any possible consumption level. Plans about consumption in period t that are made in the same period (i.e., $F_{t,t}$) assign a probability of 1 to the actual consumption level c_t. When uncertainty is resolved and consumption decisions are implemented, plans are updated and lead to new beliefs.

Instantaneous utility in periods $t = 1, 2$ is given by

$$u_t = m(c_t) + \sum_{\tau=t}^{2} \gamma_{t,\tau} N(F_{t,\tau}|F_{t-1,\tau}),$$

[16] Details about how these plans are formed are given in Appendix A.2 or in Kőszegi and Rabin (2009).

where $m(\cdot)$ is consumption utility that is three times differentiable, increasing and strictly concave, and corresponds to a "classical utility function". The 'gain-loss utility', $N(F_{t,\tau}|F_{t-1,\tau})$, reflects utility gains or losses due to changes in current 'beliefs' $F_{t,\tau}$ compared to former 'beliefs' $F_{t-1,\tau}$ about contemporaneous ($\tau = t$) and future ($\tau > t$) consumption. Depending on the distance of a period $\tau \geq t$ in the future, the impact of changes in beliefs about consumption in that period via the 'gain-loss utility' differs, which is reflected by weights $\gamma_{t,\tau} \geq 0$ with $\gamma_{t,t} = 1$. For simplicity, we use the notation $\gamma_{1,2} = \gamma$. The weight $\gamma_{1,2} = \gamma$ is decisive for an individual to adhere to her plan, i.e., to resist overconsuming in the first period relative to the previously set consumption level, as explained below.

'Gain-loss utility' N compares every percentile of the distributions of consumption according to 'beliefs' $F_{t,\tau}$ and $F_{t-1,\tau}$, using a "universal gain-loss utility function" μ. More specifically, for a possibly discrete distribution F_d, $c_{F_d}(p/100)$ is a percentile for $0 \leq p \leq 100$ with $p \in \mathbb{N}$ if $F_d(c_{F_d}(p/100)) \geq p/100$ and $F_d(c) < p/100$ for all $c < c_{F_d}(p/100)$. Then, gain-loss utility from the change in beliefs from $F_{t-1,\tau}$ to $F_{t,\tau}$ is defined as

$$N(F_{t,\tau}|F_{t-1,\tau}) = \sum_{p=1}^{100} \mu(c_{F_{t,\tau}}(p/100), c_{F_{t-1,\tau}}(p/100)),$$

where

$$\mu(\hat{c}, \tilde{c}) = \begin{cases} \eta(m(\hat{c}) - m(\tilde{c})) & \text{if } \hat{c} \geq \tilde{c} \\ -\lambda\eta(m(\tilde{c}) - m(\hat{c})) & \text{if } \hat{c} < \tilde{c}. \end{cases}$$

for two consumption levels $\hat{c}$ and $\tilde{c}$, m as defined above and parameters $\eta > 0$ and $\lambda > 0$.[17]

The parameter $\eta > 0$ simply scales the difference in consumption utility, and $\lambda > 0$ may account for loss-averse ($\lambda > 1$) or gain-seeking ($\lambda < 1$) behavior.

The parameter $\gamma \geq 0$ 'discounts' anticipated future gains or losses in 'gain-loss' utility that affect utility already in period 1. For $\gamma > 1/\lambda$, the anticipated future loss is weighted high enough to prevent the consumer from deviating from the optimal ex-ante plan, i.e.,

[17] This choice of the "gain-loss utility function" fulfills certain desirable characteristics of a reference-dependent utility function for $\lambda > 1$; see Kőszegi and Rabin (2009), p. 914. In particular, it fulfills "the explicit or implicit assumptions" about the 'value function' by Kahneman and Tversky (1979), as formulated by Bowman et al. (1999).

they resist overconsuming; see Proposition 5 in Kőszegi and Rabin (2009). When $\lambda > 1$, following Kőszegi and Rabin (2009), we can assume $\gamma < 1$. As we allow for gain-seeking behavior, i.e., $\lambda < 1$, we leave γ unrestricted, to allow for $\gamma > 1/\lambda$. Then, the proof of Proposition 8 in Kőszegi and Rabin (2009) holds for $\lambda < 1$, although they do not consider this case.

If the agent resists deviating from the plan, instantaneous utility in Period 1 is given by

$$u_1 = m(c_1) + N(F_{1,1}|F_{0,1}) + \gamma N(F_{1,2}|F_{0,2}) = m(c_1),$$

as beliefs do not change in the first period (i.e., $F_{0,t} = F_{1,t}$ for $t = 1, 2$), since in addition to adherence to the plan, no uncertainty is resolved. In Period 2, utility is given by

$$u_2 = m(c_2) + N(F_{2,2}|F_{1,2}).$$

With that, the optimization problem can be solved by equalizing the marginal utility of saving and consumption in the first period.

If the agent cannot resist deviating from the ex-ante optimal plan, their PPE specifies a higher consumption level in Period 1 compared to the optimal one; see Proposition 5 in Kőszegi and Rabin (2009).

A.2. Rational Beliefs

In this Appendix, we explain the intuition behind 'rational beliefs'. We refer to Kőszegi and Rabin (2009) for a precise definition.

'Beliefs' are the result of a plan: They "must be rationally based on credible plans for state-contingent behavior".[18] One concept of what a credible plan could be was termed 'preferred personal equilibrium (PPE)' by Kőszegi and Rabin (2009) and was used in their text, although they note that other theories of forming beliefs could also be combined with their model. Roughly speaking, a plan is a PPE if it is the preferred

[18] The most simple example of a state-contingent plan could be: "If things go well, I will spend x\$ for consumption in Period 1. If things do not work out well, I will only spent y\$ in this period" (where $x > y > 0$).

"plan among those that are credible". A plan is credible if it maximizes the mathematical expectation of the reference-dependent utility in every period given the beliefs which the plan induced *and* if continuation plans are consistent. That is: If an individual plans for very low consumption in Period 1 in order to save for Period 2, but would not make the same choice if solving the maximization problem in Period 1 – e.g., because they are present-biased or cannot live with such a low level of consumption –, this would not be a credible plan, and it is not a PPE. Using backwards induction, they would anticipate their behavior in Period 1 and consume more in Period 1 from the beginning until their entire plan is consistent with solutions evolving from a similar maximization process in Period 1. This PPE reflects the idea that individuals anticipate the implications of their plans and only make plans they know they would adhere to them.

A.3. Proofs

Proof of Proposition 1. This proof follows the rationale of the proof of Proposition 8 in Kőszegi and Rabin (2009).

We prove that the derivative of the marginal utility of increasing savings with respect to λ is positive. Equivalent to the argument in the proof of Kőszegi and Rabin's Proposition 8, this implies that $dc_1/d\lambda < 0$ for both $\gamma > 1/\lambda$ and $\gamma \leq 1/\lambda$, since in the first case, the ex-ante optimal plan involves a lower c_1 and the person adheres to this plan. In the latter case, a higher marginal utility in Period 2 makes a lower c_1 become consistent. Furthermore, since, for $\gamma \leq 1/\lambda$, the chosen c_1 will be higher than for $\gamma > 1/\lambda$, see Kőszegi and Rabin (2009), a lower c_1 will become consistent, as the agent adheres to the ex-ante optimal plan for a lower γ.

The derivation of marginal utility of increasing savings is due to Kőszegi and Rabin (2009): Let F be the cumulative distribution function of the (mean-zero) random variable

y. The expected utility in Period 2 is

$$\begin{aligned}
&\int m(c_2 + sy)\, dF(y) + \iint \mu(m(c_2 + sy) - m(c_2 + sy'))\, dF(y')\, dF(y) \\
&= \int m(c_2 + sy)\, dF(y) \\
&\quad - \frac{1}{2}\eta(\lambda - 1) \iint m(c_2 + s\max\{y, y'\}) - m(c_2 + s\min\{y, y'\})\, dF(y')\, dF(y).
\end{aligned}$$

Hence, the derivative of the expected utility in Period 2 with respect to c_2, i.e., the marginal utility from increasing savings is

$$\begin{aligned}
&\int m'(c_2 + sy)\, dF(y) \\
&\quad + \frac{1}{2}\eta(\lambda - 1) \iint m'(c_2 + s\min\{y, y'\}) - m'(c_2 + s\max\{y, y'\})\, dF(y')\, dF(y).
\end{aligned}$$

Now, unlike in the proof or Proposition 8 in Kőszegi and Rabin (2009), we take the derivative of the expression above with respect to λ:

$$\frac{1}{2}\eta \iint m'(c_2 + s\min\{y, y'\}) - m'(c_2 + s\max\{y, y'\})\, dF(y')\, dF(y).$$

This derivative is positive for any strictly concave m, any $s > 0$, $\eta > 0$, and any non-degenerate random variable y. Thus, the marginal utility from increasing savings is an increasing function of λ. □

Proof of Corollary 1. As in the proof of Proposition 1, the derivative of the marginal utility from increasing savings with respect to λ is given by

$$\frac{1}{2}\eta \iint m'(c_2 + s\min\{y, y'\}) - m'(c_2 + s\max\{y, y'\})\, dF(y')\, dF(y).$$

The derivative of this expression with respect to s evaluated at $s = 0$ is

$$\frac{1}{2}\eta(-m''(c_2)) \iint |y' - y|\, dF(y')\, dF(y),$$

which is positive for any strictly concave consumption utility function m, $\eta > 0$ and any non-degenerate random variable y. □

B. Data: Details (For Online Publication)

B.1. Parametric Estimation of a Power Utility Function

General Form for Positive Arguments Usually, the power family is defined for $x > 0$ by

$$m(x) = \begin{cases} x^b & \text{for } b > 0 \\ \ln(x) & \text{for } b = 0 \\ -x^b & \text{for } b < 0. \end{cases}$$

Considering Non-Positive Arguments Since $\ln(x)$ is not defined for $x < 0$, the case $b = 0$ must be excluded, if negative arguments are of interest. Furthermore, $b < 0$ has to be excluded as well, if the point $x = 0$ is to be considered.[19] Thus, when allowing for gains and losses, the *power family* reduces to

$$m(x) = \begin{cases} -(-x)^a & \text{for } a > 0,\ x < 0 \\ x^b & \text{for } b > 0,\ x \geq 0. \end{cases}$$

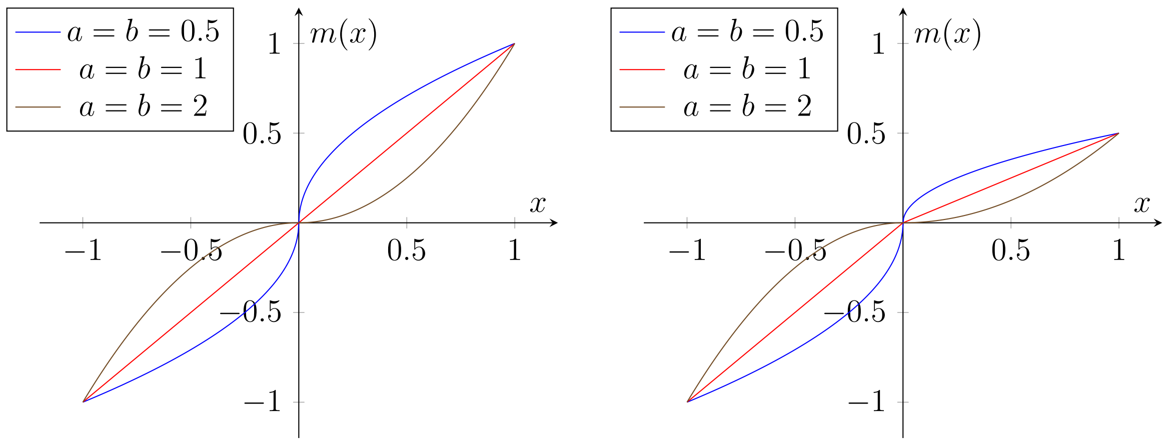
Figure 3(a) illustrates the curvature of the power family for different values of a and b.

Rescaling Arguments Arguments x of the utility function must be rescaled in order to lie within the interval $[-1, 1]$ for all the subjects in the study in order to be able to compare estimated parameters.

Due to the method used, the minimal x-value observed is $L_1 = -5{,}000{,}000$. Thus, for losses, we need a transformation $x \mapsto -\frac{x}{L_1}$, where $x \in [L_1, 0]$.

For Gains, $G_{0.5}$ is the maximum x-value for any individual, we therefore transform $x \mapsto \frac{x}{G_{0.5}}$, where $x \in [0, G_{0.5}]$.

[19] Wakker (2008, p.1336) gives a less technical explanation: "With both positive and negative x present, a negative power a or b generates an infinite distance between gains and losses. Such a phenomenon is not empirically plausible, so that negative a and b should then not be expected to occur."



(a) Curvature of the power family for different values of a and b.

(b) Estimated power utility functions plotted for different values of a and b.

Figure 3: Illustration of the Power Family Utility Function with Different Values of a and b

Rescaling Outputs By the method chosen, we need to have $m(L_1) = -1$, $m(0) = 0$ and $m(G_{.5}) = .5$. We check this: For the negative domain, we have

$$m(L_1) = -\left(\frac{L_1}{L_1}\right)^a = -(1)^a = -1,$$

independent of $a > 0$, so there is no need to rescale outputs. However, for the positive domain,

$$m(G_{0.5}) = \left(\frac{G_{0.5}}{G_{0.5}}\right)^b = 1^b = 1,$$

independent of $b > 0$. Therefore, and also to have estimates comparable for the negative and the positive domain, we rescale $m(x)$ for $x \geq 0$ and set:

$$m(x) = 0.5 \cdot \left(\frac{x}{G_{0.5}}\right)^b \qquad \text{for} \qquad x \geq 0.$$

Note that we could also leave the estimation formula untouched and multiply our outcomes by the factor 2, making them lie within the interval $[0, 1]$ instead of $[0, .5]$.

Estimation Equation The final estimation equation is thus

$$m(x) = \begin{cases} -\left(\dfrac{x}{L_1}\right)^a & \text{for } a > 0,\ x < 0 \\ 0.5 \cdot \left(\dfrac{x}{G_{0.5}}\right)^b & \text{for } b > 0,\ x \geq 0. \end{cases}$$

This equation is illustrated in Figure 3(b).

Curvature In order to classify a utility function as convex or concave based on the estimated values of the parameters a or b, we can deduct the curvature of the utility function from Figure 3 for the given values of a and b. Analytically, for classifying an individual's utility function, we calculate the second derivative of the estimated utility function.

$$m''(x) = \begin{cases} -\left(\frac{x}{L_1}\right)^a \cdot \frac{1}{x^2} \cdot a(a-1) & \text{for } a > 0,\ x < 0 \\ 0.5 \cdot \left(\frac{x}{G_{0.5}}\right)^b \cdot \frac{1}{x^2} \cdot b(b-1) & \text{for } b > 0,\ x > 0, \end{cases}$$

where $x = 0$ has to be excluded from the domain.

We immediately see that for $x > 0$,

$$m''(x) \begin{cases} < 0 \ \text{ thus } m \text{ strictly concave} & \text{if } 0 < b < 1 \\ = 0 \ \text{ thus } m \text{ linear} & \text{if } b = 1 \\ > 0 \ \text{ thus } m \text{ strictly convex} & \text{if } b > 1, \end{cases}$$

and for $x < 0$ we have

$$m''(x) \begin{cases} < 0 \ \text{ thus } m \text{ strictly concave} & \text{if } a > 1 \\ = 0 \ \text{ thus } m \text{ linear} & \text{if } a = 1 \\ > 0 \ \text{ thus } m \text{ strictly convex} & \text{if } 0 < a < 1. \end{cases}$$

C. Results: Details(On line)

C.1. Discussion: Model Choice

In this part, we briefly discuss alternatives to the model chosen and assess their appropriateness in the setting of this paper.

Usually, OLS regression is a suitable starting point for modelling empirical relationships. However, a large share of the non-savers with zero COP of savings could mask relationships observed for the fraction of participants that actually saves. It seems appropriate to take the large share of the non-savers observed in our data into account when selecting a suitable model.

A Tobit model is frequently used in similar situations. Here, it is not suitable. A central assumption of the Tobit model is that the process determining participation is the same as the process determining the amount of saving. The signs of the coefficients of the independent variables in Table 4 differ in the two equations where many are significantly different from zero, showing that this assumption is violated. Second, normality and homoscedasticity of the dependent variable model are prerequisites for using a Tobit model. In contrast to OLS, where departures from these assumptions still lead to unbiased and consistent estimates, it is less clear how sensitive the Tobit model is to departures from these assumptions. The empirical distribution of the outcome variable we observe in our data is discrete. This observed empirical distribution is a rather bad approximation of any continuous probability distribution, so the assumption of normality is not likely to hold.

More flexible models for corner solution responses that can model the participation process and the savings process separately are – in addition to the Hurdle model applied in this study – so-called inflated models. For example, the Zero-Inflated Poisson model or the Zero-Inflated Negative Binomial model for the case of a discrete dependent variable.

Zero-inflated models rely on the assumption that a zero COP value of savings can be the result of two cases: In the first case, an individual would decide to save and then chooses a saving amount of zero. In the second case, an individual would decide not to save at all. We believe that the first case is rather unrealistic, since we did not ask for changes in savings in a given limited time, but rather look at the stock of savings. We therefore conclude that these models are not appropriate in our setting.

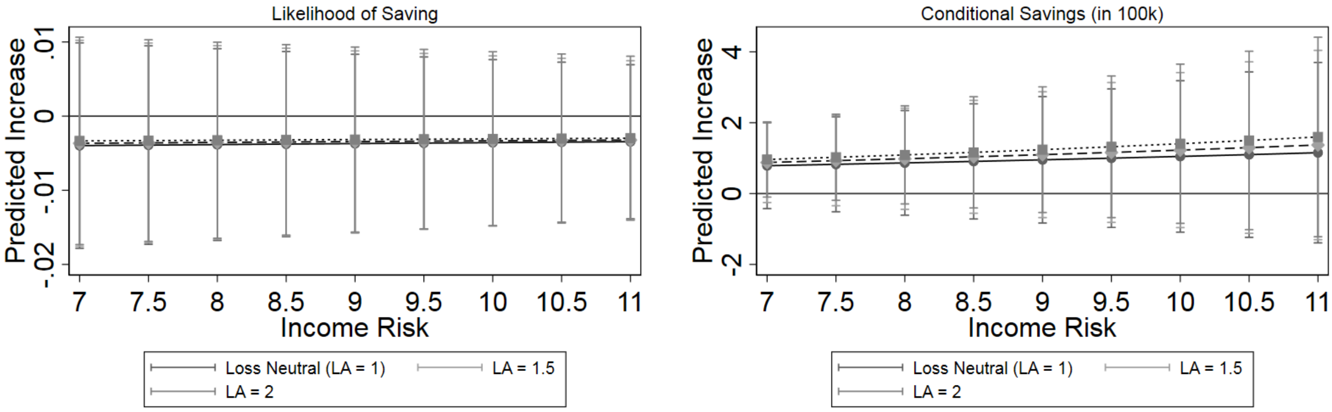
It is noteworthy that the excess zeros in the distribution of the outcome variable are not a problem of data observability, where models for censored data or sample correction models (e.g., the Heckman model) would be adequate. Only for around 1 percent of the participants are data actually missing, and these cases were excluded.

When only focusing on the positive amount of savings, no special care is needed to account for excessive zeros in the distribution of the outcome variable. In such cases, a traditional OLS model could be applied, or a log OLS model, if we expect the relationship to be proportional to the response.

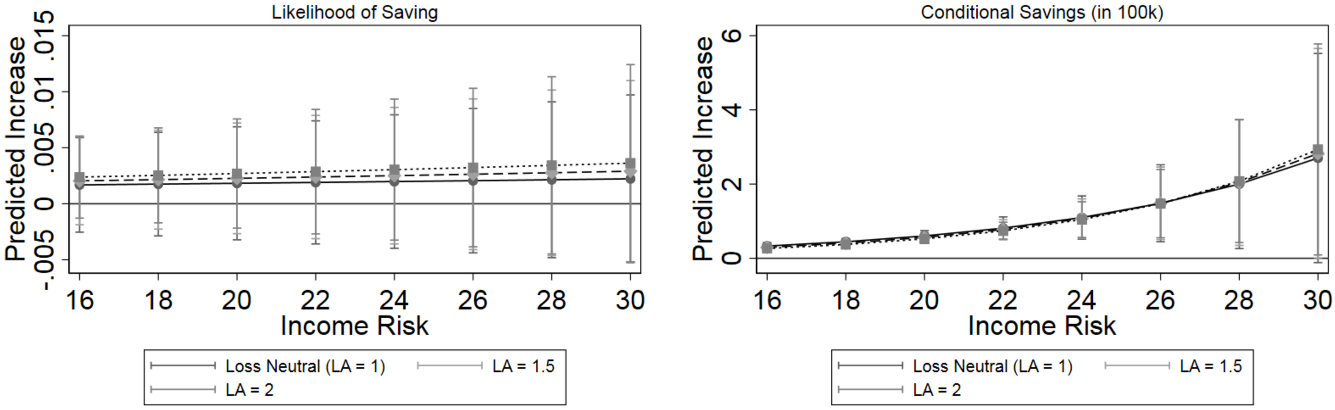
Given the discrete character of the outcome variable, and its heavily non-symmetric empirical distribution, a model that accounts for this characteristic should be applied, such as the Zero-Truncated Poisson or the Zero-Truncated Negative Binomial model. The latter is the second part of the two-part model we apply, the Negative Binomial Hurdle model. Thus, if not accounting for excess zeroes, we would model conditional savings in the same way that we do in this study, while accounting for a large proportion of non-savers.

D. Further Results and Robustness Checks (For Online Publication)

Figures 4 and 5 show conditional marginal effects for the likelihood of saving and conditional savings with confidence intervals.



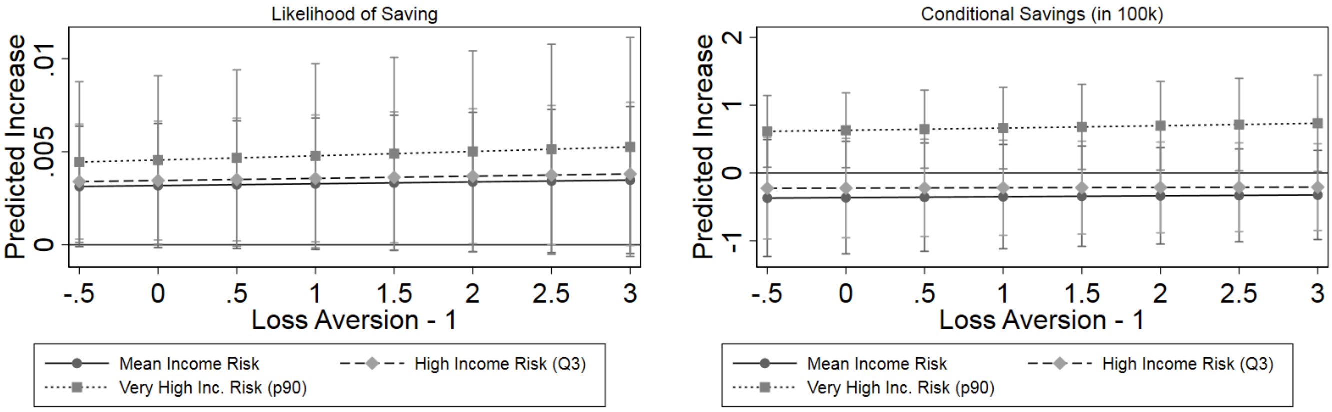
(a) Measure of Income Risk: Regional Unemployment Rate (DANE)



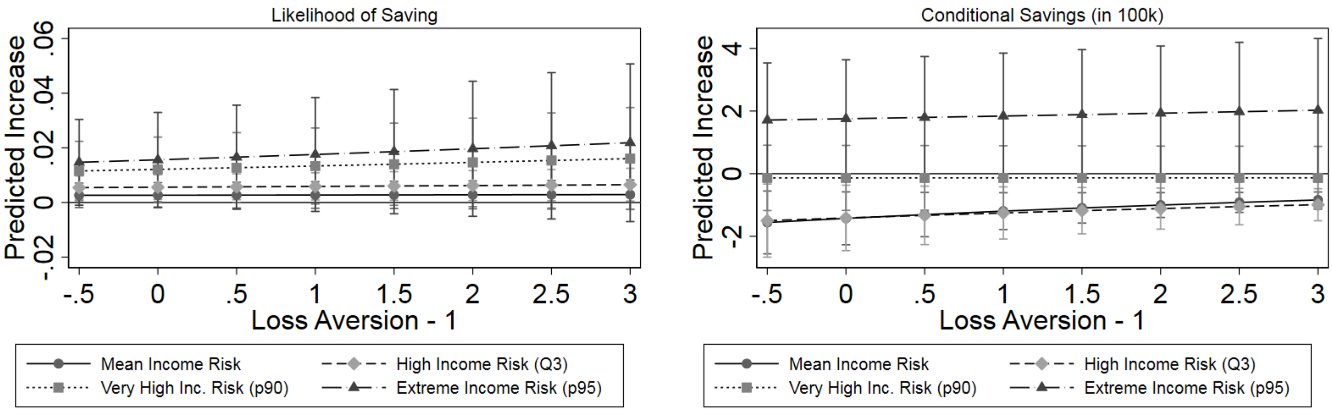
(b) Measure of Income Risk: Regional Unemployment Risk (Survey)

Figure 4: Conditional Marginal Effect of Income Risk on the Predicted Likelihood to Save (left) and on Predicted Conditional Savings (right) for Different Degrees of Loss Aversion

Note: Mean values of the covariates used for prediction. Estimates for calculating the marginal effects result from fitting Model 3; see Table 4 for the corresponding coefficients. Income Risk is expressed in percent and the predicted increase in conditional savings in 100,000 COP.



(a) Measure of Income Risk: Regional Unemployment Rate (DANE)



(b) Measure of Income Risk: Regional Unemployment Risk (Survey)

Figure 5: Conditional Marginal Effect of Loss Aversion on the Predicted Likelihood to Save (left) and on Predicted Conditional Savings (right) for Different Levels of Income Risk

Note: Mean values of the covariates used for prediction. Estimates for calculating the marginal effects result from fitting Model 3; see Table 4 for the corresponding coefficients. The predicted increase in conditional savings is expressed in 100,000 COP.

Table 5: Results from Estimating Model 2 Using a Negative Binomial Hurdle Model and Different Meta-Measures of Loss Aversion

	Loss Aversion Meta Measure 2 Measures			Loss Aversion Meta Measure 3 Measures		Loss Aversion Meta Measure 5 Measures
	(1)	(2)	(3)	(4)	(5)	(6)
Likelihood of Saving						
Loss Aversion	0.0414	0.0415	0.0276	0.0777*	0.0606	0.267
	(1.68)	(1.65)	(1.00)	(2.00)	(1.42)	(1.93)
Amount of Savings						
Loss Aversion	0.0583*	0.0655**	0.0883***	0.0885***	0.103***	0.247*
	(2.55)	(2.84)	(3.62)	(3.44)	(3.43)	(2.09)
AIC	1244	1140	1019	1138	1019	1021
Controls	25	25	25	25	25	25
Region	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Observations	640	579	509	579	509	509

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-values in parentheses.

Note: The dependent variable is the sum of self-reported savings data in various savings devices; see Section 4.1. In this Negative Binomial Hurdle model, the participation equation estimates the likelihood to engage in savings, while the second equation estimates conditional savings – the amount of savings, given that a person is saving. Loss aversion is measured by continuous and experimentally elicited meta-measures. The meta-measure comprising two measures of loss aversion is the geometric mean of loss aversion coefficients according to the definitions of loss aversion by Neilson (2002) and Köbberling and Wakker (2005). The measure including three measures is the geometric mean of the former two loss aversion coefficients and, in addition, the one building on the definition of loss aversion by Kahneman and Tversky (1979). Finally, for the last measure, the coefficients based on definitions by Bowman et al. (1999) and Wakker and Tversky (1993) are also included. For more details on the applied measures of loss aversion, see Section 4.3. Column 2 shows the results when restricting the sample to those for which the meta-measure combining three measures of loss aversion is available, and columns 3 and 5 show the results for similarly restricted samples, in order to be able to draw comparisons between the different meta-measures of loss aversion. We control for variables listed in Tables 1 and 3. Furthermore, we control for regional and occupational sectors at *localidad* level, as well as for the working sectors according to the ISIC classification of economic activities. We account for potential heteroskedasticity by using robust standard errors.

Table 6: Results from Estimating Model 3 Using a Negative Binomial Hurdle Model and Different Meta-Measures of Loss Aversion

	Regional Unemployment Rate			Regional Unemployment Risk		
	Measure 1	Measure 2	Measure 3	Measure 1	Measure 2	Measure 3
Likelihood of Saving						
Loss Aversion × Income Risk	0.00774	0.0120	0.0609	0.0121	0.0174*	0.0459**
	(0.83)	(0.82)	(0.86)	(1.55)	(1.79)	(2.48)
Loss Aversion	0.0353*	0.0698**	0.273**	0.0319	0.0635	0.131
	(1.76)	(2.12)	(2.00)	(1.15)	(1.43)	(0.80)
Income Risk	-0.0410	-0.0316	0.0336	0.0253	0.0547	0.0959**
	(-0.55)	(-0.40)	(0.36)	(0.66)	(1.29)	(2.23)
Amount of Savings						
Loss Aversion × Income Risk	0.0315**	0.0315	0.0611	0.0224***	0.0199**	0.0465
	(2.12)	(1.22)	(0.78)	(4.47)	(2.21)	(1.54)
Loss Aversion	-0.0382	-0.0204	0.0893	-0.177***	-0.129	-0.169
	(-0.88)	(-0.26)	(0.58)	(-3.25)	(-1.22)	(-0.64)
Income Risk	0.0955	0.0573	0.108	0.150***	0.167***	0.186***
	(1.12)	(0.68)	(0.75)	(3.35)	(3.69)	(2.95)
AIC	1240	1137	1023	1225	1125	1015
Controls	25	25	25	25	25	25
Region	No	No	No	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Observations	640	579	509	640	579	509

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-values in parentheses.

Note: The dependent variable is the sum of self-reported savings data in various savings devices; see Section 4.1. In this Negative Binomial Hurdle model, the participation equation estimates the likelihood to engage in savings, while the second equation estimates conditional savings – the amount of savings, given that a person is saving. Loss aversion is measured by continuous and experimentally elicited meta-measures. The meta-measure comprising two measures of loss aversion is the geometric mean of loss aversion coefficients according to the definitions of loss aversion by Neilson (2002) and Köbberling and Wakker (2005) (Measure 1). The measure including three measures is the geometric mean of the former two loss aversion coefficients and, in addition, the one building on the definition of loss aversion by Kahneman and Tversky (1979) (Measure 2). Finally, for the last measure, the coefficients based on definitions by Bowman et al. (1999) and Wakker and Tversky (1993) are also included (Measure 3). The coefficients of loss aversion are centered at 1; for more details on the applied measures of loss aversion, see Section 4.3. Income risk is centered at the mean and is based on different measures, partly building on secondary data; see Section 4.2 for details. We control for variables listed in Tables 1 and 3. Furthermore, we control for regional and occupational sectors at *localidad* level as well as for the working sectors according to the ISIC classification of economic activities, if indicated. We account for potential heteroskedasticity by using robust standard errors.