Poverty and Biased Evaluations of Uncertainty: Theory and Experimental Evidence*

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Abstract

This paper shows that biased evaluations of uncertainty generate a poverty trap. I develop a theoretical framework to study how probability weighting and ambiguity attitudes—two fundamental biases in decision making under uncertainty—affect investment choices under poverty. The model predicts that these biases can lead individuals at all wealth levels to forgo investments that are profitable in expectation, and that poverty makes such investment mistakes more likely to occur. As a result, biased evaluations of uncertainty disproportionately discourage investment among the poor, thereby contributing to the persistence of poverty. I provide empirical evidence supporting this poverty trap using data from two experiments conducted on representative samples of American households.

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1. Introduction

A substantial body of evidence suggests that individuals living in poverty often forgo opportunities that could substantially improve their economic condition. For example, they underinvest in preventive health products (Dupas and Miguel, 2017), fail to adopt technologies that raise agricultural productivity (Duflo et al., 2008, Suri, 2011, Suri and Udry, 2022), and undervalue the long-run returns to education—often leading to school dropout (Jensen, 2010, Nguyen, 2008). These patterns of behavior contribute to the perpetuation of poverty and persist even in settings where credit, liquidity, and information constraints have been relaxed (Duflo et al., 2011, Dupas and Miguel, 2017, Suri and Udry, 2022). This evidence indicates that material constraints alone are insufficient to explain persistent poverty.

In this paper, I develop an explanation for the persistence of poverty that focuses on how individuals evaluate uncertainty. Thus, constraints that are internal to the individual, rooted in the psychology of decision making under uncertainty, are placed at the center of the analysis. In particular, I propose that *probability weighting* and *ambiguity attitudes*—two well established biases of decision under uncertainty—can generate a poverty trap. These biases distort the perceived returns to investment, leading individuals to systematically undervalue opportunities that are profitable in expectation. Moreover, poverty amplifies the impact of these distortions. As a result, these biased evaluations of uncertainty disproportionately discourage investment among poor individuals, lowering expected future earnings and thereby reinforcing poverty.

I formalize the proposed mechanism using a theoretical model in which an individual, endowed with an initial level of wealth, chooses how much to invest in a risky project while allocating the remainder to immediate consumption. The model assumes that higher investment increases the probability of achieving higher returns but does not guarantee them. To provide a normative evaluation of the outcomes of this decision problem, I take expected-utility individuals as the benchmark. These individuals evaluate risk accurately and choose a level of investment that maximizes utility in the absence of bias.

To understand how biased evaluations of risk perpetuate poverty, I introduce *probability weighting* into the model (Quiggin, 1982, Tversky and Kahneman, 1992, Abdellaoui, 2000). Under probability weighting, preferences over alternatives are no longer linear in probabilities, a pattern of choice that has been robustly documented in studies of decision making under risk (see Fehr-Duda and Epper (2011) and Wakker (2010, p. 204)).[1]

A central prediction of the model is that probability weighting leads to underinvestment relative to the expected utility benchmark. This occurs because individuals place disproportionate weight on the probabilities of extreme returns—the best and/or the worst returns—while underweighting other probabilities. As a result, investments that primarily increase the likelihood of favorable but moderate outcomes are undervalued, even when they are profitable in expectation. Notably, certain forms of probability weighting can generate extreme underinvestment, leading individuals to forgo investment altogether. In particular, when probability weighting induces risk-seeking attitudes, investments with non-extreme returns become unattractive, and biased individuals optimally choose not to invest.

In the model, rich and poor individuals are assumed to exhibit the same degree of probability weighting; they are equally biased in evaluating investments. Poverty nevertheless amplifies the impact of these biases since initial wealth and investment are assumed to be complementary in generating future wealth. This assumption implies that the marginal return to investment increases with initial wealth, capturing the idea that poorer individuals must invest more to achieve the same improvement as richer individuals—due to factors such as limited market access, lower capital stocks, or weaker social networks. Therefore, poor individuals are more exposed to underinvestment induced by probability weighting: since their investments generate relatively modest expected gains, distortions of probabilities have a first-order effect on how these opportunities are evaluated. By contrast, for wealthier individuals, investment returns are sufficiently large that the influence of probability weighting becomes negligible.

To examine the long-run implications of this investment behavior, I extend the framework to a dynamic setting in which the individual chooses how much to consume and invest in each period. The results reveal a self-reinforcing dynamic between biased evaluations of risk and economic disadvantage. When wealth is low, probability weighting leads individuals to forgo profitable in-

[1]Probability weighting has also been documented outside the laboratory, including in settings with sizable stakes (Bombardini and Trebbi, 2012), gambling choices (Snowberg and Wolfers, 2010), and insurance demand (Barseghyan et al., 2013).

vestments, thereby limiting subsequent wealth accumulation. Lower future wealth, in turn, further reduces the perceived gains from investing, strengthening the behavioral distortion and sustaining low investment. In contrast, wealthier individuals, whose investments generate larger gains and for whom probability distortions matter less in relative terms, continue to invest and accumulate wealth over time. The model therefore provides a behavioral foundation for poverty traps: even without credit, information, or market frictions, biased evaluations of risk can lock the poor into persistent poverty.

I test the empirical validity of this poverty trap using data from two experiments conducted on representative samples of American households. The first experiment, originally implemented by Dimmock et al. (2021) using the American Life Panel, elicits each respondent's probability weighting function. I leverage these elicitations to test an implication of the model: lower levels of income and wealth are associated with stronger probability weighting. This equilibrium outcome arises because the poverty trap keeps biased and poor individuals persistently poor. In contrast, individuals who are less biased or less materially constrained can escape poverty. The analyses show that, on average, respondents display an inverse-S shape probability weighting function: they overweight the probabilities of extreme outcomes and underweight the probabilities of intermediate outcomes. This pattern can induce risk-seeking attitudes, thereby making feasible the key prediction of the model that individuals may forgo investments. More importantly, I find that both family income and financial wealth are negatively and significantly related to the strength of probability weighting, measured by the steepness of the inverse-S curvature, in line with the model's predictions.

While the findings from the first experiment are consistent with the model's predictions, they also admit an alternative interpretation: individuals who are more affected by probability weighting may become poor as a mere consequence of their biases. To address this concern and provide causal evidence for the model's mechanism, I draw on the experiment of Carvalho et al. (2016). In this study, respondents were randomly assigned to complete an incentivized survey either shortly before or after their monthly payday, generating exogenous variation in financial resources. I exploit this variation to examine whether individuals with fewer resources—those surveyed before payday—are more prone to underinvestment due to probability weighting in an experimental task. While I find that average investment does not differ significantly across treatment groups, a clear pattern emerges among before-payday respondents with sufficiently concave utility. For this subgroup, average investment is significantly lower due to probability weighting. This investment behavior is consistent with the poverty-trap mechanism: when marginal utility of consumption is steep, the opportunity cost of forgoing immediate consumption before payday is especially high, making investment less attractive and rendering existing probability-weighting distortions more consequential for decision-making. This evidence provides a causal test of the theory and supports its core prediction.

The paper concludes by extending the model to incorporate biased evaluations of *subjective probabilities*, commonly referred to as ambiguity attitudes (Trautmann and van de Kuilen, 2015). In this model extension, the investment project is assumed to be ambiguous, in the sense that its return distribution is unknown to the decision-maker. To model preferences in this environment, I adopt source theory developed by Baillon et al. (2025). A key feature of this approach is that it posits that under ambiguity, the phenomena of risk are amplified because there is "additional probability weighting," which captures a preference (or dislike) for known risks over unknown ones.[2] This extended model demonstrates that the behavioral poverty trap identified under risk also emerges under ambiguity. Ambiguity attitudes, through their additional probability weighting, further distort the perceived attractiveness of investment opportunities, reinforcing extreme underinvestment among the poor. Moreover, I find that the threshold level of initial wealth required to escape the poverty trap increases under ambiguity, implying that relatively wealthy individuals, who would avoid poverty under risk, may remain trapped in poverty in the case of ambiguous investments. In this sense, ambiguity makes the poverty trap more severe and more easily sustained.

1.1. Related literature and contributions

This paper contributes to several strands of research. The first is the literature on development economics and poverty traps. Classic theories explain persis-

[2] For example, in the context of the two-urn Ellsberg paradox, the preference for betting on the known urn can be rationalized by additional probability weighting applied to the unknown urn. This distortion further underweights the probability of favorable outcomes in the ambiguous urn, making the known urn relatively more attractive.

tent poverty through mechanisms external to the individual such as credit constraints (Banerjee and Newman, 1993), non-convex technologies (Dasgupta and Ray, 1986, Galor and Zeira, 1993), and social interactions (Bowles et al., 2011a, Chapter 6). More recently, attention has shifted toward behavioral mechanisms to explain poverty, including time-inconsistent preferences (Banerjee and Mullainathan, 2010, Bernheim et al., 2015, Laajaj, 2017) and riskless reference-dependence with aspirations as reference points (Bogliacino and Ortoleva, 2013, Dalton et al., 2016, Genicot and Ray, 2017). I contribute to this literature by proposing a new behavioral poverty trap rooted in the psychology of decision making under uncertainty. Whereas previous behavioral models largely abstract from uncertainty, this paper highlights how poverty and biased evaluations of uncertainty interact. Specifically, I show theoretically and empirically that probability weighting and ambiguity attitudes—two empirically robust biases of decision under uncertainty—can generate and sustain poverty traps.

The second contribution is to the literature on decision making under risk and ambiguity. The paper shows how recent advances in decision theory offer valuable insights into relevant economic phenomena. For instance, it uses the distinction emphasized by (Wakker, 2010) between *pessimism (optimism)*— the motivational component of probability weighting captured by the convexity or concavity of the probability weighting function—and *likelihood insensitivity*—the cognitive component of probability weighting that generates an inverse-S shape (Wakker, 2010). This distinction is not inconsequential: the model and empirical results demonstrate that only the latter, the cognitive limitations to accurately perceive probabilities, can generate a poverty trap. Thus, the framework identifies a purely *cognitive* channel of decision making under uncertainty that alone can generate persistent poverty. Another tool borrowed from the literature of decision theory is the difference between probability weighting caused by risk and that caused by ambiguity, which is conceptualized by the theory of Baillon et al. (2025). This distinction is crucial for incorporating ambiguity attitudes into the model in a tractable way. It also shows that, in the more realistic setting of ambiguity, the poverty trap extends to individuals with higher initial wealth. As a result, in real-world environments where ambiguity is pervasive, this type of behavioral poverty trap is easier to sustain.

Overall, the paper's contribution is twofold: it introduces a new behavioral mechanism linking poverty and decision biases, and it empirically validates this mechanism using large-scale, representative data. By connecting the psychology of risk evaluation to the economics of poverty, the paper provides a unified explanation for why the poor may remain poor even in the absence of traditional constraints.

2. Theoretical Framework

This section studies decision-making under risk, that is, environments in which the distribution of returns is objectively known to the individual. I begin by introducing a two-period model that formalizes investment behavior under probability weighting. I then embed this environment in a repeated t-period setting to examine the dynamic implications for wealth accumulation and the emergence of poverty traps.

2.1. The Two-Period Model

Consider an individual who lives for two periods, $t = 0$ and $t = 1$, and who is endowed with an initial level of wealth $x_0 \in [\underline{x}, \bar{x}]$, where $\underline{x} \geq 0$. At $t = 0$, she allocates a fraction $e \in [0, 1]$ of her wealth to a risky investment, leaving $(1 - e)x_0$ for immediate consumption. The choice of e determines the distribution of wealth at $t = 1$.

Let z denote the stochastic return to investment. At the time the individual chooses e, the return has not yet been realized and takes values in the bounded interval $[\underline{x}, \bar{x}]$. The random variable z has cumulative distribution function $F(\cdot|e)$. The effect of e on the distribution of returns is characterized by the following assumption.

Assumption 1. *The cumulative distribution function $F(z|e)$ is twice continuously differentiable in e and z, and satisfies the following properties:*

(i) ***First-Order Stochastic Dominance:*** $F_e(z|e) < 0$ *for all z.*

(ii) ***Diminishing Returns to Investment:*** $F_{ee}(z|e) > 0$ *for all z.*

Assumption 1 embodies two properties that are central to the analysis. First, for an individual endowed with any given level of initial wealth x_0, higher investments strictly dominate lower ones in the sense of first-order stochastic dominance. This means that the probability of obtaining a high return increases with e. Second, the cumulative distribution function is convex in e, implying diminishing marginal returns to investment. In the absence of probability weighting, this convexity guarantees that the optimization problem is well behaved and admits an interior solution (Mirrlees, 1999, Rogerson, 1985).

The model further assumes that final wealth, the wealth level obtained in $t = 1$, results from the interaction between the return on investment z and initial wealth x_0. This relationship is described by the production function $b(x_0, z)$, which satisfies the following properties:

Assumption 2. *The wealth production function $b : [\underline{x}, \bar{x}] \times [\underline{x}, \bar{x}] \to \mathbb{R}^+$ is twice continuously differentiable and satisfies the following properties:*

(i) ***Monotonicity:*** *$b_{x_0}(x_0, z) > 0$ and $b_z(x_0, z) > 0$ for all x_0, z.*

(ii) ***Complementarity:*** *$b_{x_0 z}(x_0, z) > 0$ for all x_0, z.*

(iii) ***Diminishing returns in initial wealth:*** *$b_{x_0 x_0}(x_0, z) \leq 0$ for all x_0, z.*

(iv) ***Lower-boundary normalization:*** *$b(\underline{x}, z) = 0$ for all z.*

(v) ***Top-region gain:*** *There exists a set $H \subset [\underline{x}, \bar{x}]$ and a constant $\kappa > 1$ such that $b(\bar{x}, z) \geq \kappa \, \bar{x}$ for all $z \in H$.*

According to this assumption, final wealth increases with both initial wealth and the return on investment. In addition, the wealth production function b exhibits diminishing returns to initial wealth: the marginal contribution of an additional unit of initial wealth to final wealth decreases as initial wealth rises. More importantly, initial wealth and investment returns are *complements* in generating final wealth: for any given realization of z, richer individuals achieve higher final wealth. This complementarity captures the idea that initial wealth amplifies the gains from successful investment—whether because richer individuals, face fewer market barriers, possess more productive assets, or benefit from stronger social networks. Finally, the top-region gain condition guarantees that investment is profitable in expectation for some levels of wealth.

I now turn to the individual's preferences. Choosing a higher level of investment e reduces utility from immediate consumption but increases the expected utility of future wealth. This trade-off is captured by the following functional:

$$\mathbb{E}\big(u(z, e)\big) = u\big(x_0(1 - e)\big) + \delta \int_{\underline{x}}^{\bar{x}} u\Big(b(x_0, z)\Big) \mathrm{d}F(z|e). \tag{1}$$

The first expression in (1) captures the utility from immediate consumption at $t = 0$ and the second expression the expected utility of future wealth. The parameter $\delta \in (0, 1]$ denotes the standard discount factor.

Throughout, it is assumed that the consumption utility function, u, satisfies the following properties:

Assumption 3. *The consumption utility function $u : \mathbb{R}^+ \to \mathbb{R}$ is twice continuously differentiable and satisfies the following properties:*

(i) ***Monotonicity:*** $u'(b) > 0$ *for all* $b > 0$.

(ii) ***Concavity:*** $u''(b) < 0$ *for all* $b > 0$.

(iii) ***Normalization:*** $u(0) = 0$.

(iv) ***Curvature upper bound:*** *For all* x_0, z,

$$-\frac{u''\big(b(x_0, z)\big)}{u'\big(b(x_0, z)\big)} < \frac{b_{zx_0}(x_0, z)}{b_z(x_0, z)\, b_{x_0}(x_0, z)}.$$

Assumption 3 ensures diminishing marginal utility of consumption. Under expected utility (henceforth EU), this property implies that the individual is risk averse. In addition, the last condition (curvature upper bound) ensures that the complementarity between initial wealth and investment returns (Assumption 2) dominates the diminishing marginal utility of final wealth implied by u (Assumption 3). As a result, individuals with lower initial wealth experience smaller increases in consumption utility from a given investment return than wealthier individuals. This assumption is standard in related models (e.g., Dalton et al. (2016)) and is satisfied by common functional forms. For example, with CRRA utility $u(b) = b^{1-\gamma}$ and a Cobb-Douglas technology $b(x_0, z) = x_0^{\mu} z^{1-\mu}$, the condition reduces to $\gamma < 1$.

2.2. Probability Weighting Functions and Rank-Dependent Utility

The standard assumption that individuals evaluate probabilities accurately is relaxed. Instead, the decision maker may transform objective probabilities through a *probability weighting function*, denoted by $w(p)$. This function captures systematic deviations from expected-utility and plays a central role in shaping the individual's risk attitudes. The following assumption is imposed on $w(p)$:

Assumption 4. *The probability weighting function $w : [0, 1] \to [0, 1]$ is twice continuously differentiable and satisfies the following properties:*

(i) ***Impossibility and Certainty:*** $w(0) = 0$ *and* $w(1) = 1$.

(ii) ***Monotonicity:*** $w'(p) > 0$ *for all* $p \in (0, 1)$.

(iii) ***Inflection Point:*** *there exists* $\tilde{p} \in [0,1]$ *such that* $w''(p) < 0$ *for* $p < \tilde{p}$ *and* $w''(p) > 0$ *for* $p > \tilde{p}$.

(iv) ***Interior Point:*** *if* $\tilde{p} \in (0,1)$, *then there exists* $\hat{p} \in (0,1)$ *such that* $w(\hat{p}) = \hat{p}$.

(v) ***Certainty Effect:*** *if* $\tilde{p} = 0$, *then* $\lim_{p \to 0^+} w'(p) > 1$ *and* $\lim_{p \to 1^-} w'(p) < 1$.

(vi) ***Possibility Effect:*** *if* $\tilde{p} = 1$, *then* $\lim_{p \to 1^-} w'(p) > 1$ *and* $\lim_{p \to 0^+} w'(p) < 1$.

(vii) ***Certainty and Possibility Effects:*** *if* $\tilde{p} \in (0,1)$, *then* ${}_{p \to 0^+} w'(p) > 1$ *and* $\lim_{p \to 1^-} w'(p) > 1$.

According to the above assumption, the probability weighting function is a strictly increasing and continuous function that maps the unitary interval onto itself. It always has two fixed points: one at impossibility, i.e. $p = 0$, and one at certainty, i.e. $p = 1$. Besides, $w(p)$ can have three possible shapes: concave, convex, or inverse-S, which are determined by the location of the inflection point $\tilde{p} \in [0,1]$. When the function has the inverse-S shape (because $\tilde{p} \in (0,1)$) an additional fixed point is assumed, which I denote by $\hat{p} \in (0,1)$.

The preferences of the agent with probability weighting are characterized by rank-dependent utility (henceforth RDU) (Quiggin, 1982):

$$RDU\big(u(z,e)\big) = u\big(x_0(1-e)\big) + \delta \int_{\underline{x}}^{\bar{x}} u\Big(b(x_0,z)\Big) \mathrm{d}\Big(w\big(1 - F(z|e)\big)\Big). \tag{2}$$

RDU generalizes expected utility by applying probability weighting to the decumulative distribution $1 - F(z|e)$. Thus, for a given investment choice $e' \in [0,1]$, the individual evaluates outcomes according to their *rank*, defined as the probability of obtaining a higher level of return than a return level $z \in [\underline{x}, \bar{x}]$, namely $1 - F(z|e')$. This rank is transformed by the probability weighting function as $w\big(1 - F(z|e')\big)$, where w satisfies the properties stated in Assumption 4. In this way, RDU transforms decumulative probabilities through the probability weighting function.

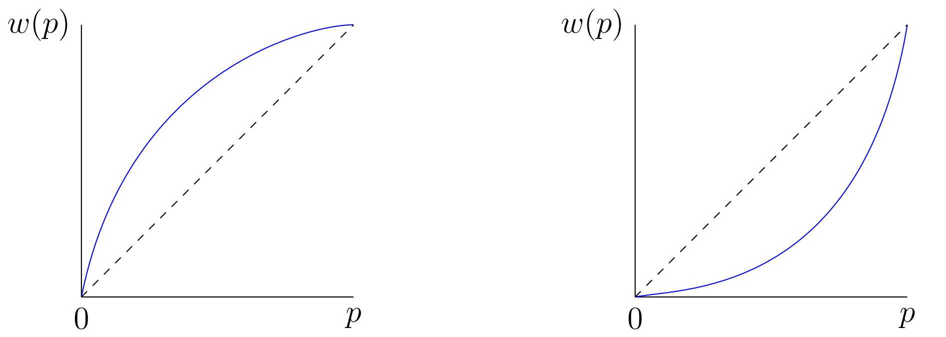
Now suppose that the RDU individual considers an outcome infinitesimally below z. The associated change in perceived rank is given by the differential $\mathrm{d}\Big(w\big(1 - F(z|e')\big)\Big)$, which corresponds to the weighting measure of the integral in (2). Accordingly, in the RDU framework, the utility $u(b(\cdot, z))$ associated with return level z is weighted by its marginal contribution to the perceived rank, $\mathrm{d}\Big(w\big(1 - F(z|e')\big)\Big)$. Integrating these weighted utilities over all $z \in [\underline{x}, \bar{x}]$ yields the RDU valuation of the investment.

Notably, under RDU, the individual's risk attitudes are jointly determined by the curvature of the functions u and w. The risk attitude generated by the curvature of u is common to EU and RDU, while that generated by the curvature of w is exclusive to RDU. This influence of probability weighting on risk attitude under RDU is known as *probabilistic risk attitude* (Wakker, 1994), and it captures the influence of deviations from expected utility in decision making under risk. The goal of this model is to study how this additional source of risk attitude interacts with poverty.

2.3. Motivational and Cognitive Factors of Probability Weighting

To comprehensively investigate the relationship between poverty and probability weighting, I follow Wakker (2010) in distinguishing between two distinct components of probability weighting. The first stems from pessimism and optimism toward risk. This component captures the idea that, when making decisions under risk, the individual might irrationally believe that unfavorable outcomes, in the case of pessimism, and favorable outcomes, in the case of optimism, realize more often than they actually do.

Pessimism is represented in the model by a *convex* probability weighting function, which assigns greater weight to the probabilities of the lowest levels of return. Conversely, optimism is represented by a *concave* probability weighting function, which assigns greater weight to the probabilities of the highest levels of return. Figure 1 provides examples of optimism and pessimism.



(a) Optimism (b) Pessimism

Figure 1: Examples of Optimism and Pessimism

Definition 1. *Optimism (Pessimism) is characterized by a weighting function, $w(p)$, with the properties of Assumption 4 and $\tilde{p} = 1$ ($\tilde{p} = 0$).*

In the analysis below, I examine how the severity of probability weighting—whether arising from stronger optimism or pessimism—affects investment behavior. The following definition, due to Yaari (1987), provides a formal basis for understanding different degrees of optimism and pessimism.

Definition 2. *An agent i with weighting function $w_i(p)$ is more optimistic (pessimistic) than an agent with weighting function w_j if $w_i(p) = \theta\big(w_j(p)\big)$ where the function $\theta : [0,1] \to [0,1]$ is twice continuously differentiable with $\theta' > 0$ and $\theta'' < 0$ ($\theta'' > 0$).*

We are now in a position to establish how stronger optimism or pessimism influences risk attitudes. The following remark shows that these components of probability weighting have opposite effects: stronger optimism makes the individual more risk seeking, while stronger pessimism makes the decision maker more risk averse. The proofs of the theoretical results are provided in Appendix A.

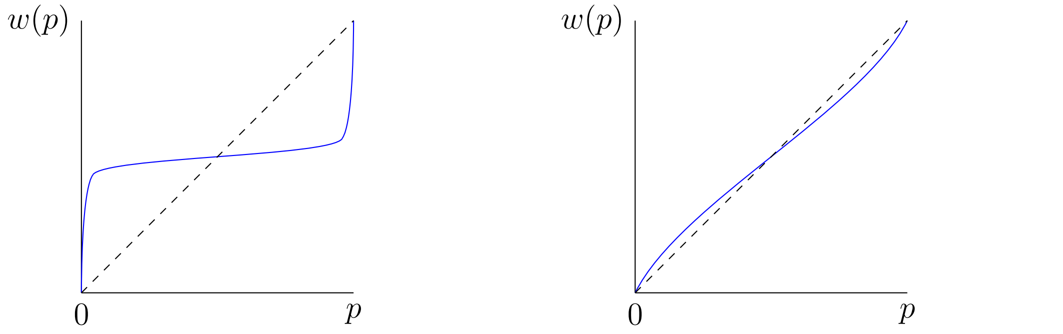
Remark 1. *For given investment e and initial wealth x_0 levels, stronger optimism (pessimism) decreases (increases) risk aversion.*

The second type of probability weighting is cognitive and is referred to as likelihood insensitivity (Tversky and Wakker, 1995, Wakker, 2010). It captures the idea that individuals distort probabilities due to cognitive and perceptual limitations. These limitations manifest as extremity-orientedness: individuals are insufficiently sensitive to changes in intermediate probabilities, leading them to overweight the probabilities of extreme outcomes, both best and worst.

I characterize likelihood insensitivity using an inverse-S probability weighting function (see Figure 2). An individual with such a probability weighting function assigns excessive weight to the probabilities of extreme returns and insufficient weight to the probabilities of intermediate returns.

Definition 3. *Likelihood insensitivity is characterized by a weighting function, $w(p)$, with the properties of Assumption 4, together with $\tilde{p} = 0.5$, and $\hat{p} = 0.5$.*

The previous definition of likelihood insensitivity assumes that probabilities of intermediate outcomes are perceived to be close to 0.5. This property was assumed by (Quiggin, 1982) and reflects the notion that when assessing the likelihood of intermediate outcomes, the insensitive individual will have



(a) Extreme likelihood insensitivity (b) Moderate likelihood insensitivity

Figure 2: Examples of likelihood insensitivity

a crude perception of these probabilities as being close to “50-50”—either the event under consideration happens or it won’t.

It will be useful for the analyses below to characterize individuals by the severity of probability weighting arising from likelihood insensitivity. The following definition, adapted from Baillon et al. (2025), formalizes this notion: stronger likelihood insensitivity corresponds to a probability weighting function with a more pronounced inverse-S shape, reflecting reduced discrimination of intermediate probabilities.

Definition 4. *An individual i with weighting function w_i is more likelihood insensitive than an individual j with weighting function w_j if $w_i = \phi\big(w_j(p)\big)$ where $\phi : [0,1] \to [0,1]$ is twice continuously differentiable and exhibits the inverse-S shape described in Definition 3.*

The following remark states that an individual exhibiting a stronger degree of likelihood insensitivity assigns greater weight to the probabilities of the highest and lowest returns, and less weight to other probabilities.

Remark 2. *If individual i is more likelihood insensitive than individual j in the sense of Definition 4, then her weighting function exhibits $w_i(p) > w_j(p)$ for all $p \in (0, 0.5)$ and $w_i(p) < w_j(p)$ for all $p \in (0.5, 1)$.*

Unlike the case of optimism and pessimism, Remark 2 does not specify whether greater likelihood insensitivity leads to increased risk aversion or risk seeking. In fact, this effect depends on the probability distribution of investment returns, $F_z(z|e)$. When that distribution is right-skewed, stronger likelihood insensitivity increases risk aversion: more probability mass is concentrated in low returns, so overweighting the probabilities of these outcomes amplifies the perceived likelihood of unfavorable outcomes, reducing the attractiveness of investment. Conversely, when the probability distribution of returns is left-skewed, stronger likelihood insensitivity induces greater risk seeking.

The following lemma presents a key preliminary result. It shows that more severe probability weighting—whether driven by stronger optimism, stronger pessimism, or stronger likelihood insensitivity—expands the range of probabilities that are underweighted relative to the EU benchmark.

Lemma 1. *For given investment e and initial wealth x_0 levels, stronger pessimism, stronger optimism, or stronger likelihood insensitivity expands the set of probabilities $p \in (0,1)$ for which the probability weighting function satisfies $w'(p) < 1$.*

Lemma 1 states that, irrespective of the type of probability weighting or the risk attitude it induces, greater severity of probability weighting leads individuals to underweight a broader range of probabilities.

To understand the intuition behind this result, consider an individual who becomes more pessimistic. This stronger pessimism increases the weight assigned to the probability of the lowest return. Because the probability weighting function must, on average, have a slope equal to one—since $w(0) = 0$ and $w(1) = 1$— it follows that

$$\int_{\underline{x}}^{\bar{x}} w'(1 - F(z|e))F_z(z|e)\mathrm{d}z = 1.$$

As a result, an increase in the weight placed on the worst outcome must be offset by a reduction in the weights assigned to other outcomes. Consequently, the set of probabilities that receive insufficient weight, relative to the EU benchmark, necessarily expands. In the case of increased pessimism, this expansion affects the probabilities of intermediate and high returns. A similar reasoning applies when an individual becomes more optimistic or more likelihood insensitive.

2.4. Probability Weighting and Investment Choice

We are now in a position to examine how probability weighting influences the investment decision in this two-period setting. To do so, I contrast the optimal investment level chosen by RDU individual with that chosen by an otherwise identical EU decision maker. The following proposition characterizes the optimal choice of the EU individual.

Proposition 1. *Assume that Assumptions 1-3 hold. The optimal investment level chosen by the EU individual, e_u^*, is unique, interior in the set $[0,1]$, and increasing in x_0.*

The EU decision maker chooses a strictly positive level of investment. Moreover, poorer EU individuals invest less than richer ones. This latter property of Proposition 1 is driven by two features of the model. First, the complementarity between initial wealth and returns to investment (Assumption 2), which reduces the marginal return to investment for the poor. Second, the bounded curvature of u (Assumption 3), which guarantees that marginal utility remains sufficiently high at larger wealth levels.

The following result focuses on probability weighting due to pessimism and shows that sufficiently strong pessimism leads the RDU individual to underinvest relative to the EU benchmark.

Proposition 2. *Assume that Assumptions 1-4 hold and that the individual exhibits pessimism (Definition 1). Then:*

(i) The optimal investment level chosen by the RDU individual, e_r^*, is unique, interior in the set $[0,1]$, and increasing in x_0.

(ii) There exists a threshold degree of pessimism such that, if the individual is more pessimistic than that threshold (in the sense of Definition 2) then $e_r^* < e_u^*$.

An RDU individual with sufficiently strong pessimism underinvests relative to an otherwise identical EU individual. This occurs because pessimism induces greater risk aversion: by assigning disproportionate weight to the worst outcome, the individual underweights improvements in the probabilities of favorable returns (Lemma 1), thereby reducing her willingness to invest in the risky project.

It should be stated that the threshold degree of pessimism required to generate underinvestment depends on the productivity of investment. When investment only modestly increases the probability of favorable outcomes, even moderate pessimism is sufficient to induce underinvestment. By contrast, when investment substantially raises these probabilities, only severe pessimism leads to investment below the EU benchmark.

We next study how optimism and likelihood insensitivity influence investment. The following proposition shows that these two forms of probability weighting lead low-wealth individuals to forgo profitable investments. Hence, they can generate extreme underinvestment, whereby poor individuals choose not to invest at all even when the investment is objectively profitable.

Proposition 3. *Assume that Assumptions 1-4 hold. There exists a threshold degree of probability weighting, capturing either optimism or likelihood insensitivity such that, for any individual whose degree of probability weighting is at least as large as this threshold (in the sense of Definitions 2 and 4), there exists an associated threshold level of initial wealth $\hat{x}_0 \in (\underline{x}, \bar{x}]$ with the property that the optimal investment choice satisfies:*

$$e_r^* = \begin{cases} 0, & \textit{if } x_0 \leq \hat{x}_0, \\ 1, & \textit{if } x_0 > \hat{x}_0. \end{cases}$$

Moreover, the threshold level of initial wealth, $\hat{x}_0$, is strictly increasing in the degree of optimism or likelihood insensitivity.

Sufficiently severe optimism leads the individual to assign excessive weight to the probability of the best outcome and insufficient weight to all other probabilities (Lemma 1). The risk-seeking attitude generated by this incorrect evaluation of probabilities causes her to forgo investments that improve other favorable, yet more moderate, outcomes. As a result, she forgoes investments that are profitable on average.

An individual with sufficiently strong likelihood insensitivity evaluates risk in a similar way, and therefore also exhibits a risk-seeking behavior that leads her to forgo profitable investments. However, unlike the optimist, she also focuses excessively on the worst outcome. Essentially, this individual would pass over any opportunity that does not considerably alter the probabilities of extreme returns, thereby forgoing investments that would, on average, be profitable.

Because initial wealth amplifies the utility gains from investment (Assumptions 2 and 3), poor individuals, who face smaller payoffs from investment, are more susceptible to this extreme non-investment behavior. For them, the benefits of investing are objectively smaller and therefore more easily undervalued under probability weighting, this vulnerability makes complete non-investment optimal among the biased and poor.

The mathematical rationale behind Proposition 3 is as follows. The concavity of the probability weighting function, whether due to optimism or likelihood insensitivity, can introduce non-convexities into the optimization problem. As a result, the optimal solution might lie at one of the boundaries of the feasible set $[0, 1]$. Hence, when an investment is undervalued due to strong probability weighting (Lemma 1), the individual optimally chooses not to invest at all. This stands in contrast to the EU case, where the absence of such non-convexities yields an interior optimal investment level.

To conclude this simple two-period model, I present a comparative static that will be useful for interpreting a set of empirical results. The following corollary shows that stronger utility curvature—provided it remains within the bounds imposed by Assumption 3—makes individuals more susceptible to the extreme underinvestment described in Proposition 3. Intuitively, greater utility curvature steepens the marginal utility cost of foregone consumption, thereby expanding the initial wealth region in which the distorted marginal benefits from investment fail to compensate for its immediate utility cost.

Corollary 1. *As* $-\frac{u''\big(b(x_0,z)\big)}{u'\big(b(x_0,z)\big)}$ *becomes larger, the threshold* $\hat{x}_0$ *from Proposition 3 increases.*

2.5. Behavioral Poverty Traps from Probability Weighting

Thus far, we have shown that poverty and probability weighting generate underinvestment. However, if this investment behavior only delays wealth accumulation and leads, in the long run, to the same equilibrium as that reached by the rich, poverty would be only transitory. To demonstrate that this is not always the case, and that the underinvestment due to probability weighting can generate persistent poverty, I extend the problem to a repeated setting.

Suppose there are periods $t = 0, \ldots, T$. In each period t, the agent begins with wealth $x_t \in [\underline{x}, \bar{x}]$ and chooses an investment level $e_t \in [0, 1]$ to trade off current consumption against next-period wealth. The stochastic return to investment in period t is represented by the random variable z_t, whose distribution is given by the cumulative distribution function $F(z_t \mid e_t)$, which satisfies the properties stated in Assumption 1. In addition, given current wealth x_t and return z_t, end-of-period wealth is determined by the function $b(x_t, z_t)$ with the properties in Assumption 2.

To keep the analysis tractable and allow a transparent characterization of steady states, I formulate the dynamic problem in terms of expected wealth. Thus, from the perspective of period t, wealth at $t+1$ is evaluated in expectation, conditional on current wealth and investment. This future-period expected wealth serves as the relevant state variable because investment decisions depend on perceived expected returns to investment, and future choices are shaped by the agent's perceived expected economic position rather than by the full distribution of realized shocks. Focusing on mean dynamics therefore captures whether equilibrium behavior leads predictably to persistent low wealth, abstracting from idiosyncratic realizations that are not central to the mechanism.[3]

Wealth then evolves in expectation according to the following law of motion:

$$x_{t+1} = \int_{\underline{x}}^{\bar{x}} b(x_t, z_t) \mathrm{d}F\left(z_t|e_t\right). \tag{3}$$

In words, next-period wealth is given by the expected return to investment undertaken in the current period.

Throughout, it is assumed that in each period t the agent chooses the investment level e_t to maximize intertemporal utility over periods t and $t+1$. This framework admits two interpretations. First, the agent can be viewed as myopic, making decisions in each period that trade off current consumption against next-period wealth without explicitly considering subsequent periods. This assumption is consistent with the notion of *isolation*, which is commonly adopted in experimental and behavioral economics when modeling individuals with probability-weighting preferences (Cubitt et al., 1998, Hey and Lee, 2005, Baltussen et al., 2012). Second, it also accords with the idea that individuals who exhibit probability weighting display dynamic inconsistency: even if they form a long-term investment plan—equivalent to solving the full dynamic optimization problem— they are likely to deviate from it because their distorted perception of probabilities alters how they evaluate future risks (Karni and Safra,

[3]Formally, let $\tilde{x}_{t+1}$ denote realized wealth at the beginning of period $t+1$. Then $\tilde{x}_{t+1} = b(x_t, z_t)$, and the state variable is defined by the conditional expectation:

$$x_{t+1} \equiv \mathbb{E}[\tilde{x}_{t+1} \mid x_t, e_t] = \int_{\underline{x}}^{\bar{x}} b(x_t, z_t)\, dF(z_t \mid e_t).$$

Throughout, I study the deterministic recursion obtained by identifying x_{t+1} with this conditional expectation.

1990, Gilboa and Schmeidler, 1993, Sarin and Wakker, 1998).[4]

We turn to characterize the long-run equilibrium when the evolution of wealth follows the law of motion given in (3). The following proposition establishes that, under EU, the induced wealth dynamics admit a unique steady state.

Proposition 4. *Assume Assumptions 1-3 hold. For the EU decision maker, there exists a unique, interior, and locally stable steady state* x_u^*.

Under EU, the optimal investment policy e_u^* is interior and increasing in current wealth (Proposition 1). Because current initial wealth and investment returns are complementary ($b_{xz} > 0$), higher current wealth raises the marginal return to investment, implying that expected next-period wealth increases with x_t. At sufficiently high wealth levels, however, diminishing returns to current wealth ($b_{xx} < 0$) cause the expected wealth-transition curve to flatten, so that expected wealth grows more slowly than the 45-degree line ($x_{t+1} = x_t$). By contrast, at low wealth levels, diminishing returns are weak and the complementarity between current wealth and investment ensures that expected wealth grows faster than current wealth. Together, these forces imply that the expected wealth-transition curve crosses the identity line exactly once, yielding a unique steady state at which expected wealth neither increases nor decreases.

Before turning to the long-run equilibria under probability weighting, I introduce an additional assumption that ensures individuals with very low current wealth cannot accumulate expected wealth without investing.

Assumption 5. *There exist* $\epsilon > 0$ *and* $k < 1$ *such that for all* $x_t \in (\underline{x}, \underline{x} + \epsilon)$,

$$\int b(x_t, z)\, dF(z \mid 0) \;\leq\; \underline{x} \;+\; k\,(x_t - \underline{x}).$$

Assumption 5 does not impose any non-convexity or threshold in the production technology. It simply places a local slope restriction on the wealth transition when investment is zero: near the lower boundary, i.e. as $x_t \to \underline{x}$, expected wealth cannot grow more than proportionally with current wealth. The

[4]Alternatively, the framework can be interpreted as an overlapping-generations (OLG) model with impure altruism. In this interpretation, each generation lives for a single period, transfers its wealth to the next generation, and derives utility from this bequest. Investment then represents the share of resources allocated to descendants, or, equivalently, to the productive capital stock of the next generation.

production function b remains fully smooth and concave, exactly as specified in the baseline model. The assumption merely rules out the knife-edge case in which zero investment would generate automatic wealth accumulation for very poor individuals.

We are now in a position to show that probability weighting can generate a poverty trap. The next proposition demonstrates that when agents exhibit sufficiently strong probability weighting arising from likelihood insensitivity or optimism, their investment behavior can sustain a low-wealth steady state in which the poor perpetuate their condition.

Proposition 5. *Assume that Assumptions 1-5 hold and that the individual is at least as optimistic or likelihood insensitive as the threshold degree of optimism or likelihood insensitivity from Proposition 3. Then there exists a threshold level of initial wealth* $\tilde{x}_0 \in [\underline{x}, \bar{x}]$ *such that:*

(i) if $x_0 \leq \tilde{x}_0$*, the individual converges to the low-wealth steady state* $x_r^* = \underline{x}$*;*

(ii) if $x_0 > \tilde{x}_0$*, the individual converges to the high-wealth steady state* $x_r^* = x_H > \tilde{x}_0$.

At low levels of wealth, small investment levels are mistakenly perceived as ineffective at raising the probability of favorable outcomes. As a result, likelihood-insensitive or optimistic individuals choose not to invest at all, causing expected wealth to remain low. As wealth increases, however, investment becomes more effective: due to the complementarity between current wealth and returns ($b_{xz} > 0$), and because higher investment raises success probabilities in the sense of first-order stochastic dominance, the perceived gains from investing rise sharply. Together, these forces—extreme underinvestment at low wealth and rapidly increasing responsiveness to investment at intermediate wealth—generate an S-shaped expected wealth transition function. This shape implies the existence of two stable steady states: a low-wealth poverty trap, in which individuals remain poor because they do not invest, and a high-wealth equilibrium x_H, in which sustained investment supports long-run wealth accumulation.

Proposition 5 provides an explanation for the empirical regularity that the poor frequently forgo profitable opportunities. For example, they may erroneously perceive the returns to additional schooling as too small to justify the cost in foregone current consumption (Jensen, 2010, Nguyen, 2008), or misjudge the benefits of effective preventive health products (Dupas and Miguel, 2017).

In both cases, the model implies that probability weighting distorts the perceived returns to investment, leading individuals to undervalue opportunities that would, on average, improve their future economic prospects.

To conclude the model, I show that pessimism does not generate a poverty trap. Instead, pessimistic probability weighting leads to a unique steady-state equilibrium, characterized by lower long-run wealth than under expected utility but without the multiplicity of steady states required for persistent poverty.

Corollary 2. *Under the conditions of Proposition 5, suppose instead that the individual exhibits sufficiently severe pessimism (in the sense of Proposition 2). Then there exists a unique, locally stable steady state $x_r^* \in (\underline{x}, \bar{x})$, which lies strictly below the steady state under expected utility: $x_r^* < x_u^*$.*

Sufficiently strong pessimism leads individuals to invest less than under the EU benchmark. However, unlike optimism or likelihood insensitivity, pessimism does not induce corner solutions: the pessimist still chooses an interior investment level. Consequently, the investment response remains monotonic—current wealth and investment continue to rise together. This ensures that wealth dynamics converge to a unique, globally stable steady state. Pessimism therefore reduces long-run expected wealth but does not generate a poverty trap.

The behavioral poverty trap proposed in this paper is characterized by Proposition 5. Probability weighting leads poor individuals to forgo profitable opportunities, causing them to exhibit the lowest investment levels in society and trapping them in a low steady state. Consequently, despite having opportunities to improve their condition through profitable investments, the poor ultimately attain the lowest final expected wealth; their poverty is perpetuated by their erroneous perception of risk.

3. Correlational Evidence of the Behavioral Poverty Trap

In this section, I draw on the data from Dimmock et al. (2021) to evaluate the empirical validity of the poverty trap predicted by the theoretical framework. Their study implemented an incentivized experiment in the American Life Panel, a representative sample of U.S. households. Although the original aim of Dimmock et al. (2021) was to examine the relationship between probability weighting and household portfolio diversification, these data offer the opportunity to investigate whether probability weighting is associated with differences in wealth and income, consistent with the poverty trap mechanism derived in Section 2.

Dimmock et al. (2021) elicited the probability weighting function for each respondent using the method of Abdellaoui (2000). This method allows the researcher to elicit the utility and probability weighting functions in a non-parametric way. This is achieved by implementing a set of binary lotteries that keep probabilities fixed, in order to elicit utility function curvature, and another set of binary lotteries that keep outcomes fixed and vary probabilities, in order to elicit probability weighting function curvature. Therefore, these data successfully identify these two components of risk attitude in the case of RDU preferences.

A disadvantage of the elicitation in Dimmock et al. (2021) is that it confounds probability weighting due to likelihood insensitivity with probability weighting due to pessimism and optimism. To deal with this confound, I fit the respondent's answers to the questions designed to elicit probability weighting to parametric forms of probability weighting that can separate and identify these factors. Accordingly, the data are first fitted to Prelec (1998)'s probability weighting function, which has two parameters, each roughly capturing each component of probability weighting, and is empirically desirable because it accounts for changes at small and large probabilities (Wakker, 2010). Formally, for each respondent i, the following function is estimated:

$$w(p_{ij}) = \exp\Big(- \beta_i \big(- \ln(p_{ij}) \big)^{\alpha_i} \Big), \tag{4}$$

where the index j represents the questions designed to elicit probability weighting. To estimate the parameters α_i and β_i in (4), I used non-linear least squares, a method that has been widely used to estimate the parameters of the probability weighting function (Abdellaoui et al., 2011, Li et al., 2018, Dimmock et al., 2021).

The estimate $\hat{\alpha}_i$ in (4) captures the respondent i's likelihood insensitivity (Wakker, 2010). In particular, the closer $\hat{\alpha}_i$ is to 0, the more insensitive the respondent is, and, conversely, a value of $\hat{\alpha}_i$ closer to 1 implies a perception of probabilities closer to EU. Therefore, I use $-\hat{\alpha}_i$ (if $\hat{\alpha}_i < 1$) as a continuous index of likelihood insensitivity that I refer to as "Inverse-S." Furthermore, the estimate $\hat{\beta}_i$ in (4) indicates whether respondent i exhibits pessimism or optimism (Wakker, 2010). If $\hat{\beta}_i < 1$, the respondent exhibits optimism, while $\hat{\beta}_i > 1$ indicates pessimism. Additionally, the magnitude of $\hat{\beta}_i$ captures the degree of optimism or pessimism: higher values of $\hat{\beta}_i$ reflect stronger pessimism (if $\hat{\beta}_i > 1$), while lower values denote stronger optimism (if $\hat{\beta}_i < 1$). Hence, I use $\hat{\beta}_i$ as a continuous index of optimism and pessimism that I refer to as "Opt./Pess."

Apart from probability weighting, I also estimate each respondent's utility function. The survey questions designed to elicit utility curvature are used to estimate the following utility function:

$$u(x_{ik}) = x_{ik}^{1-\gamma_i}. \tag{5}$$

where the index k represents the questions designed to elicit utility curvature. The parameter γ_i is estimated using non-linear least squares, jointly with the parameters of the probability weighting function.

Table 1 presents descriptive statistics of $\hat{\alpha}_i$ and $\hat{\beta}_i$.[5] I find that respondents exhibited likelihood insensitivity and pessimism on average, since the average value of $\hat{\alpha}_i$ is less than 1 and that of $\hat{\beta}_i$ is greater than 1. Figure 3a illustrates the median probability weighting function, which is also characterized by pessimism and likelihood insensitivity. These findings are further corroborated when the estimates are analyzed at the individual level. Specifically, a majority of respondents, 2012 out of 2640, exhibit $\hat{\alpha}_i < 1$, which indicates likelihood insensitivity. Furthermore, a majority of subjects, 1872 out of 2640, exhibit $\hat{\beta}_i > 1$, which indicates pessimism. These results are consistent with previous experimental findings (Abdellaoui, 2000, Abdellaoui et al., 2011, Bruhin et al., 2010, L'Haridon and Vieider, 2019).

A key advantage of these data is that the same respondents reported their income and wealth in previous survey waves. This allows me to examine how these outcomes are related to individuals' estimated degrees of likelihood insensitivity and pessimism. The analysis focuses on four measures: "Finan-

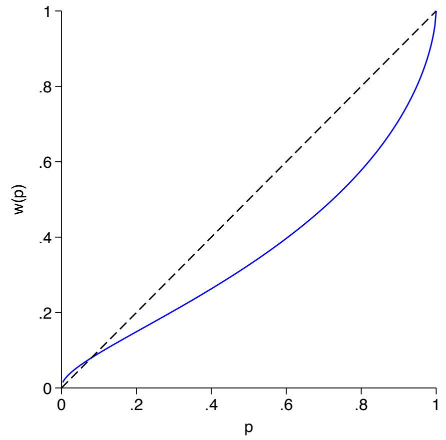
[5] I applied a 95% winsorization to the estimates of β_i in order to reduce the effect of outliers. Prior to transforming the data, the mean of $\hat{\beta}_i$ was equal 6.148, which is considerably higher than average estimates reported in previous studies. Moreover, the standard deviation of $\hat{\beta}_i$ was 27.92, which indicates a considerably high variance.

Table 1: Estimates of Probability Weighting Functions

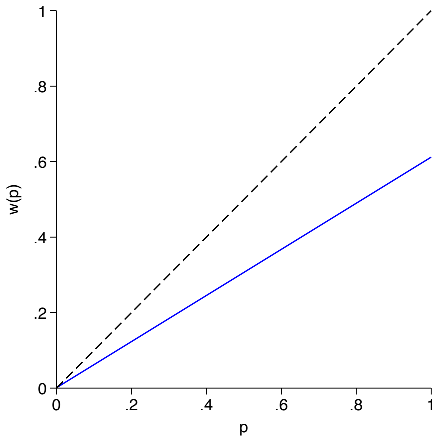
	Prelec (1998)		**Chateauneuf et al. (2007)**	
	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{s}_i$	$\hat{c}_i$
Mean	0.815	1.855	0.594	0.028
25th perc.	0.361	0.932	0.257	-0.118
50th perc.	0.630	1.411	0.611	0.001
75th perc.	0.972	2.329	0.891	0.056
St. Dev.	1.211	1.550	0.358	0.067

This table presents the descriptive statistics for estimates of probability weighting obtained at the respondent level. The first two columns present the descriptive statistics of the parameters when the form $w(p_{ij}) = \exp\Big(-\beta_i\big(-\ln(p_{ij})\big)^{\alpha_i}\Big)$, due to Prelec (1998), is assumed. Columns 3 and 4 present the descriptive statistics of the parameters when the form $w(p_{ij}) = \begin{cases} 0 & \text{if } p = 0, \\ c_i + s_i \cdot p_{ij} & \text{if } p \in (0,1), \\ 1 & \text{if } p = 1. \end{cases}$, due to Chateauneuf et al. (2007), is assumed.

Figure 3: Median probability weighting functions



(a) using Prelec (1998)



(b) using Chateauneuf et al. (2007)

Note: The blue lines represent the median probability weighting function in the sample while the dashed lines represent the accurate perception of probabilities benchmark.

cial Wealth", defined as the household's reported holdings in bonds, certificates of deposit, treasury bills, checking accounts, savings accounts, and stocks; "Return Stock", measuring the household's reported investment in individual stocks and stock mutual funds in retirement accounts; "Family Income", which is the household's reported annual income; and "Housing Wealth", capturing the household's reported real estate holdings.

Table 2 reports descriptive statistics for these income and wealth variables. All measures are continuous and expressed in dollars (or thousands of dollars), and in each case the standard deviation exceeds the mean, indicating substantial dispersion. To stabilize this variability and reduce the influence of extreme values, I apply a natural logarithmic transformation, following Dimmock et al. (2016b) and Dimmock et al. (2021). Specifically, I use the transformation $ln(y_i + 1)$, where y_i denotes the outcome variable. This approach also mitigates concerns related to selection on non-zero values arising from the presence of multiple zero observations. As a robustness check, I additionally estimate specifications using the quartic-root transformation, $(y_i)^{1/4}$, as recommended by Thakral and Tô (2023), which similarly addresses issues related to skewness and zero-valued outcomes.

Table 2: Descriptive Statistics of Income and Wealth

Variable	**Unit**	**Mean**	**25th Perc.**	**50th Perc.**	**75th Perc.**	**St. Dev.**	**Obs.**
Financial Wealth	1000s USD	139.673	0	2.500	38	1897.933	1954
Return Stock	1 USD	260275.800	30000	114000	350000	439687.8	951
Family Income	1000s USD	76.516	32.5	67.500	112.5	53.350	2659
Housing Wealth	1000s USD	483.909	0	100	250	13054.750	1943

This table presents descriptive statistics for the variables that capture the respondents' self-reported income and wealth. The variables are "Financial Wealth" which captures the household's self-reported holdings in bonds, certificates of deposit, treasury bills, checking accounts, savings accounts, and stocks in thousands of US dollars, "Return Stock" which captures the household's self-reported return on individual stocks and stock mutual funds in retirement accounts in US dollars, "Family Income" which captures the household's self-reported income in thousands of US dollars, and "Housing Wealth" which captures the household's self-reported housing wealth in thousands of US dollars.

Each transformed income and wealth variable is regressed on the indexes of probability weighting. Estimating separate regressions—where each variable reported in Table 2 serves in turn as the dependent variable—is useful because these measures capture different dimensions of the respondent's economic position. This approach therefore offers insight into the specific contexts in which the proposed poverty trap is more likely to operate. For example, Return Stock reflects income with lower liquidity relative to that included in Family Income, and may therefore play a more limited role in shaping investment behavior among the poorest households. Similarly, Housing Wealth represents a lower liquidity wealth position relative to that in Financial Wealth, which, again, might be less important in the case of the poorest households.

In all regression specifications, I control for respondents' utility curvature, as any empirically relevant relationship between poverty and probability weighting must emerge above and beyond differences in risk attitudes driven by utility curvature alone. In additional specifications, I include a set of demographic and socioeconomic controls that may moderate the relationship between probability weighting and income or wealth. These controls include age, gender, ethnicity, educational attainment, state of residence, primary language, and employment status.

Table 3 reports the OLS estimates. The results show that higher likelihood insensitivity, as captured by the index Inverse-S, is associated with lower financial wealth, lower return on stocks, and lower family income. In particular, a 0.1 increase in the index predicts a 12.2% decline in financial wealth, a 12.4% reduction in return to stocks, and a 1.84% decrease in family income.[6] In contrast, the coefficient on Inverse-S is not significant when Housing Wealth is used as the dependent variable. This lack of significance suggests that for this measure of wealth, which as mentioned above is less relevant in the case of poorest households, the model's predictions cannot be empirically supported.[7] Table 10 in Appendix E further confirms the robustness of the findings using a quartic-root transformation of the dependent variables, indicating that these findings are not an artifact of the specific transformation used to stabilize variance, but are robust to alternative transformations.

To provide a more direct interpretation of the relationship between poverty and probability weighting, I classify households as poor or non-poor according to U.S. poverty guidelines. I find that poor respondents exhibit an Inverse-S index that is 0.0463 units higher, approximately 0.038 standard deviations,

[6]These results become more noticeable when the change in insensitivity is quantified in terms of standard deviations of the index; a one-standard-deviation increase in the likelihood insensitivity index, is associated with a 79% reduction in financial wealth and return to stocks, and a 20% reduction in family income.

[7]It must be noted that the same qualitative results are obtained without winsorization (see Table 7 in Appendix E).

than that of non-poor respondents. Using the estimated coefficients from Table 3, this difference implies that poor respondents hold approximately 5.8% less financial wealth, earn 5.8% lower returns to stocks, and report 0.86% lower annual income *solely due to probability weighting from likelihood insensitivity*. It should be emphasized that these estimates must be interpreted as lower bounds on the overall influence of probability weighting. They are based on probability weighting measures elicited through well-defined lottery choices, whereas the theoretical framework in Section 2 concerns distortions in the perceived probabilities of returns to real-life investments. Such probabilities are typically more ambiguous than those in lotteries, which may further amplify biased evaluations of uncertainty and underinvestment; a mechanism explored in the model extension presented in Appendix D.

The regression results in Table 3 further show that pessimism, as measured by the Opt./Pess. index, is not significantly associated with income or wealth. This null finding is robust to alternative transformations of the dependent variables, including the quartic-root specification reported in Table 7. The absence of a statistically significant relationship is consistent with the theoretical prediction that pessimism alone does not generate a poverty trap (Corollary 2).

For robustness, I repeat the analysis using the parametric specification of probability weighting proposed by Chateauneuf et al. (2007):

$$w(p_{ij}) = \begin{cases} 0 & \text{if } p = 0, \\ c_i + s_i \cdot p_{ij} & \text{if } p \in (0,1), \\ 1 & \text{if } p = 1. \end{cases} \tag{6}$$

The parameters c_i and s_i in (6) are estimated jointly with the utility curvature parameter γ_i in (5) using non-linear least squares. Columns 3 and 4 of Table 1 report descriptive statistics for these estimates.[8] The results corroborate the earlier finding that respondents display both likelihood insensitivity and pessimism. The fact that $\hat{s}_i < 1$ on average indicates insensitivity to changes in probabilities, while the condition $1 - \hat{c}_i + \hat{s}_i > 0$ implies pessimistic probability weighting, with unfavorable outcomes receiving greater weight than favorable

[8]No winsorization is applied to these parameters. When winsorization is applied to the estimated values of c_i, which is the analog of the parameter β_i in Prelec (1998)'s weighting function, its resulting mean is 0.0261 and its standard deviation is 0.067, which are very close to the mean and standard deviation reported in Table 1. This suggests that the results are not driven by outliers.

Table 3: The Relationship between Prelec (1998)'s Probability Weighting Function and Income or Wealth

Variable y_i	(1) Financial Wealth	(2) Financial Wealth	(3) Return Stock	(4) Return Stock	(5) Family Income	(6) Family Income	(7) Housing Wealth	(8) Housing Wealth
Inverse-S	-1.543***	-1.301***	-1.675***	-1.283***	-0.255***	-0.186***	-0.278	-0.192
	(0.362)	(0.324)	(0.394)	(0.371)	(0.060)	(0.055)	(0.193)	(0.170)
Optimism/Pessimism	-0.005	-0.060	-0.029	-0.096	-0.001	-0.009	0.010	-0.028
	(0.092)	(0.084)	(0.101)	(0.097)	(0.016)	(0.015)	(0.049)	(0.044)
Utility Curvature	0.014**	0.013**	0.015**	0.013**	0.001	0.001	0.005	0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.003)	(0.003)
Constant	5.899***	2.178*	4.234***	-3.335***	10.828***	9.837***	3.288***	-3.187***
	(0.238)	(1.320)	(0.253)	(1.262)	(0.041)	(0.247)	(0.126)	(0.743)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
R^2	0.014	0.216	0.012	0.129	0.008	0.153	0.002	0.233
N	1902	1901	2245	2244	2629	2628	1921	1920

This table presents OLS estimates of the model $\ln(y_i + 1) = b_0 + b_1$Inverse-S$_i$ $+ b_2$ Opt./Pess.$_i$ $+ b_3$U.curv$_i$+Controls$_i'\Gamma + \varepsilon_i$. The variable y_i captures the respondent's i self-reported income and wealth. It can be one of the following variables: "Financial Wealth", "Return Stock", "Family Income", or "Housing Wealth". "Inverse-S" is the respondent i's index of likelihood insensitivity obtained from an estimation of Prelec (1998)'s probability weighting function. "Opt./pess." is the respondent's i's index of optimism and pessimism obtained from an estimation of Prelec (1998)'s probability weighting function. "U.curv" is the respondent i's curvature of the utility function obtained from an estimation of a CRRA utility. Robust standard errors are presented in parentheses. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

ones.

Following Wakker (2010) and Abdellaoui et al. (2011), I use the individual-specific parameter estimates from (6) to construct indexes of likelihood insensitivity and pessimism, which are then employed as explanatory variables in regressions where measures of income and wealth serve as the dependent variables. The results, reported in Table 8 in Appendix E, corroborate the central finding that likelihood insensitivity is significantly associated with lower financial wealth, lower returns on stocks, and lower family income, whereas the effect of pessimism is less robust and often statistically insignificant.

Overall, the empirical evidence is consistent with the predictions of the model. However, it is important to emphasize that this analysis is correlational and does not establish causality. The observed relationships could also reflect an alternative mechanism: individuals may fall into poverty because they exhibit sufficiently strong probability weighting, regardless of their initial wealth. This interpretation contrasts with the model's central conjecture, which posits that poverty itself amplifies the effects of probability weighting, making individuals more prone to underinvestment and thereby reinforcing their low-wealth status. The next section provides causal evidence to more directly test this prediction.

4. Experimental Evidence of the Behavioral Poverty Trap

In this section, I use the data from Carvalho et al. (2016) to provide a causal test of the model's predictions. Their study conducted experiments with two panels of representative U.S. households to examine how financial resources shape economic decision-making. In each experiment, respondents were randomly assigned to one of two groups, with each group completing an incentivized survey either shortly before or shortly after monthly payday. The survey elicited risk and time preferences and included a set of questions designed to measure decision-making quality.

The elicitation of risk preferences in Carvalho et al. (2016) does not allow for a clean separation of participants' probability-weighting and utility functions. However, I recover these preference components using the set of questions originally designed to assess decision-making quality. These items were administered only to participants in the GfK KnowledgePanel; accordingly, the empirical analysis in this section focuses on that sample.

Carvalho et al. (2016) measure decision-making quality using the method developed by Choi et al. (2007). In this method, participants are asked to choose the fraction of their endowment to invest in good x_1, with the remaining fraction automatically allocated to good x_2. Respondents are informed that with probability 0.5 only the payoff from x_1 is realized, and with the complement probability, i.e. 0.5, only the payoff from x_2 is realized. The survey includes 25 such investment problems, which vary both the size of the endowment available to participants and the relative price of investing in one good versus the other.

Participants' risk preferences were recovered using the Money Metric Index (MMI) method of Halevy et al. (2018). The key advantage of this method is its ability to identify probability-weighting and utility functions *conditional on a given level of decision-making quality*. This is possible because the MMI exploits a theoretical result that cleanly separates two components of observed behavior: (i) the consistency of choices with the maximization of a nonsatiated utility function, i.e. the criterion used by Carvalho et al. (2016) to measure decision-making quality, and (ii) *misspecification*, which captures the extent to which the assumed parametric forms provide a good fit to the data. This separation is particularly valuable for our purposes, as it allows us to abstract from variation in decision-making quality and focus directly on the estimated risk-preference parameters.

In line with the theoretical model, a participant i in the experiment makes choices in each investment problem by maximizing the following utility functional:

$$RDU_i = w_i(0.5) \cdot u_i\big(\max\{x_1, x_2\}\big) + (1 - w_i(0.5)) \cdot u_i\big(\min\{x_1, x_2\}\big), \tag{7}$$

where the probability weight assigned to the favorable outcome, $w_i(0.5)$, is specified as:

$$w_i(0.5) = \frac{1}{2 + \beta_i}, \text{ with } \beta_i > -1. \tag{8}$$

The parameter β_i governs the direction and magnitude of the probability distortion. When $\beta_i > 0$, the probability assigned to the favorable outcome, $\max\{x_1, x_2\}$, is underweighted, causing the decision maker to invest less in the higher-payoff asset than an EU decision maker with the same utility curvature would. Conversely, when $\beta_i < 0$ the probability of the favorable outcome is overweighted, leading to overinvestment in this asset relative to the EU benchmark. Finally, when $\beta_i = 0$ the individual evaluates probabilities objectively and behaves in accordance with EU.

The function in (8) corresponds to the probability transformation of Gul (1991) evaluated at $p = 0.5$. This specification is widely used in the decision-making-quality literature (Choi et al., 2007, Halevy et al., 2018) because the parameter β captures the *certainty effect*, a relevant deviation from expected utility that is frequently observed in these budgetary environments. Beyond its prevalence in the literature, this parametric form of probability weighting is adopted for three reasons. First, for binary lotteries, the Gul (1991)'s Disappointment Aversion model and Rank-Dependent Utility coincide, making this representation an appropriate reduced-form representation of RDU preferences. Second, it ensures consistency with Halevy et al. (2018), who developed the MMI method and employ the same functional form in an identical budgetary environment. Third, the experimental design in Carvalho et al. (2016) elicits choices only at a single probability value ($p = 0.5$) making it impossible to identify richer two-parameter weighting functions such as those of Prelec (1998)'s or Chateauneuf et al. (2007)'s forms. As a consequence, a single-point index such as (8) is the only empirically identifiable measure of probability weighting in this setting. In what follows, and wherever necessary, I relate the empirical implications of β to the parametric weighting functions used in the previous section.

Consistent with the empirical analysis of Section 3, I also assume that the participant's consumption utility function belongs to the CRRA family:

$$u_i(z) = \begin{cases} \frac{z^{1-\gamma_i}}{1-\gamma_i} & \text{if } \gamma_i \geq 0 \text{ and } \gamma_i \neq 1, \\ \ln(z) & \text{if } \gamma_i \geq 0 \text{ and } \gamma_i = 1. \end{cases} \tag{9}$$

The parameter γ_i captures risk aversion due to utility curvature. I apply the MMI method to estimate the parameters β_i and γ_i for each respondent. As a robustness check, I also estimate an alternative specification in which consumption utility belongs to the CARA family. In this case, utility is parametrized as

$u_i(z) = -\exp\big(-A_i z\big)$ with $A_i \geq 0$.The MMI method is again used to estimate the parameters β_i and A_i.

Table 4 reports descriptive statistics for the estimates $\hat{\gamma}_i$, $\hat{\beta}_i$, and $\hat{A}_i$.[9] The average estimate of $\hat{\beta}_i$ is equal to 0.393, implying that respondents evaluated the probability 0.5 to be on average equal to 0.417. Under the Prelec (1998) one-parameter specification, $w(p) = \exp(-(-\ln(p)^{\alpha})$, this extent of probability underweighting corresponds to $\alpha = 0.37$, indicating substantial likelihood insensitivity.[10] Similarly, under the neo-additive function $w(p) = sp$ (when $c = 0$) the same underweighting arises when the insensitivity parameter is equal to $s = 0.834$.[11] A comparable pattern emerges when the utility function is assumed to follow a CARA specification: the probability of the favorable outcome is estimated to be equal to 0.390. Hence, subjects on average underweighted the probability of the best outcome. This finding implies that, relative to EU decision-makers with the same utility curvature, participants on average underinvested in the higher-payoff asset; due to probability weighting they systematically chose portfolios that invest less in the most favorable outcome.

The theoretical framework developed in this paper predicts that poverty amplifies the underinvestment induced by probability weighting. In the experimental setting considered here, such underinvestment manifests as choosing portfolios that invest less in the higher-payoff asset than an EU decision maker with the same utility curvature would. To assess this prediction empirically, I classify each respondent as either an RDU- or EU-maximizer based on the estimated value of the parameter $\hat{\beta}_i$. Specifically, respondent i is classified as an EU type if the null hypothesis $\hat{\beta}_i = 0$ cannot be rejected; otherwise, the respondent is classified as RDU. Following Halevy et al. (2018), this test is implemented by constructing a 95% confidence interval for $\hat{\beta}_i$ using a bootstrap resampling procedure.[12] Notably, because the estimated parameter $\hat{\beta}_i$ is positive for the majority of respondents, classification as RDU almost always corresponds to underin-

[9]The variable $\hat{\gamma}_i$ has been winsorized, since it originally included a maximum value of 331, which lacks clear empirical interpretation, and exhibited a variance of 528, indicating excessive variability in the data.

[10]Instead, if $\alpha = 1$, then Prelec (1998)'s weighting function reduces $w(p) = p^{\beta}$, in this case, the observed underweighting of $p = 0.5$ is matched when $\beta = 1.26$, corresponding to pessimistic probability weighting.

[11]Conversely, setting $s = 1$, the neo-additive probability weighting function becomes $w = c + p$, and this underweighting behavior can be obtained when $c = -0.083$.

[12]In particular, 1,000 bootstrap resamples of each individual dataset are generated to construct these confidence intervals.

Table 4: Risk preference estimates obtained from the MMI method

	CRRA utility		CARA utility	
	$\hat{\beta}_i$	$\hat{\gamma}_i$	$\hat{\beta}_i$	$\hat{A}_i$
Mean	0.393	0.515	0.566	0.501
25th perc.	0.102	0.265	0.164	0.023
50th. perc.	0.238	0.399	0.341	0.037
75th. perc.	0.526	0.817	0.703	0.067
St. Dev.	0.608	0.327	0.709	2.37

This table presents the descriptive statistics for estimates of probability weighting and utility curvature obtained for each participant using the MMI method (Halevy et al., 2018). The first two columns present estimates obtained when utility is assumed to belong to the CRRA family, i.e. $u_i(z) = \begin{cases} \frac{z^{1-\gamma_i}}{1-\gamma_i} & \text{if } \gamma_i \geq 0 \text{ and } \gamma_i \neq 1, \\ \ln(z) & \text{if } \gamma_i \geq 0 \text{ and } \gamma_i = 1. \end{cases}$ Columns 3 and 4 present estimates obtained when utility is assumed to belong to the CARA family, i.e. $u(z) = -\exp\big(-Az\big)$, where $A \geq 0$. Probability weighting is assumed to follow the parametric form $\omega_i = \frac{1}{2+\beta_i}$ with $\beta_i > -1$.

vestment relative to the expected-utility benchmark. Accordingly, throughout the empirical analysis, deviations from EU predominantly reflect underinvestment.

The results indicate that 622 respondents out of 1131 (55% of the sample) are RDU, while 509 are classified as EU. Similarly, when a CARA utility function is assumed, 682 respondents are classified as RDU (60% of the sample) and 449 as EU.[13] Importantly, among respondents classified as RDU, 555 exhibit a positive and statistically significant estimate of $\hat{\beta}_i$, implying underinvestment in the higher-payoff asset, whereas only 67 respondents (5.9% of the sample) exhibit a negative and statistically significant $\hat{\beta}_i$. Thus, in this setting, classification as RDU overwhelmingly corresponds to underinvestment relative to the EU benchmark.

The first analysis of these data relates respondents' economic circumstances to their classification of risk preference (RDU versus EU). Specifically, I examine whether, as predicted by the model, individuals classified as RDU, and thus who underinvest in the experiment, experience in worse economic conditions than those classified as EU. In turn, economic conditions are measured by in-

[13]The probability $p = 0.5$ is typically not subject to strong perceptual distortion (Abdellaoui, 2000). Therefore, the finding that between 55% and 60% of the sample distort this probability indicates a relatively high incidence of probability weighting.

dicators for having below-median expenditures, below-median cash holdings, and below-median checking and savings balances. The focus on these variables follows from Carvalho et al. (2016) who used these variables to capture financial circumstances and their relationship to being assigned to the treatment or control.[14]

The regression estimates reported in Table 5 indicate that individuals facing worse economic conditions are more likely to be classified as RDU. In particular, individuals with below-median expenditures and below-median checking and savings balances are 8.9% and 7.4%, respectively, more likely to exhibit significant probability weighting that leads to underinvestment in the higher-payoff asset relative to the EU benchmark. Additionally, the estimated relationship between below-median cash holdings and RDU classification is positive but not statistically significant.

The robustness checks reported in Table 12 in Appendix E show that these conclusions remain robust when the sample is restricted to respondents who reported being in difficult economic circumstances. In that analysis, one of the examined subgroups includes individuals reporting living "check to check", while another—partially overlapping—subgroup reports experiencing a caloric crunch. Taken together, these results reinforce the findings of the previous section: probability weighting is more pronounced among individuals in poorer economic circumstances. Moreover, these data provide novel insight by showing that such biased evaluations of risk translate into underinvestment, consistent with the poverty-trap mechanism proposed in the theoretical model.

I now turn to the second part of the analysis, which examines whether the model's predictions can be causally validated. Specifically, I test whether respondents assigned to the treatment group—those surveyed before payday—are more likely to make investment decisions that deviate from EU. To assess this, I regress the risk-preference classification (RDU vs. EU) on a treatment indicator labeled "Before Payday." All specifications control for utility curvature, captured by the individual estimate $\hat{\gamma}_i$ in the case of CRRA utility. Moreover, in additional specifications, I further account for individual heterogeneity by including controls for decision-making quality, measured by Varian's Index (Varian, 1982); cognitive ability, proxied by the Stroop test; and demographic char-

[14]In addition, the focus on median-based indicators follows Carvalho et al. (2016), who find stronger relationships between financial circumstances and the payday treatment when outcomes are measured relative to the median.

Table 5: The Effects of Economic Circumstances on the Probability of Deviating from Expected Utility

	(1) RDU	(2) RDU	(3) RDU	(4) RDU	(5) RDU	(6) RDU
Low Expenditures	0.226***	0.227***				
	(0.065)	(0.079)				
Low Cash Holdings			0.074	0.093		
			(0.081)	(0.081)		
Low Checkings Balance					0.201**	0.201**
					(0.097)	(0.098)
$\hat{\gamma}_i$	-0.864***	-0.891***	-0.855***	-0.884***	-0.867***	-0.898***
	(0.140)	(0.131)	(0.141)	(0.132)	(0.139)	(0.133)
Varian Index	-5.748***	-5.681***	-5.815***	-5.736***	-5.788***	-5.732***
	(0.888)	(1.033)	(0.892)	(1.037)	(0.888)	(1.041)
Accuracy Stroop test		0.063*		0.063*		0.060*
		(0.036)		(0.036)		(0.035)
Constant	0.736***	0.364	0.815***	0.451	0.703***	0.363
	(0.117)	(0.385)	(0.116)	(0.375)	(0.139)	(0.369)
Controls	NO	YES	NO	YES	NO	YES
Log-likelihood	-745.229	-715.168	-749.189	-718.526	-746.839	-716.563
N	1131	1114	1131	1114	1131	1114

This table presents probit estimates of the model $\text{RDU}_i = b_0 + b_1\text{Low Financial Circumstances}_i + b_2\hat{\gamma}_i + b_3\text{Before Payday}\times\hat{\gamma}_i + \text{Controls}_i'\Gamma + \varepsilon_i$. The dependent variable "RDU$_i$" is a binary variable that takes a value 1 if respondent i's preferences are classified as Rank-Dependent Utility and 0 otherwise. In Columns (1) and (2) the variable "Low Expenditures" is a binary variable that takes a value of 1 if respondent i has lower than median expenditures in the past 7 days and 0 otherwise. In Columns (3) and (4) the variable "Low Cash Holdings" is a binary variable that takes a value of 1 if respondent i has lower than median cash holdings and 0 otherwise. In Columns (5) and (6) the variable "Low Checking Balance" is a binary variable that takes a value of 1 if respondent i has lower than median checking and savings balances and 0 otherwise. The variable $\hat{\gamma}_i$ captures subject's i utility curvature. "Varian Index" captures the extent to which participant's i responses are consistent with the maximization of a non-satiated utility function. Accuracy Stroop Test captures the performance of respondent i on the Stroop test. Bootstrapped standard errors with 100 repetitions in parentheses. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

acteristics, including ethnicity, age, education, gender, employment status, and state of residence. Because the dependent variable (RDU) is constructed from estimated parameters and thus incorporates additional sampling variation, all regressions use bootstrapped standard errors.

Table 6 reports the regression estimates. The results in columns (1), (3) and (5) indicate that the treatment—being surveyed before payday—does not significantly increase the likelihood of being classified as RDU. This conclusion remains unchanged after the inclusion of control variables. The absence of a statistically significant effect is consistent with the findings of Carvalho et al. (2016), who document that temporary financial strain does not directly alter risk attitudes. I extend their result by showing that such short-term fluctuations in financial resources also do not affect adherence to EU. A plausible interpretation is that the influence of poverty on probability weighting is more likely to manifest under sustained and more meaningful forms of economic scarcity, rather than through transient shifts in financial resources.

Recall that the strength of the behavioral poverty trap predicted by the model crucially depends on utility curvature (see Assumption 3 and Corollary 1). I incorporate this interplay in the empirical analysis by including an interaction term between the variable Before Payday and the estimated utility curvature coefficient $\hat{\gamma}_i$. The corresponding estimates appear in columns (2), (4), and (6) of Table 6. The coefficient on the interaction term Before Payday $\times\hat{\gamma}_i$ indicates that being financially constrained, combined with greater concavity of the utility function, increases the likelihood that investment decisions deviate from the EU benchmark. This conclusion is illustrated in Figure 4, which plots the average treatment effect across different values of $\hat{\gamma}$. Furthermore, Table 14 and Figure 6 in Appendix E demonstrate that these findings are robust when assuming a CARA specification for consumption utility.

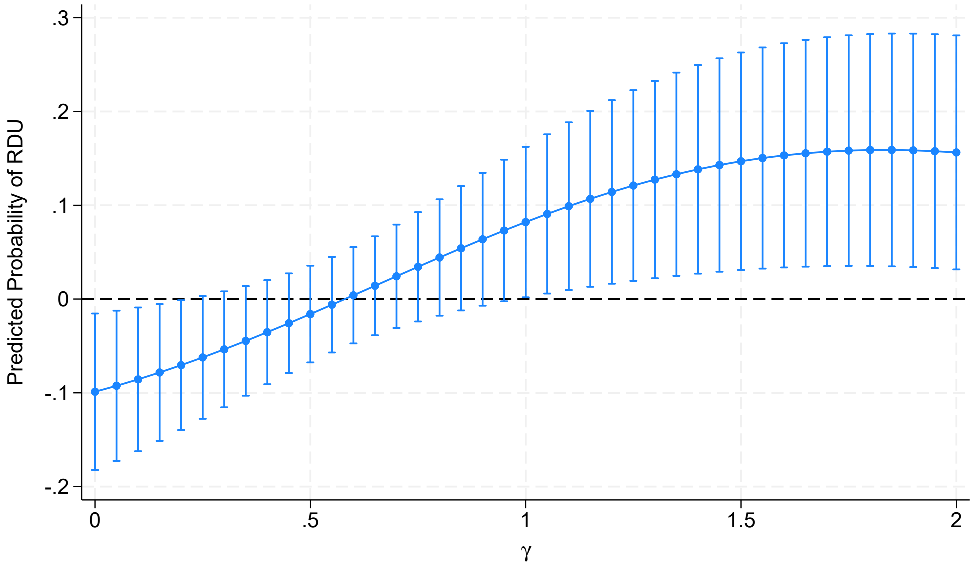
This result is consistent with Corollary 1, which predicts that financial constraints are more likely to induce underinvestment relative to the EU benchmark as utility curvature increases. Individuals who experience a steep disutility from reduced immediate consumption face a high utility cost of investing, making probability-weighting distortions more consequential for investment evaluation. Financial constraints before payday further increase the relevance of these distortions by making investment even less profitable. By contrast, when utility curvature is moderate, the utility cost of reduced immediate con-

Table 6: The Effects of Payday on the Probability of Deviating from Expected Utility

	(1) RDU	(2) RDU	(3) RDU	(4) RDU	(5) RDU	(6) RDU
Before Payday	-0.026	-0.265**	-0.031	-0.279**	-0.030	-0.315**
	(0.078)	(0.127)	(0.070)	(0.122)	(0.071)	(0.138)
$\hat{\gamma}_i$	-0.385***	-0.626***	-0.878***	-1.131***	-0.882***	-1.172***
	(0.117)	(0.155)	(0.132)	(0.176)	(0.130)	(0.184)
Before Payday$\times\hat{\gamma}_i$		0.460**		0.473**		0.544***
		(0.198)		(0.200)		(0.208)
Varian Index			-5.416***	-5.465***	-5.745***	-5.821***
			(1.003)	(1.010)	(1.025)	(1.035)
Stroop Test Accuracy			0.079***	0.077***	0.063*	0.060*
			(0.029)	(0.029)	(0.036)	(0.035)
Constant	0.338***	0.465***	0.401*	0.552**	0.487	0.648*
	(0.084)	(0.101)	(0.223)	(0.228)	(0.381)	(0.384)
Controls	NO	NO	NO	NO	YES	YES
Log-likelihood	-772.598	-770.595	-734.005	-731.978	-719.144	-716.541
N	1131	1131	1114	1114	1114	1114

This table presents probit estimates of the model $\text{RDU}_i = b_0 + b_1\text{Before Payday}_i + b_2\hat{\gamma}_i + b_3\text{Before Payday}\times\hat{\gamma}_i + \text{Controls}_i'\Gamma + \varepsilon_i$. The dependent variable RDU_i is a binary variable that takes a value of 1 if respondent i is classified to have Rank-dependent utility preferences and 0 otherwise. "Before Payday" is a binary variable that takes a value of 1 if respondent i is assigned to the group that completed the survey before payday and 0 otherwise. The variable $\hat{\gamma}_i$ captures subject's i utility curvature. "Varian Index" captures the extent to which participant's i responses are consistent with the maximization of a non-satiated utility function. Stroop Test Accuracy captures the performance of respondent i on the Stroop test questions. Bootstrapped standard errors with 100 repetitions in parentheses. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Figure 4: Marginal effects of Payday for different levels of γ



Note: Bars represent 95% confidence intervals.

sumption before payday might be insufficient to materially affect investment behavior.

It is important to emphasize that the results in Table 6 and Figure 4 show that the average treatment effect becomes significant only when $\gamma > 1$. At first glance, this finding appears to stand in contrast to commonly imposed upper bounds on utility curvature, such as those used by Dalton et al. (2016), as well as with the bound implied by the final property of Assumption 3 when the wealth function takes the commonly-used form $b(x_0, z) = x_0^{\mu} z^{1-\mu}$, both of which require $\gamma < 1$. However, these curvature bounds are derived under specific functional-form assumptions on the wealth function technology. Alternative production functions can accommodate the empirical finding that $\gamma > 1$. In particular, when the wealth function is both supermodular and non-separable in initial wealth and investment returns, the curvature restriction in Assumption 3 can be satisfied even for values $\gamma > 1$. For example, if $b(x_0, z) = (1+ax_0z)^{\kappa}$ with $\kappa > 1$, then the condition from Assumption 3 becomes:

$$1 + \frac{\kappa a x_0 z}{1 + (\kappa + 1) a x_0 z} \geq \gamma,$$

which is compatible with utility curvature exceeding one.[15] These wealth-production

[15] Another example of a production function that could rationalize these results is a CES pro-

technologies correspond to environments in which wealth accumulation is highly supermodular: higher initial wealth amplifies the marginal returns to investment, and higher returns in turn magnify the benefits of initial wealth. In such settings, inputs are not easily substitutable, and small differences in initial wealth translate into disproportionately large differences in final wealth. Interpreted through this lens, the empirical results suggest that participants perceive the process of wealth accumulation as strongly reinforcing—so that investment in the experiment is especially effective in boosting future wealth for those who are already relatively wealthy.

To conclude this analysis, I comment on the robustness of the interaction between the treatment effect and utility curvature. This relationship is further supported by analyses that restrict the sample to respondents reporting difficult economic circumstances. The estimates presented in Table 13 in Appendix E reveal substantial heterogeneity in treatment effects. Specifically, for some subgroups, the level of utility curvature at which the treatment effect becomes statistically significant is lower than in the full-sample analysis. Figures 5a and 5b illustrate this pattern for respondents reporting annual incomes below \$20,000 and for those receiving income in a single monthly payment, respectively. These findings reinforce the interpretation developed above: the treatment effect is amplified when individuals experience a sharper decline in consumption utility due to the lower wealth experienced before payday. When financial constraints enhance that drop in consumption utility, even moderately strong curvature implies a substantial utility cost of forgoing immediate consumption. Consequently, probability weighting more readily distorts investment decisions, making its adverse effects detectable at lower levels of utility curvature within these financially vulnerable groups.

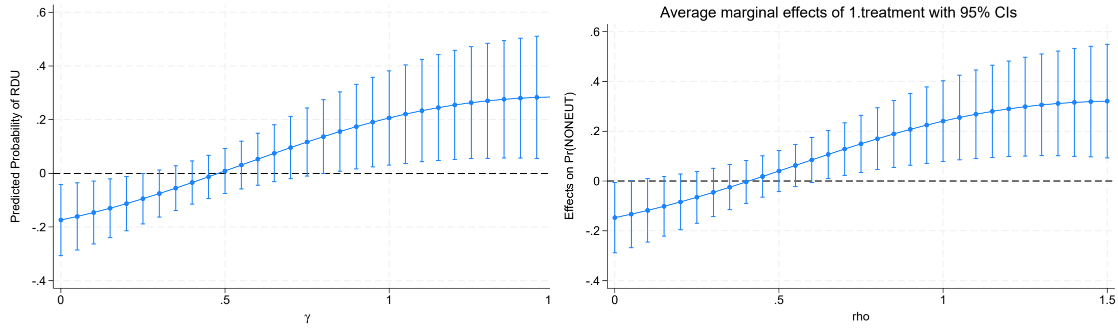
5. Extensions

5.1. Ambiguity Attitudes and Poverty Traps

The theoretical framework developed in Section 2 can be readily extended to incorporate ambiguity attitudes. To do so, a framework in which the probabil-

duction function $b(x_0, z) = \left(x_0^\rho + z^\rho + \phi(x_0 z)^{\frac{\rho}{2}}\right)^{\frac{1}{\rho}}$ where $\rho \in (0, 1)$ and $\phi > 0$. In this case, when ϕ is sufficiently large, the condition from Assumption 3 holds.

Figure 5: Marginal effects of Payday for different levels of γ and Different Subgroups



(a) Subgroup Income less than 20,000 USD (b) Subgroup One Payment per Month

Note: Bars represent 95% confidence intervals.

ities of returns are ambiguous is considered. In such a setting, an individual with ambiguity attitudes may be averse or prone to investing in an ambiguous asset relative to an equally profitable but risky asset (for which probabilities are known).

I model this behavior using Source Theory (Baillon et al., 2025), which posits that under ambiguity, the phenomena of risk are amplified through *additional probability weighting*. For example, ambiguity aversion—manifested as an aversion to invest in the ambiguous asset compared to the risky one—arises when the individual's weighting function used to evaluate the uncertainty generated by the ambiguous asset is more convex than her probability weighting function, i.e. the weighting function used to evaluate the risky asset. This increased convexity of the weighting function makes the individual more pessimistic about favorable outcomes for the ambiguous investment relative to the risky one.

The full analytical treatment of this extension is provided in Appendix C. Because ambiguity attitudes are modeled as additional probability weighting, the poverty trap characterized in Propositions 3 and 5 emerges under weaker conditions. For instance, an individual who is more insensitive to changes in likelihood under ambiguity than under risk due to cognitive limitations, referred to as *a-insensitive* by Baillon et al. (2018), exhibits a higher threshold $\hat{x}_0$ (Proposition 3), making her prone to extreme underinvestment even at relatively high initial wealth levels x_0. As a result, she is more likely to become trapped in the low-wealth steady state described in Proposition 5.

Overall, this extension shows that when a profitable investment is ambiguous, perhaps due to limited familiarity with it or because it involves a technological innovation, the poor are more likely to forgo it, thereby reinforcing their condition.

5.2. Reference Dependence and Poverty Traps

There is ample evidence suggesting that individuals evaluate risky alternatives relative to a reference point (Kahneman and Tversky, 1979, Tversky and Kahneman, 1992, Von Gaudecker et al., 2011, Baillon et al., 2020). This way of evaluating risky alternatives represents a deviation from EU because decision makers display different risk attitudes toward outcomes evaluated as *gains*, i.e. outcomes surpassing the reference point, compared to outcomes evaluated as *losses*, i.e. outcomes that fall short of the reference point. One of the factors driving this difference is loss aversion, the notion that losses result in a greater reduction in utility than the increase in utility from commensurate gains.

I incorporate reference dependence into the model by characterizing individual risk preferences using Cumulative Prospect Theory (Tversky and Kahneman, 1992). For brevity, the full analysis is presented in Appendix D. This extension of the model demonstrates that under reference dependence the extreme underinvestment behavior among the poor (Proposition 3), and thus the behavioral poverty trap from Proposition 5, emerge under similar conditions. The underlying reason for this similarity is that the components of reference dependence, loss aversion and diminishing sensitivity, do not restore the global concavity of the investment problem treated in Section 2, and therefore do not impede poor and biased individuals from forgoing profitable investments.

This model extension demonstrates that loss aversion increases the threshold of initial wealth $\hat{x}_0$ (Proposition 3). As a result, under reference-dependent preferences, even individuals with relatively high initial wealth may become trapped in a low-investment, low-wealth accumulation dynamic. This occurs because the reference point is assumed to coincide with the individual's *status quo* or initial wealth (Terzi et al., 2016, Baillon et al., 2020). Consequently, any investment outcome that yields wealth below this reference point is considered a loss and evaluated with disproportionately high disutility due to loss aversion. This steep penalty in utility discourages investment not only among the poor but also among wealthier individuals, thereby extending the scope of the poverty trap.

6. Conclusion

I developed a novel poverty trap generated by individuals' biased evaluations of objective and ambiguous probabilities. These distortions in the evaluation of uncertainty lead individuals to misjudge returns to investment, causing opportunities that are profitable in expectation to be undervalued. I further demonstrate that these distortions disproportionately affect the poor. As a result, poor individuals are more likely to forgo profitable investments, reinforcing their low economic status.

This poverty trap is empirically validated using two experiments conducted on representative samples of U.S. households. The empirical analyses further show that (i) the cognitive component of probability weighting is systematically related to poverty, whereas the motivational component is not, and (ii) tighter financial constraints—proxied by stronger utility curvature—amplify the underinvestment driven by probability weighting.

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A. Proofs of Theoretical Results

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A.1. Preliminary results and their proofs

Lemma A1. *If agent i is more optimistic than agent j, then $w_i(p) > w_j(p)$ for all $p \in (0,1)$. Alternatively, if agent i is more pessimistic than agent j, then $w_i(p) < w_j(p)$ for all $p \in (0,1)$.*

Proof. According to Definition 1, $w_i(p) = \theta\big(w_j(p)\big)$. Under that equivalence, the following equality holds:

$$\frac{w_i''(p)}{w_i'(p)} = \frac{\theta_i''(p)}{\theta_i'(p)} w_j'(p) + \frac{w_j''(p)}{w_j'(p)}. \tag{A.1}$$

Since $\theta''(p) < 0$, the previous equation implies that

$$\frac{w_i''(p)}{w_i'(p)} < \frac{w_j''(p)}{w_j'(p)}. \tag{A.2}$$

Let $p_0, p_1 \in [0,1]$ such that $p_1 > p_0$. Integrate (A.2) over $[p_0, p_1]$ to obtain:

$$\int_{p_0}^{p_1} \frac{w_i''(s)}{w_i'(s)} \mathrm{d}s < \int_{p_0}^{p_1} \frac{w_j''(s)}{w_j'(s)} \mathrm{d}s \Leftrightarrow \frac{w_j'(p_1)}{w_j'(p_0)} > \frac{w_i'(p_1)}{w_i'(p_0)}. \tag{A.3}$$

Integrating the resulting inequality with respect to $p_0 \in [0, p_1)$ gives

$$\int_0^{p_1} w_i'(p_1) w_j'(s) \mathrm{d}s < \int_0^{p_1} w_j'(p_1) w_i'(s) \mathrm{d}s \Leftrightarrow \frac{w_j'(p_1)}{w_j(p_1)} > \frac{w_i'(p_1)}{w_i(p_1)}. \tag{A.4}$$

Integrating again, but this time with respect to $p_1 \in (p_0, 1]$ leads to

$$\int_{p_0}^{1} \frac{w_j'(s)}{w_j(s)} \mathrm{d}s > \int_{p_0}^{1} \frac{w_i'(s)}{w_i(s)} < \mathrm{d}s \Leftrightarrow w_i(p_0) > w_j(p_0) \text{ for any } p_0 \in (0,1). \tag{A.5}$$

Similar steps lead to the conclusion that when i is more pessimistic than j, then $w_j(p_0) > w_i(p_0)$ for any $p \in (0,1)$.

■

Remark 1

Proof. Using integration by parts, rewrite (2) as:

$$RDU\big(u(z,e)\big) = u\big(x_0(1-e)\big)+u\big(b(x_0,\underline{x})\big)+\int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big)b_z(x_0,z)w_j\big(1-F(z|e)\big)\mathrm{d}z \tag{A.6}$$

Consider an individual j with probability weighting function w_j, and let her suffer from optimism (Definition 1). Similarly, consider an individual i with probability weighting function w_i, and let her be more optimistic than j in the sense of Definition 2. Using (A.6) it can be established that:

$$\begin{aligned} &RDU_i\big(u(z,e)\big) - RDU_j\big(u(z,e)\big) \Leftrightarrow \\ \int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big)b_z(x_0,z)&\Big(w_i\big(1-F(z|e)\big) - w_j\big(1-F(z|e)\big)\Big)\mathrm{d}z. \end{aligned} \tag{A.7}$$

According to Lemma A1, it must be that $w_i(p) > w_j(p)$ for any $p \in (0,1)$. Hence, equation (A.7) implies that $RDU_i\big(u(z,e)\big) > RDU_j\big(u(z,e)\big)$ for given e.

Denote by M_j and M_i the certain and fixed monetary amounts that make i and j, respectively, indifferent between investing a fraction e of their initial wealth and obtaining those monetary amounts. Since $RDU_i\big(u(z,e)\big)-RDU_j\big(u(z,e)\big) > 0$ for all z and a given e, it must be that $M_i > M_j$. Thus, i strictly prefers to invest e and obtain $RDU_i\big(u(z,e)\big)$ over getting M_j, whereas j is indifferent between these two choices. Consequently, i is more risk seeking.

■

Remark 2

Proof. Consider individuals j and i and let them suffer from likelihood insensitivity in the sense of Definition 3. Let i be more likelihood insensitive than j. According to Definition 4, $w_i(p) = \phi\big(w_j(p)\big)$. Under that equivalence, the following inequality holds:

$$\frac{w_i''(p)}{w_i'(p)} = \frac{\phi_i''(p)}{\phi_i'(p)}w_j'(p) + \frac{w_j''(p)}{w_j'(p)}. \tag{A.8}$$

Since $\phi''(p) < 0$ in $p \in (0, 0.5)$, then it must be that in that segment:

$$\frac{w_i''(p)}{w_i'(p)} < \frac{w_j''(p)}{w_j'(p)}. \tag{A.9}$$

Alternatively, if $p \in (0.5, 1)$, then, using similar steps, $\frac{w_i''(p)}{w_i'(p)} > \frac{w_j''(p)}{w_j'(p)}$.

Let $p_0, p_1 \in [0, 0.5]$ such that $p_1 > p_0$. Integrate (A.9) over $[p_0, p_1]$ to obtain:

$$\int_{p_0}^{p_1} \frac{w_i''(s)}{w_i'(s)} \mathrm{d}s < \int_{p_0}^{p_1} \frac{w_j''(s)}{w_j'(s)} \mathrm{d}s \Leftrightarrow \frac{w_j'(p_1)}{w_j'(p_0)} > \frac{w_i'(p_1)}{w_i'(p_0)}. \tag{A.10}$$

Integrating (A.10) with respect to $p_0 \in [0, p_1)$ gives:

$$\int_0^{p_1} w_i'(p_1) w_j'(s) \mathrm{d}s < \int_0^{p_1} w_j'(p_1) w_i'(s) \mathrm{d}s \Leftrightarrow \frac{w_j'(p_1)}{w_j(p_1)} > \frac{w_i'(p_1)}{w_i(p_1)}. \tag{A.11}$$

Integrate now (A.11) but this time with respect to $p_1 \in [p_0, 1]$ gives:

$$\int_{p_0}^{1} \frac{w_j'(s)}{w_j(s)} \mathrm{d}s > \int_{p_0}^{1} \frac{w_i'(s)}{w_i'(s)} \mathrm{d}s \Leftrightarrow w_i(p_0) > w_j(p_0) \text{ for any } p_0 \in (0, 0.5) \tag{A.12}$$

Following similar steps it is possible to arrive to $w_i(p_0) < w_j(p_0)$ for any $p_0 \in (0.5, 1)$.

■

Lemma A2. *Fix x_0. There exists a degree of optimism and likelihood insensitivity such that the objective in (2) is not concave in e, and the solution lies at the boundary of $[0, 1]$. An individual whose probability weighting function is more optimistic or likelihood-insensitive than this threshold, in the sense of Definitions 2 and 4, also exhibits a non-concave objective.*

Proof. Fix x_0 and let

$$V(e) := u\big(x_0(1-e)\big) + \delta \int_{\underline{x}}^{\bar{x}} u\big(b(x_0, z)\big) d\Big(w\big(1 - F(z|e)\big)\Big),$$

Differentiate $V(e)$ twice with respect to e to obtain:

$$V''(e) = x_0^2 u''\big(x_0(1-e)\big) + \delta \int_{\underline{x}}^{\bar{x}} u\big(b(x_0, z)\big) \Big[w''\big(1 - F(z \mid e)\big)\big(F_e(z \mid e)\big)^2 - w'\big(1 - F(z \mid e)\big) F_{ee}(z \mid e)\Big] dz. \tag{A.13}$$

By Assumption 3, $u'' < 0$; by Assumption 1, $F_e(z \mid e) < 0$ and $F_{ee}(z \mid e) \geq 0$; by Assumption 4, $w'(p) > 0$ for all $p \in (0, 1)$; and $u(b(x_0, z)) \geq 0$ for all z.

(i) Concavity for a baseline weighting function. Consider first a weighting function w_0 satisfying Assumption 4 and $w_0''(p) < 0$ for all $p \in (0, 1)$, that is, w_0

is concave on $[0,1]$. Substituting w_0 for w in (A.13) gives:

$$
\begin{aligned}
V''(e;w_0) =& x_0^2 u''\big(x_0(1-e)\big) \\
&+ \delta \int_{\underline{x}}^{\bar{x}} u\big(b(x_0,z)\big)\Big[w_0''\big(1-F(z|e)\big)\big(F_e(z|e)\big)^2 - w_0'\big(1-F(z|e)\big)F_{ee}(z|e)\Big]\,dz.
\end{aligned} \tag{A.14}
$$

Notice that each term in the integral is non-positive. Since $w_0''(1-F(z|e)) \leq 0$ and $\big(F_e(z|e)\big)^2 > 0$, the first term is such that:

$$u\big(b(x_0,z)\big)\, w_0''\big(1-F(z|e)\big)\big(F_e(z|e)\big)^2 \;\leq\; 0.$$

Moreover, $w_0'(1-F(z|e)) > 0$ and $F_{ee}(z|e) \geq 0$ imply that the second term exhibits:

$$-u\big(b(x_0,z)\big)\, w_0'\big(1-F(z|e)\big)F_{ee}(z|e) \;\leq\; 0.$$

Thus the integral in (A.13) is non-positive, and the first term $x_0^2 u''(x_0(1-e))$ is strictly negative. Hence

$$V''(e;w_0) < 0 \quad \text{for all } e \in [0,1],$$

and $V(\cdot;w_0)$ is strictly concave on $[0,1]$.

(ii) Loss of concavity under a sufficiently curved weighting function. Consider now another weighting function w_1 satisfying Assumption 4 such that

- $w_1''(p) > w_0''(p)$ for all p in some interval $I \subset (0,1)$, and
- $w_1' - w_0'$ is bounded on $[0,1]$.

In particular, we may take w_1 so that $w_1''(p)$ is strictly positive and arbitrarily large on I, while keeping w_1' strictly positive and finite.

For each $\theta \in [0,1]$, define the convex combination:

$$w_\theta := (1-\theta)w_0 + \theta w_1.$$

Each w_θ satisfies Assumption 4, and because (A.13) is linear in w' and w'', we have:

$$V''(e;w_\theta) = (1-\theta)V''(e;w_0) + \theta V''(e;w_1).$$

Let us rewrite the equation above as:

$$V''(e;w_\theta) = A(e) + \theta B(e),$$

where

$$
\begin{aligned}
A(e) &:= V''(e;w_0) \\
&= x_0^2 u''(x_0(1-e)) + \delta \int_{\underline{x}}^{\bar{x}} u\big(b(x_0,z)\big)\Big[w_0''\big(1-F(z|e)\big)\big(F_e(z|e)\big)^2 - w_0'\big(1-F(z|e)\big)F_{ee}(z|e)\Big]dz,
\end{aligned}
$$

$$
\begin{aligned}
B(e) := \delta \int_{\underline{x}}^{\bar{x}} u\big(b(x_0,z)\big)\Big\{&\big[w_1''\big(1-F(z|e)\big) - w_0''\big(1-F(z|e)\big)\big]\big(F_e(z|e)\big)^2 \\
&- \big[w_1'\big(1-F(z\mid e)\big) - w_0'\big(1-F(z\mid e)\big)\big]F_{ee}(z\mid e)\Big\}dz.
\end{aligned}
$$

From part (i), $A(e) = V''(e;w_0) < 0$ for all e. Moreover, because $F(\cdot \mid e)$ has full support on $(\underline{x},\bar{x})$ by Assumption 1, there exists $e_0 \in (0,1)$ and a measurable set $S \subset (\underline{x},\bar{x})$ of positive measure such that $1-F(z|e_0) \in I$ for all $z \in S$. On this set S, we have $w_1''(1-F(z\mid e_0)) - w_0''(1-F(z\mid e_0)) > 0$ by construction. Since $u(b(x_0,z)) \geq 0$ and $(F_e(z|e_0))^2 > 0$, the contribution of the first term in the integrand of $B(e_0)$ over S,

$$
\int_S u\big(b(x_0,z)\big)\,\big[w_1''(1-F(z\mid e_0)) - w_0''(1-F(z\mid e_0))\big]\big(F_e(z\mid e_0)\big)^2\,dz,
$$

is strictly positive. The remaining part of the integrand, involving the differences $w_1' - w_0'$, is finite and bounded by assumption.

Thus, by choosing w_1 sufficiently curved on I (that is, making $w_1'' - w_0''$ sufficiently large on I while keeping $w_1' - w_0'$ bounded), we can ensure that the positive contribution from the $w_1'' - w_0''$ term dominates the bounded contribution from the $w_1' - w_0'$ term, yielding

$$
B(e_0) > 0.
$$

At e_0, we therefore have $A(e_0) < 0$ and $B(e_0) > 0$. Since $V''(e_0;w_\theta) = A(e_0) + \theta B(e_0)$ is affine (and hence continuous) in θ, there exists a unique $\theta^* := -\frac{A(e_0)}{B(e_0)} \in (0,1)$ such that $V''(e_0;w_{\theta^*}) = 0$ and $V''(e_0;w_\theta) > 0$ for all $\theta > \theta^*$. Hence, for sufficiently large θ (that is, when the weighting function w_θ is sufficiently curved relative to w_0), the objective $V(\cdot;w_\theta)$ fails to be concave in e.

Since $V(\cdot;w_\theta)$ is twice continuously differentiable on the compact interval $[0,1]$ and satisfies $V''(e_0;w_\theta) > 0$ for some $e_0 \in (0,1)$, the objective is not concave in e. Consequently, the first-order condition is not sufficient for global optimality, and the maximization problem need not admit an interior solution.

In particular, whenever $V'(\cdot; w_\theta)$ does not vanish at an interior point, the global maximizer of $V(\cdot; w_\theta)$ over $[0, 1]$ lies at one of the boundaries $e \in \{0, 1\}$.

Finally, let w be any probability weighting function that is more optimistic or likelihood-insensitive than w_{θ^*} in the sense of Definitions 2 and 4. Such a weighting function exhibits weakly greater curvature than w_{θ^*} on a set of probabilities of positive measure. Since the expression for $V''(e)$ in (A.13) is monotone in w'', it follows that $V''(e) > 0$ at some interior e for all such w. Hence, for any weighting function more optimistic or likelihood-insensitive than w_{θ^*}, the objective is non-concave in e, and the optimal choice of e generically lies at the boundary of $[0, 1]$. ■

A.2. Proofs of Main Theoretical Results

Lemma 1

Proof. Consider individual j with probability weighting function w_j and let this individual suffer from optimism in the sense of Definition 1. Due to the continuity of $w_j(p)$ for all p, and since $\lim_{p\to 0^+} w_j'(p) > 1$ and $\lim_{p\to 1^-} w_j'(p) < 1$ (Assumption 4), there must exist a probability $p_k \in (0,1)$ such that $w_j'(p_k) = 1$. Hence, $w_j'(p) > 1$ if $p < p_k$ and $w_j'(p) < 1$ if $p > p_k$.

Let individual i with probability weighting function w_i exhibit stronger optimism than j (Definition 2). As in the case of w_j, there must exist a $p_l \in (0,1)$ such that $w_i'(p) > 1$ if $p < p_l$ and $w_i'(p) < 1$ if $p < p_l$. Moreover, according to Lemma A1 $w_i(p) > w_j(p)$ for all $p \in (0,1)$. Thus, the second equivalence in (A.4) when evaluated at p_k implies:

$$w_i'(p_k) < 1 = w_j'(p_k). \tag{A.15}$$

We now proceed by contradiction. Suppose that $p_l \geq p_k$, then $w_i'(p_l) = 1 \leq w_i'(p_k)$ which contradicts the inequality in (A.15). Hence, it must be that $p_k > p_l$. The set $p > p_l$, that induces $w_i'(p) < 1$, is larger than the set $p > p_k$. Under pessimism, i.e. when i is more pessimistic than j, the arguments of the proof can be mirrored to obtain the result that the set $p < p_l$ is larger than the set $p < p_k$. ■

Proposition 1

Proof. Fix x_0. Using integration by parts, the expected utility in (1) can be rewritten as:

$$\mathbb{E}\big(u(z,e)\big) = u\big(x_0(1-e)\big) + u\big(b(x_0,\underline{x})\big) - \int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big) b_z(x_0,z) F(z|e)\mathrm{d}z. \tag{A.16}$$

Denote by e_u^* the investment level that satisfies the first-order condition obtained by differentiating (A.16) with respect to e:

$$-u'\big(x_0(1-e_u^*)\big)x_0 - \int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big) b_z(x_0,z) F_e(z|e_u^*)\mathrm{d}z = 0. \tag{A.17}$$

Step 1 (Existence and interiority). Differentiating (A.16) again with respect to

e yields

$$u''\big(x_0(1-e_u^*)\big)x_0^2 - \int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big)b_z(x_0,z)F_{ee}(z|e_u^*)\mathrm{d}z. \tag{A.18}$$

Because $b_z(x_0, z) \geq 0$ (Assumption 2), $u' \geq 0$ and $u'' < 0$ (Assumption 3), and $F_{ee}(z \mid e) > 0$ (Assumption 1), the expression in (A.18) is strictly negative. Thus $\mathbb{E}[u(z, e)]$ is strictly concave in e, implying that e_u^* is unique and interior to $[0, 1]$. Existence of e_u^* follows from concavity of $\mathbb{E}[u(z, e)]$, compactness of the choice set, and continuity of u, b, and F.

Step 2 (Comparative statics in x_0). Differentiating the first-order condition (A.17) with respect to x_0 and applying the implicit function theorem gives:

$$\frac{\mathrm{d}e_u^*}{\mathrm{d}x_0} = -\frac{u''\Big(x_0(1-e_u^*)\Big)x_0\Big(1-e_u^*\Big)-\int_{\underline{x}}^{\bar{x}}\Big(u''\Big(b(x_0,z)\Big)b_z(x_0,z)b_{x_0}(x_0,z)+u'\Big(b(x_0,z)\Big)b_{zx_0}(x_0,z)\Big)F_e(z|e_u^*)\mathrm{d}z}{u''\Big(x_0(1-e_u^*)\Big)x_0^2-\int_{\underline{x}}^{\bar{x}}u'\Big(b(x_0,z)\Big)b_z(x_0,z)F_{ee}(z|e_u^*)\mathrm{d}z}. \tag{A.19}$$

According to equation (A.18), the denominator of the right-hand side of (A.19) is negative. Moreover, the numerator in that equation shows that if

$$\int_{\underline{x}}^{\bar{x}} u''\big(b(x_0,z)\big)b_z(x_0,z)b_{x_0}(x_0,z) + u'\big(b(x_0,z)\big)b_{z,x_0}(x_0,z)\mathrm{d}z > 0, \tag{A.20}$$

then $\frac{de_u^*}{dx_0} > 0$: the optimal investment level increases with initial wealth. In turn, the condition in (A.20) holds when

$$-\frac{u''\big(b(x_0,z)\big)}{u'\big(b(x_0,z)\big)} < \frac{b_{z,x_0}(x_0,z)}{b_z(x_0,z)\,b_{x_0}(x_0,z)} \quad \forall z, x_0,$$

which is implied by Assumption 3. ∎

Proposition 2

Proof. Fix x_0. Consider an RDU individual j with probability weighting function w_j and let this individual suffer from pessimism in the sense of Definition 1.

Step 1 (Optimal Level of Investment). Denote by e_r^* the optimal level of investment. According to Lemma A2, e_r^* is unique and interior, and satisfies the following first-order condition (obtained from deriving (A.6) with respect to e):

$$-u'((1-e_r^*)x_0)x_0+\int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big)b_z(x_0,z)w_j'\big(1-F(z|e_r^*)\big)F_e(z|e_r^*)\mathrm{d}z=0. \quad \text{(A.21)}$$

Under expected utility (EU), the corresponding optimal investment e_u^* satisfies (A.16).

Step 2 (e_r^* is lower than e_u^*). We proceed by contradiction. Suppose that the pessimistic RDU individual chooses at least as much as the EU individual: $e_r^* \geq e_u^*$ for all z. Using (A.16) and (A.21), this assumption can be expressed as:

$$\begin{aligned} -\int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big)b_x(x_0,z)w_j'\big(1-F(z|e_r^*)\big)F_e(z|e_r^*)\Big)\mathrm{d}z \geq \\ -\int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big)b_z(x_0,z)\Big(F_e(z|e_u^*)\Big)\mathrm{d}z. \end{aligned} \quad \text{(A.22)}$$

Since $u' > 0$ and $b_z > 0$, the inequality (A.22) can hold only if

$$-\int_{\underline{x}}^{\bar{x}} w_j'\big(1-F(z|e_r^*)\big)F_e(z|e_r^*)\mathrm{d}z \geq -\int_{\underline{x}}^{\bar{x}} F_e(z|e_u^*)\mathrm{d}z. \quad \text{(A.23)}$$

Assumption 1 implies $F_{ee}(z \mid e) > 0$, so the assumption $e_r^* \geq e_u^*$ implies:

$$F_e(z|e_r^*) \geq F_e(z|e_u^*) \text{ for all } z \Rightarrow -\int_{\underline{x}}^{\bar{x}} F_e(z|e_r^*)\mathrm{d}z \leq -\int_{\underline{x}}^{\bar{x}} F_e(z|e_u^*)\mathrm{d}z. \quad \text{(A.24)}$$

Combining (A.23) and (A.24) gives:

$$\begin{aligned} -\int_{\underline{x}}^{\bar{x}} w_j'\big(1-F(z|e_r^*)\big)F_e(z|e_r^*)\mathrm{d}z \geq -\int_{\underline{x}}^{\bar{x}} F_e(z|e_r^*)\mathrm{d}z \\ \Leftrightarrow -\int_{\underline{x}}^{\bar{x}} \Big(w_j'\big(1-F(z|e_r^*)\big)-1\Big)F_e(z|e_r^*)\mathrm{d}z \geq 0. \end{aligned} \quad \text{(A.25)}$$

Therefore, $e_r^* \geq e_u^*$ can hold only if $w_j'(1-F(z \mid e_r^*)) \geq 1$ for most $z \in [\underline{x}, \bar{x}]$.

Under pessimism, the weighting function satisfies $w_j'(p) < 1$ for most probabilities, except near the lower tail ($p \to 0$) corresponding to the worst outcomes. Let j be extremely pessimistic, with

$$\lim_{z \to \underline{x}^+} w_j'(1-F(z|e_r^*))f(z|e_r^*) = K,$$

where $K > 1$ is arbitrarily large. Since the weighted probabilities must integrate to one, $-\int_{[\underline{x},\bar{x}]} w_j'\big(1-F(z|e_r^*)\big)f(z|e_r^*)\mathrm{d}z = 1$, it follows that

$$-\int_{[\underline{x},\bar{x}]\setminus\{\underline{x}\}} w_j'\big(1-F(z|e_r^*)\big)f(z|e_r^*)\mathrm{d}z < \frac{1}{K}. \tag{A.26}$$

By definition of the cumulative distribution, $F_e(\underline{x} \mid e) = 0$, implying:

$$\lim_{z\to\underline{x}^+} w_j'\big(1-F(z|e_r^*)\big)F_e(z|e_r^*) = 0. \tag{A.27}$$

Equations (A.26) and (A.27) jointly yield

$$-\int_{\underline{x}}^{\bar{x}} w_j'\big(1-F(z|e_r^*)\big)F_e(z|e_r^*)\mathrm{d}z < 1. \tag{A.28}$$

Thus, inequality (A.25) cannot hold, contradicting the assumption that $e_r^* \geq e_u^*$. Hence, under sufficiently strong pessimism, $e_r^* < e_u^*$.

Step 3 (stronger degrees of pessimism). Consider now an RDU individual i with probability weighting function w_i and who is less pessimistic than j. According to Definition 2, $w_i(p) = \theta^{-1}(w_j(p))$ where θ is a convex probability weighting function with the properties of Assumption 4. Lemma 1 states that decreasing the convexity of θ redistributes probability weight away from $\underline{x}$ toward higher outcomes, $[\underline{x},\bar{x}]\setminus\{\underline{x}\}$. By continuity of w (Assumption 4), there exists an intermediate degree of convexity θ such that it holds that $e_r^* = e_u^*$. All individuals more pessimistic than this threshold weighting function must exhibit $e_r^* < e_u^*$.

Step 4 (comparative static). Differentiating equation (A.21) and applying the implicit function theorem yields:

$$\frac{\mathrm{d}e_r^*}{\mathrm{d}x_0} = -\frac{u''\Big(x_0(1-e_r^*)\Big)x_0\Big(1-e_r^*\Big) - \int_{\underline{x}}^{\bar{x}}\Big(u''\Big(b(x_0,z)\Big)b_z(x_0,z)b_{x_0}(x_0,z)+u'\Big(b(x_0,z)\Big)b_{z,x_0}(x_0,z)\Big)w_j'\Big(1-F(z|e_r^*)\Big)F_e(z|e_r^*)\mathrm{d}z}{u''\Big(x_0(1-e)\Big)x_0^2+\int_{\underline{x}}^{\bar{x}}u'\Big(b(x_0,z)\Big)b_z(x_0,z)\Big(w_j'\Big(1-F(z|e)\Big)F_{ee}(z|e)-w_j''\Big(1-F(z|e)\Big)(F_e(z|e))^2\Big)\mathrm{d}z}. \tag{A.29}$$

Lemma A2 shows that the denominator in the right-hand side of (A.29) is negative under pessimism. Hence, $\frac{\mathrm{d}e_r^*}{\mathrm{d}x_0} > 0$ if

$$\int_{\underline{x}}^{\bar{x}} u''\big(b(x_0,z)\big)b_z(x_0,z)b_{x_0}(x_0,z) + u'\big(b(x_0,z)\big)b_{z,x_0}(x_0,z)\mathrm{d}z > 0. \tag{A.30}$$

The condition in (A.38) holds if $-\frac{u''\left(b(x_0,z)\right)}{u'\left(b(x_0,z)\right)} < \frac{b_{z,x_0}(x_0,z)}{b_z(x_0,z)b_{x_0}(x_0,z)}$ for all z and x_0, which is ensured by Assumption 3. Hence, $\frac{\mathrm{d}e_r^*}{\mathrm{d}x_0} > 0$

■

Proposition 3

Proof. Consider an RDU individual whose degree of optimism or likelihood insensitivity is sufficiently strong that the objective in (2) is no longer concave in e (Lemma A2). In this case, an interior investment choice cannot satisfy optimality, and the maximizer must lie at a boundary. Hence, the optimal investment level is $e_r^* \in \{0, 1\}$.

Let $\Delta W(z) := w(1 - F(z|1)) - w(1 - F(z|0))$ and

$$V(x_0, z) := \delta \int_{\underline{x}}^{\bar{x}} u'\big(b(x_0, z)\big)b_z(x_0, z)\Delta W(z)\mathrm{d}z. \tag{A.31}$$

The optimal action is:

$$e_r^*(x_0) = \begin{cases} 1, & V(x_0, z) \geq u(x_0), \\ 0, & V(x_0, z) < u(x_0). \end{cases} \tag{A.32}$$

Step 1 (Continuity and strict monotonicity of V). By Assumptions 1-3, b, F and u are continuous which implies that V is continuous. Differentiating (A.32) with respect to x_0 yields

$$V_{x_0}(x_0, z) = \delta \int_{\underline{x}}^{\bar{x}} \left[u''\big(b(x_0, z)\big)b_z(x_0, z)\big)b_{x_0}(x_0, z) + u'\big(b(x_0, z)\big)b_{x_0 z}(x_0, z)\big)\right]\Delta W(z)\mathrm{d}z. \tag{A.33}$$

Since

$$-\frac{u''\big(b(x_0, z)\big)}{u'\big(b(x_0, z)\big)} < \frac{b_{z,x_0}(x_0, z)}{b_z(x_0, z)\, b_{x_0}(x_0, z)} \quad \forall z, x_0,$$

and because $F(z|1) < F(z|0)$ (Assumption 1) while w is strictly increasing (Assumption 4), then $\Delta W(z) > 0$. Therefore $V_{x_0}(x_0, z) > 0$ for all x_0.

Step 2 (Behavior near the lower boundary). By the boundary condition $b(\underline{x}, z) = 0$ for all z (Assumption 2), the integral term vanishes at $\underline{x}$, hence $V(\underline{x}, z) - u(\underline{x}) < 0$. Thus $e_r^* = 0$ at $x_0 = \underline{x}$.

Step 3 (Behavior near the upper boundary). The fact that $F(z|1) < F(z|0)$ for all z (Assumption 1) implies the existence of a set $H \subseteq [\underline{x}, \bar{x}]$ and a constant η such that $\int_{z \in H} F(z|0) - F(z|1) \geq \eta$. Since the weighting function is strictly increasing (Assumption 4) and continuously differentiable, there exists $\lambda > 0$ such that $w'(p) \geq \lambda$ for all $p \in [0, 1]$. Hence, for all $z \in H$,

$$\Delta W(z) \geq \lambda\big(F(z|0) - F(z|1)\big), \tag{A.34}$$

and integrating over H gives $\int_H \Delta W(z), dz \geq \lambda\eta$.

Next, by the top-region gain property of Assumption 2, there exists a constant $\kappa > 1$ such that $b(\bar{x}, z) \geq \kappa\bar{x}$ for all $z \in H$. Let $R(\bar{x}, \kappa) := \frac{u(\kappa\bar{x})}{u(\bar{x})} > 1$. Then, the continuation value at the upper boundary satisfies:

$$\begin{aligned} V(\bar{x}, z) &= \delta \int_{\underline{x}}^{\bar{x}} u'\big(b(\bar{x}, z)\big) b_z(\bar{x}, z)\Delta W(z)\mathrm{d}z - u(\bar{x}) \\ &\geq \delta \int_H u'\big(b(\bar{x}, z)\big) b_z(\bar{x}, z)\Delta W(z)\mathrm{d}z - u(\bar{x}) \end{aligned} \tag{A.35}$$

Because $b(\bar{x}, z) \geq \kappa\bar{x}$ and u is increasing, the last expression in the above equation is bounded below by

$$\delta u(k\bar{x}) \int_H \Delta W(z)\mathrm{d}z \geq \big(\delta\lambda\eta R(\bar{x}, k) - 1\big)u(\bar{x}) \tag{A.36}$$

Therefore, if $\delta\lambda\eta R(\bar{x}, \kappa) > 1$, then $V(\bar{x}, z) > u(\bar{x})$.

Step 4. Existence and uniqueness. We have $V(\underline{x}, z) < 0$, $V(\bar{x}) > 0$ if $\delta\lambda\eta R(\bar{x}, \kappa) > 1$, and ΔV strictly increasing in x_0. Suppose that $\delta\lambda\eta R(\bar{x}, \kappa) > 1$, by the intermediate value theorem there is a unique $\hat{x_0} \in (\underline{x}, \bar{x})$ with $\Delta V(\hat{x}_0, z) = 0$. Thus $e_r^*(x_0) = 0$ for $x_0 < \hat{x}_0$ and $e_r^*(x_0) = 1$ for $x_0 > \hat{x}_0$. If $\delta\lambda\eta R(\bar{x}, \kappa) \leq 1$, then the existence of $\hat{x_0}$ is not guaranteed and $e_r^*(x_0) = 0$.

Step 5. Comparative Static. Step 1 showed that $V(x_0, z) > 0$. Consider two individuals i and j and let the former exhibit less optimism (or insensitivity). Let

$$\begin{aligned} \Delta W_{ij}(z) &:= w_i\big(1 - F(z|1)\big) - w_i\big(1 - F(z|0)\big) - \Big[w_j\big(1 - F(z|1)\big) - w_j\big(1 - F(z|0)\big)\Big] \\ &= \int_{1-F(z|0)}^{1-F(z|1)} w_i'(s) - w_j'(s)\, ds. \end{aligned} \tag{A.37}$$

Lemma 1 states that optimism and likelihood insensitivity, the weighting function satisfies $w_j'(p) < w_j'(p)$ for most probabilities except near the extremes ($p \to 0$ or $p \to 1$). Thus, stronger optimism or likelihood insensitivity generates

$$\int_{[\underline{x},\bar{x}]\setminus\{\underline{x},\bar{x}\}} \Delta W_{ij}(z)\mathrm{d}z < 0. \tag{A.38}$$

By the definition of a cumulative distribution function:

$$\lim_{z\to\underline{x}^+} w_j'\big(1 - F(z|e_r^*)\big)F_e(z|e_r^*) = 0 \text{ and } \lim_{z\to\bar{x}^-} w_j'\big(1 - F(z|e_r^*)\big)F_e(z|e_r^*) = 0. \tag{A.39}$$

Equations (A.40) and (A.38) jointly yield:

$$\int_{[\underline{x},\bar{x}]} \Delta W_{ij}(z)\mathrm{d}z < 0. \tag{A.40}$$

Therefore, $V_i(x_0, z)$ and $V_j(x_0, z)$, the utility (A.32) for i and j respectively, exhibit:

$$V_i(x_0, z) - V_j(x_0, z) < 0. \tag{A.41}$$

Let the change in optimism/insensitivity between i and j be infinitesimal, and define the difference in utility given in (A.41) in that case as $V_{ij}(\hat{x}_0(ij), z; ij)$. Moreover, since $V_{x0}(x_0, z) > 0$, as shown by Step 1, the implicit function theorem gives:

$$\frac{d\,\hat{x}_0(ij)}{dij} = -\frac{V_{ij}(\hat{x}_0(ij); ij)}{V_{x_0}(\hat{x}_0(ij); ij)} > 0. \tag{A.42}$$

■

Corollary 1

Proof. Consider pessimism and suppose that it generates $e_u^* - e_r^* > 0$. Use (A.17) and (A.21) to rewrite the assumed inequality as:

$$-\int_{\underline{x}}^{\bar{x}} u'\big(b(x_0, z)\big)b_x(x_0, z)\Big(F_e(z|e_u^*) - w_j'\big(1 - F(z|e_r^*)\big)F_e(z|e_r^*)\Big)\mathrm{d}z > 0. \tag{A.43}$$

Since $u' > 0$ and $b_z > 0$ (Assumption 3), the condition in (A.43) holds if

$$-\int_{\underline{x}}^{\bar{x}} \Big(F_e(z|e_u^*) - w_j'\big(1 - F(z|e_r^*)\big)F_e(x|e_r^*)\Big)\mathrm{d}z > 0. \tag{A.44}$$

To understand how $e_u^* - e_r^*$ changes with utility curvature, differentiate (A.43) with respect to b to obtain:

$$-\int_{\underline{x}}^{\bar{x}} \left(u''\big(b(x_0,z)\big)b_z(x_0,z) + u'\big(b(x_0,z)\big)\frac{b_{zz}(x_0,z)}{b_z(x_0,z)}\right)\Big(F_e(z|e_u^*) - w_j'\big(1 - F(z|e_r^*)\big)F_e(z|e_r^*)\Big)\mathrm{d}z. \tag{A.45}$$

The inequality given in (A.44) and the derivative in (A.45) imply that underinvestment becomes more severe among the poor if $-\frac{u''\left(b(x_0,z)\right)}{u'\left(b(x_0,z)\right)}$ becomes larger.

Next, consider optimism or likelihood insensitivity. Equation (A.33) demonstrates that if $-\frac{u''\left(b(x_0,z)\right)}{u'\left(b(x_0,z)\right)}$ becomes larger, then $V_{x0}(x_0,z)$ becomes less positive. Since $V(\underline{x},z) < 0$ and $V(\bar{x},z) > 0$ if $\delta\lambda\eta R(\bar{x},\kappa) > 1$ then, the value $\hat{x}_0 \in [\underline{x},\bar{x}]$ such that $V(\hat{x},z) = 0$ exists, is unique, but takes place at a higher value in the set $[\underline{x},\bar{x}]$ since $V_{x0}(x_0,z)$ increases more slowly with x_0.

■

Proposition 4

Proof. Let

$$M_u(x_0) := \int_{\underline{x}}^{\bar{x}} b(x_0,z)\, dF\big(z|e_u^*\big), \tag{A.46}$$

and

$$G(x_0) := M_u(x_0) - x_0. \tag{A.47}$$

Step 1 (continuity, monotonicity, and concavity). By Assumptions 1-3, b and F are twice continuously differentiable. From Proposition 1 the optimal choice e_u^* is interior and increasing in x_0. Hence M_u and G are continuous in x_0.

Fix any $e \in [0,1]$ and define

$$H(x_0;e) := \int b(x_0,z)\mathrm{d}F(z|e).$$

Since, $b_{x_0x_0} \leq 0$ (Assumption 2), the map $x_0 \mapsto b(x_0,z)$ is concave for each$z$. The integral $\int b(x_0,z)\mathrm{d}F(z|e)$ is a weighted average of concave functions, and is therefore concave in x_0.

Differentiating $M_u(x_0) = H\big(x_0; e_u^*(x_0)\big)$ twice gives:

$$M_u''(x_0) = \partial_{x_0x_0}H\big(x_0;e_u^*(x_0)\big) + 2\,\partial_{x_0e}H\big(x_0;e_u^*(x_0)\big)\,e_u^{*\prime}(x_0) + \partial_{ee}H\big(x_0;e_u^*(x_0)\big)\,\big(e_u^{*\prime}(x_0)\big)^2. \tag{A.48}$$

The first term satisfies $\partial_{x_0 x_0} H \leq 0$ by concavity of $H(\cdot; e)$. Under strict first-order stochastic dominance, $F_{ee} \geq 0$ implies $\partial_{ee} H = -\int b(x_0, z)\, dF_{ee}(z \mid e) \leq 0$. Finally, Assumption 2 (complementarity $b_{x_0 z} > 0$) implies $\partial_{x_0 e} H = -\int b_{x_0}(x_0, z)\, dF_e(z \mid e) \leq 0$ because $F_e \leq 0$. Hence, we have $M_u''(x_0) \leq 0$: M_u is concave in x_0.

Step 2 (behavior at the lower boundary). By the normalization $b(\underline{x}, z) = 0$ for all z (Assumption 2),

$$M_u(\underline{x}) = 0 \quad \Rightarrow \quad G(\underline{x}) = M_u(\underline{x}) - \underline{x} = -\underline{x} \leq 0.$$

Moreover, with $b_{x_0} > 0$ and $e_u^*(\underline{x}) \to 0$, accumulation is initially weak: for x_0 just above $\underline{x}$, $M_u(x_0) < x_0$ and hence $G(x_0) < 0$.

Step 3 (growth somewhere). By strict first-order stochastic dominance in e (Assumption 1), there exists a set $H \subset [\underline{x}, \bar{x}]$ and a constant $\eta > 0$ such that:

$$\int_H \Big(F(z|0) - F(z|e_u^*) \Big)\, dz \;\geq\; \eta.$$

By Assumption 2, there exists$\kappa > 1$ such that $b(\bar{x}, z) \geq \kappa \bar{x}$ for all $z \in H$. By continuity of b in x_0, for x_0 close enough to $\bar{x}$ we also have $b(x_0, z) \geq \frac{\kappa}{2}\, x_0$ on H. Therefore, for this value of x_0,

$$\int b(x_0, z)\, dF(z \mid e_u^*(x_0)) \;\geq\; \int_H b(x_0, z)\, dF(z \mid e_u^*) \;\geq\; \frac{\kappa}{2} \int_H dF(z \mid e_u^*) \;\geq\; \frac{\kappa}{2}\, \eta\, x_0.$$

Hence,

$$M_u(x_0) \;\geq\; \tfrac{\kappa}{2} \eta\, x_0.$$

Since $\kappa > 1$, we can (by the choice of H and η ensured by strict FOSD) choose x_0 large enough such that $\frac{\kappa}{2}\eta > 1$, implying $M_u(x_0) > x_0$ and hence $G(x_0) > 0$, for some $\bar{x}_0 \in (\underline{x}, \bar{x}]$.

Step 4 (existence, uniqueness, and local stability). Since $G(\underline{x}) \leq 0$ and $G(\bar{x}_0) > 0$, continuity of G ensures at least one fixed point. Because M_u is strictly concave, $G(x_0) = M_u(x_0) - x_0$ can cross zero at most once, so the steady state x_u^* is unique. At that point, concavity ensures $0 < M_u'(x_u^*) < 1$, so the equilibrium is locally (and globally) stable.

■

Proposition 5

Proof. Define

$$M_r(x_0) := \int_{\underline{x}}^{\bar{x}} b\big(x_0, z\big)\, dF\big(z \mid e_r^*(x_0)\big). \tag{A.49}$$

and let $x_{t+1} = M_r(x_t)$ denote the wealth transition map under RDU.

By Assumptions 1-2, b and F are twice continuously differentiable. Consider an RDU individual with a degree of optimism or pessimism such that the objective in (2) is not concave in e (Lemma A2). In this case, Proposition 3 shows that e_r^* is a step function with a unique cutoff $\hat{x}_0$. Hence, M_r is continuous in x_0.

Step 1 (Behavior near the lower boundary). The normalization $b(\underline{x}, z) = 0$ for all z implies $M_r(\underline{x}) = 0$. For individuals with sufficiently low initial wealth, Proposition 3 implies $e_r^* = 0$. In that case,

$$M_r(x_0) = \int b(x_0, z)\, dF(z|0).$$

By Assumption 5, there exist $\epsilon > 0$ and $k < 1$ such that for all $x_0 \in (\underline{x}, \underline{x} + \epsilon)$,

$$M_r(x_0) \;\le\; \underline{x} + k\,(x_0 - \underline{x}) \;<\; \underline{x} + 1 \cdot (x_0 - \underline{x}) \;=\; x_0.$$

Hence, near the lower boundary, the transition curve lies strictly below the 45Â° line, and wealth decumulates toward $\underline{x}$ when initial wealth is sufficiently small.

Step 2 (Intermediate and high wealth behavior). As x_0 increases, the complementarity $b_{x_0 z} > 0$ raises the marginal return to investment , increasing the attractiveness of investing. Beyond the threshold $\hat{x}_0$ (Proposition 3), the individual switches to $e_r^* = 1$. Because $F_e < 0$, higher investment shifts the distribution of returns to the right, increasing expected wealth. Given $bx_0 > 0$, we then have

$$M_r(x_0) > x_0 \quad \text{for } x_0 > \hat{x}_0.$$

The discrete jump in $e_r^*(x_0)$ induces a nonconvexity in M_r, giving it an S-shaped form and implying at least two intersections with the 45Â° line over $(\underline{x}, \bar{x})$.

Step 3 (Steady states and stability). By construction M_r is continuous in $[\underline{x}, \bar{x}]$. From Step 1, $M_r(\underline{x}) - \underline{x} < 0$. From Step 2, there exists $x_0' \in [\hat{x}_0, \bar{x}]$ such that $M_r(x_0') \ge x_0'$. Moreover, for sufficiently large x_0 diminishing returns in initial wealth ($bx_0x_0 \le 0$) ensure $M_r'(x_0) < 1$ and $M_r(x_0) < x_0$. Hence, M_r crosses the

45° line at least twice:

$$M_r(\underline{x}) - \underline{x} < 0, \quad M_r(x_0') - x_0' > 0, \qquad M_r(\bar{x}) - \bar{x} < 0.$$

By the intermediate value theorem, there exist at least two fixed points $x_L, x_H \in [\underline{x}, \bar{x}]$ such that $M_r(x_L) = x_L$ and $M_r(x_H) = x_H$, with $x_L < x_H$ and.

Local stability follows from the slope criterion of one-dimensional iterative maps: a fixed point x^* is locally stable if and only if $|M_r'(x^*)| < 1$. At the lower intersection x_L, $M_r(x_t)$ crosses $x_{t+1} = x_t$ from below, implying $M_r'(x_L) > 1$ and instability. At the upper intersection x_H, $0 < M_r'(x_H) < 1$ due to $b_{x_0x_0} \leq 0$, ensuring local (and global) stability of x_H.

Let $\tilde{x}_0 := x_L$. For any initial condition $x_0 < \tilde{x}_0$, the sequence $x_{t+1} = M_r(x_t)$ converges to $\underline{x}$, whereas for $x_0 > \tilde{x}_0$, it converges to x_H. Thus, $\tilde{x}_0$ uniquely separates the basins of attraction of the low- and high-wealth steady states. ■

Corollary 2

Proof. **Step 1 (Monotonicity/concavity and boundary behavior).** The transition function $M_r(x_0)$ is given by (A.49). From Proposition 2, the optimal effort e_r^* is unique and interior in $(0, 1)$. Since $b_{x_0x_0} \leq 0$, $F_{ee} > 0$, and $e_r^{*\prime}$ is bounded, it follows that $M_r''(x_0) \leq 0$ for sufficiently large x_0 (eventual concavity). At the lower boundary, $b(\underline{x}, z) = 0$ for all z (Assumption 2), so $M_r(\underline{x}) = 0$ and hence $M_r(\underline{x}) - \underline{x} \leq 0$.

Step 2 (Pessimism reduces optimal investment and next-period wealth). Under sufficiently strong pessimism, $e_r^* < e_u^*$ for all x_0 (Proposition 2). Since $F_e(x|e) < 0$ (strict FOSD), lower effort shifts the conditional distribution downward, implying

$$M_r(x_0) \;\leq\; M_u(x_0) \qquad \forall\, x_0. \tag{A.50}$$

Step 3 (Existence and uniqueness of the RDU steady state). Under EU, M_u is continuous, strictly increasing, eventually concave, and crosses the 45° line exactly once (Proposition 4), yielding a unique and locally stable steady state x_u^*. From (A.50) and the shared boundary condition $M_r(\underline{x}) = M_u(\underline{x}) = 0$, we have

$$M_r(x_0) - x_0 \;\leq\; M_u(x_0) - x_0 \quad \forall\, x_0.$$

Because $M_u(x_0) - x_0$ is positive for some intermediate wealth (by complementarity) and negative for large x_0 (by concavity and $M_u'(x_0) < 1$), continuity of M_r ensures that it too must cross the $45°$ line at least once. Moreover, since M_r is increasing and eventually concave, any two distinct crossings would imply a third by the intermediate value property, which concavity rules out. Hence, there exists a unique fixed point x_r^* such that $M_r(x_r^*) = x_r^*$.

Local stability follows from the standard slope condition: at a fixed point, concavity of M_r, the negative term $-x_0 e_r^*(x_0)$, and diminishing marginal improvements in F imply $0 < M_r'(x_r^*) < 1$, so trajectories of $x_{t+1} = M_r(x_t)$ converge locally to x_r^*.

Step 4 (RDU steady state lies below EU). rom (A.50), $M_r(x_0) \leq M_u(x_0)$ for all x_0, with strict inequality on a set of positive measure. Since both maps are increasing and cross the identity exactly once, the fixed point of the lower map must occur at a lower wealth level:

$$x_r^* < x_u^*.$$

■

B. Technical Extensions

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B.1. Production Thresholds

In the main text, the return on investment z is distributed according to the conditional cumulative distribution function $F(z \mid e)$, which satisfies $F_e(z \mid e) < 0$ and $F_{ee}(z \mid e) \geq 0$ (Assumption 1). This specification implies that a higher level of investment increases the probability of obtaining a high return. A disadvantage of this formulation is that even an individual who invests nothing can have a (possibly small) probability of achieving very high returns. This is unrealistic in many real-world settings where a minimum level of investment is required before favorable outcomes can occur. For example, applying an extremely small amount of fertilizer may not increase crop yields at all; only when a minimum dosage is reached productivity improves.

To capture this feature in the model, I modify the return process by introducing a *production threshold* in the distribution of returns.

Assumption 1 (Replacement: Threshold in the return distribution)**.** *Let $\hat{e} \in (0,1)$ and set the lower wealth bound $\underline{x} = 0$. Define the conditional cumulative distribution function:*

$$G(z \mid e) = \begin{cases} D(z), & \text{if } e < \hat{e}, \\ F(z \mid e), & \text{if } e \geq \hat{e}, \end{cases}$$

where:

- *$F(\cdot \mid e)$ is twice continuously differentiable, satisfies $F_e(z \mid e) < 0$ and $F_{ee}(z \mid e) > 0$ for all z, and corresponds to the specification in Assumption 1;*
- *D is the degenerate cumulative distribution function:*

$$D(z) = \begin{cases} 0, & z < 0, \\ 1, & z \geq 0. \end{cases}$$

According to Assumption 1, investments lower than the threshold $e < \hat{e}$ generate the lowest return, which for simplicity we set at $\underline{x} = 0$. Only when investment exceeds the threshold ($e \geq \hat{e}$) do nontrivial returns become feasible, and further increases in e improve the distribution in the sense of first-order stochastic dominance.

All other assumptions from the baseline model (Assumptions 2–5,) remain unchanged. Under these assumptions, the utility of the individual is:

$$RDU\big(u(x,e)\big) = \begin{cases} u\big(x_0(1-e)\big) & \text{if } e < \hat{e}. \\ u\big(x_0(1-e)\big) + \delta \int_0^{\bar{x}} u\Big(b(x_0,z)\Big) \mathrm{d}\Big(w\big(1-F(z|e)\big)\Big) & \text{if } e \geq \hat{e}. \end{cases} \tag{B.1}$$

When $e < \hat{e}$, the individual only derives utility from current consumption , as no future return is obtained. For $e \geq \hat{e}$, the decision problem coincides with that of the main model presented in Section 2. The utility of the individual is identical to that presented in the main text (equation (2)), and the main results of the paper immediately follow.

The following result shows that the behavioral poverty trap described by Propositions 3 and 5 emerges when the density function $G(x|e)$ is assumed. Moreover, it shows that a standard poverty trap can be obtained; that is a situation whereby poor individuals, who would otherwise not be trapped in poverty, cannot afford to invest above $\hat{e}$ and therefore are locked in a low wealth steady state.

Proposition B1. *Suppose that Assumptions 1–5, hold. Let e_r^* denote the optimal investment in the baseline (no-threshold) RDU problem (Proposition 2) and let $\hat{x}_0$ be the unique wealth cutoff from Proposition 3. Then the optimal investment level under the return distribution G is:*

$$e_r^{**}(x_0) = \begin{cases} 0, & \textit{if } x_0 < \hat{x}_0 \textit{ under optimism or likelihood insensitivity}, \\ 0, & \textit{if } e_r^*(x_0) < \hat{e} \textit{ under pessimism}, \\ e_r^*(x_0), & \textit{if } e_r^*(x_0) \geq \hat{e} \textit{ under pessimism}, \\ 1, & \textit{if } x_0 > \hat{x}_0 \textit{ under optimism or likelihood insensitivity}. \end{cases}$$

Moreover, any individual for whom $e_r^{**} = 0$ is trapped at the boundary steady state $x_r^* = 0$.

Proof. If $e_r^{**} < \hat{e}$, then by (B.1), $RDU = u((1-e)x_0)$, which is strictly decreasing in e; thus, $e_r^{**} = 0$. If $e_r^{**} \geq \hat{e}$, the objective is identical to that in the main model, and therefore the results of Propositions 2 and 3 apply directly. Under pessimism, Proposition 2 implies that e_r^* is interior in $[0,1]$. If $e_r^*(x_0) \geq \hat{e}$, then $e_r^{**} = e_r^*(x_0)$; otherwise, $e_r^{**} = 0$. Under optimism or likelihood insensitivity, Proposition 3 implies that $e_r^*(x_0) \in \{0,1\}$ depending on whether $x_0 < \hat{x}_0$ or $x_0 > \hat{x}_0$, leading to the stated result.

Finally, if $e_r^{**} = 0$, then from Step 1 of the proof of Proposition 5 we obtain $M_r(x_0) < x_0$ (Assumption 5) , and from Assumption 2 ($b(\underline{x}, z) = 0$ for all z), we have $M_r(x_0) = 0$. Thus, $x_r^* = 0$ is an absorbing steady state. ■

In a setting where a minimum level of investment must be reached before favorable outcomes become attainable, a standard poverty trap arises. This occurs because Assumption 1 introduces a non-convexity in the production technology, a well-known source of poverty traps (Galor and Zeira, 1993, Bowles et al., 2011b). Such non-convexity ensures that the poorest individuals, who cannot afford to invest above the threshold $\hat{e}$, optimally choose zero investment and thus remain trapped at low wealth levels. Importantly, this mechanism also implies that pessimistic individuals, who would otherwise avoid a poverty trap under the baseline model (Corollary 2), become trapped once the investment threshold is introduced. Furthermore, individuals with intermediate wealth levels, who can afford to invest beyond $\hat{e}$, the behavioral poverty trap described in the main text reemerges: due to optimism or likelihood insensitivity, they forgo profitable investment opportunities, which will keep them poor.

C. Ambiguity Attitudes and Poverty Traps

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This Appendix incorporates ambiguity in the model. To that end, I slightly modify the theoretical framework by considering a setting in which the individual chooses how much to invest in one of two projects. One of the projects is risky so the probabilities of obtaining a particular level of return are objectively known. The other project is ambiguous, which means those probabilities are not known. Intuitively, the ambiguous situation may arise when an individual has limited experience with this type of projects. Notice when the individual chooses a level of investment in the risky project, the results of the previous section follow which will serve as the benchmark of the present analysis.

Let $[\underline{x}, \bar{x}]$ be the set of possible returns on the ambiguous good. Notice that this set coincides with the set of possible returns on the risky good discussed in the main body of the paper. An event is any subset $E \subset [\underline{x}, \bar{x}]$. The set of all possible events in $[\underline{x}, \bar{x}]$ is denoted by Σ, which I endow with the Borel σ-algebra.

C.1. Ambiguity Attitudes

To define the concept of ambiguity attitudes, let us consider a situation in which $[\underline{x}, \bar{x}]$ be described by the partition $\{E_1, E_2\}$. Specifically, let E_1 be the event $z > \hat{z}$, where $\hat{z}$ is some return level under the ambiguous project, and let E_2 be its complement. Denote by $(M, E_1; 0, E_2)$ a bet that pays the monetary amount $M > 0$, when E_1 is true and nothing otherwise. Abundant empirical research shows that most individuals exhibit the preference :

$$(M, p; 0, 1-p) \succ (M, E_1; 0, E_2), \tag{C.1}$$

where p is the objective probability that $z > \hat{z}$ realizes under the risky good. The same individuals also typically exhibit the preference:

$$(M, 1-p; 0, p) \succ (M, E_2; 0, E_1). \tag{C.2}$$

The preferences in (C.1) and (C.2) imply an *aversion* to betting on events generated by the ambiguous project that violate the normative model of subjective expected utility (Savage, 1954).[16] This *ambiguity averse* behavior has been documented in prominent laboratory experiments (Trautmann and van de Kuilen, 2015). Moreover, recent research also shows that when the events under consideration are extreme, individuals exhibit ambiguity seeking (Abdellaoui et al., 2011, Baillon et al., 2018, Baillon and Emirmahmutoglu, 2018). I refer to "ambiguity attitudes" as the conjunction of ambiguity aversion and a-insensitivity, which captures the latter empirical regularity that individuals are ambiguity seeking in the case of unlikely events.

C.2. Ambiguity attitudes and Choquet Expected Utility

One of the most used models to incorporate ambiguity attitudes is the Choquet Expected Utility (Schmeidler, 1989). In the context of our model, this theory is described by the functional:

$$RDU\big(u(z,e)\big) = u\big((1-e)x_0\big) + \delta \int_{[\underline{x},\bar{x}]} u\Big(b(x_0,z)\Big)\mathrm{d}W, \tag{C.3}$$

where W is a function with the following properties: i) $W(\varnothing|e) = 0$, ii) $W([\underline{x},\bar{x}]|e) = 1$, and iii) $W(E_1|e) < W(E_2|e)$ for any $E_1, E_2 \in \Sigma$ such that $E_1 \subset E_2$. This model generalizes subjective expected utility by allowing W to be non-additive, a feature that accounts for ambiguity attitudes by giving up probabilistic beliefs. For instance, ambiguity aversion (the aversion to invest in the ambiguous project) is incorporated in this model by assuming that W is convex.[17]

The main problem of modeling ambiguity attitudes using the model in (C.3) is that there might be potentially many functions W that can account for an individual's ambiguity attitudes (Abdellaoui et al., 2011, Wakker, 2010). This makes the identification of ambiguity attitudes indeterminate and renders a comparison between choices under ambiguity and choices under risk difficult. I address this problem by adopting an alternative approach to model ambiguity attitudes known as *Source Theory* (Abdellaoui et al., 2011, Baillon et al., 2025). Under ambiguity in Source Theory, the phenomena of risk are amplified because there is

[16] Formally, assume without loss of generality that $u(0) = 0$. Under subjective expected utility, the preference in (C.1) implies $P(E_1) \cdot u(M) < p \cdot u(M) \Leftrightarrow P(E_1) < p$ and the preference in (C.2) implies $P(E_2) < 1 - p$. Note that the inequalities $P(E_1) < p$ and $P(E_2) < 1 - p$ violate probability laws.

[17] Using the explanation given in the previous footnote, the convexity of W is consistent with the inequalities $W(E_1) < 0.4$ and $W(E_2) < 0.6$.

"extra probability weighting."

C.3. Ambiguity attitudes and Source Theory

To model ambiguity attitudes with Source Theory, we must incorporate probabilistic beliefs into the framework. This is done by assuming that each project generates an algebra of events, which is called a *source*. Intuitively, the risky and ambiguous goods represent distinct random mechanisms, each generating its own set of events and, thus, each being a source of uncertainty (Tversky and Fox, 1995). A crucial assumption of this theory is that probabilistic beliefs hold *within* sources of uncertainty but not *between* them (Chew and Sagi, 2008). Accordingly, denote by P the probability measure generated by Σ, i.e. the algebra of events generated by the ambiguous good, and, as before, let $F(z|e)$ be the probability measure when probabilities are known.

This approach makes it possible to define attitudes toward probabilities of different sources. In the case of the ambiguous investment, there exists a function w_s with the properties of Assumption 4, such that, for any e:

$$W(E|e) = w_s\big(1 - P(E|e)\big)\text{for any } E \in [\underline{x}, \bar{x}]. \tag{C.4}$$

where $P(E|e)$ denotes the individual's subjective probability belief. The function w_s carries subjective probabilities to decision weights and is referred to as the *source function*. Importantly, it can exhibit a different shape than w, the probability weighting function, and this difference between w_s and w identifies ambiguity attitudes, i.e. the "extra probability weighting."

For instance, when w_u is more convex (concave) than w, the individual exhibits ambiguity aversion (seeking), i.e. she irrationally believes that unfavorable (favorable) events are more likely in the case of the ambiguous project than in the case of the risky one. Moreover, if w_s exhibits a more pronounced inverse-S shape than w, the decision maker exhibits a-insensitivity, i.e. she erroneously assigns more probability weight to extreme events in the case of the ambiguous investment than to equally unlikely events in the case of the risky investment (Baillon et al., 2018). This tendency to evaluate events in the ambiguous good leads her to be ambiguity seeking for extreme events.

Substituting (C.4) in (C.3) gives the following evaluation of returns in the case of the ambiguous investment:

$$RDU_s\big(u(x,e)\big) = u\big((1-e)x_0\big) + \delta \int_{[\underline{x},\bar{x}]} u\Big(b(x_0,z)\Big) \mathrm{d}w_s\big(1-P(z|e)\big) - c(e). \quad \text{(C.5)}$$

where integration is over the cumulative distribution of $P(E|e)$ transformed by the source function w_s. Notice that equation (C.5) is analogous to (2) for the case of unknown probabilities. Furthermore, because this equation features the function w_s—which is endowed with the properties of Assumption 4— and due to the regularity conditions imposed on the set Σ, the results presented in Propositions 2 and 3 immediately follow for the ambiguous project. Therefore, a poor individual with a-insensitivity or ambiguity seeking, forgoes profitable investments that are ambiguous.

However, the most relevant result of this analysis arises when we compare the optimal investment in the ambiguous project for an individual with preferences characterized by (C.5) to the same individual's investment in the risky good. Proposition C1 states that ambiguity attitudes, regardless of its type, exacerbates the poverty trap described in Proposition 5.

Proposition C1. *Assume that Assumptions 1-4 hold and that individual preferences under ambiguity are characterized by Source Theory (eq.(C.5)). For an ambiguity seeking or a-insensitive individual, the optimal level of investment, e_a^*, is*

$$e_a^* = \begin{cases} 0, & x_0 < \hat{x}_a, \\ 1, & x_0 \geq \hat{x}_a, \end{cases}$$

where $\hat{x}_a > \hat{x}_0$, and $\hat{x}_0$ is the threshold from Proposition 3. Thus, ambiguity attitudes enlarge the range of initial wealth levels trapped in poverty as described by Proposition 5.

Proof. **Part 1 (Optimal investment choice).** Consider an individual j who exhibits ambiguity seeking or a-insensitivity. Denote her source function by w_{sj}, and her probability weighting function by w_j. The phenomenon of a-insensitivity implies that w_{sj} has an inverse-S shape that is steeper than w_j. Ambiguity seeking implies that w_{sj} is concave, and to a greater extent than w_j. Hence these phenomena can be modeled as strong likelihood insensitivity and strong optimism. Thus, according to Proposition 3, the choice of investment in this case is:

$$e_a^* = \begin{cases} 0, & x_0 < \hat{x}_a, \\ 1, & x_0 > \hat{x}_a, \end{cases}$$

where $\hat{x}_a \in (\underline{x}, \bar{x}]$ is a threshold of initial wealth.

Part 2 (Higher Threshold under Ambiguity) According to Proposition 3, the threshold $\hat{x}_0$ increases in the curvature of w_{sj}. Thus, stronger likelihood insensitivity or optimism leads to a higher $\hat{x}_0$. Since a-insensitivity and ambiguity seeking are modeled as stronger likelihood insensitivity and stronger optimism, then $\hat{x}_a > \hat{x}_0$.

Part3 (Poverty Trap under Ambiguity) According to Proposition 5, choosing $e_a^* = 0$ leads to a low steady state $x^* = 0$. ■

Ambiguity attitudes can be interpreted as introducing "extra" probability weighting relative to risk. Thus, an individual who would forgo investing in a risky project, and as a result be trapped in poverty, would also exhibit the same behavior under ambiguity, where distortions of probability perception are more pronounced. More importantly, the higher threshold $\hat{x}_a$ implies that individuals with initial wealth in $x_0 \in [\hat{x}_0, \hat{x}_a]$, who would not be trapped in poverty in a situation of risk, would forgo equally profitable projects if they are ambiguous. The extra probability weighting implies that more weight is given to probabilities of extreme events under the ambiguous good, leading individuals to erroneously regard the ambiguous investment as less profitable than the risky one.

C.4. Empirical Evidence Supporting the Poverty Trap due to Ambiguity Attitudes

To conclude this section, I discuss empirical evidence supporting the prediction that ambiguity attitudes lead to underinvestment, with a disproportionately greater impact on the poor. Dimmock et al. (2016a) designed an experiment to elicit ambiguity attitudes in a representative sample of Dutch households, while Dimmock et al. (2016b) did so for a representative sample of American households. Dimmock et al. (2016a) find that a-insensitivity is related to low stock market participation and a lower level of private business ownership, and Dimmock et al. (2016b) find such relations for ambiguity aversion. These studies show that ambiguity attitudes generate underinvestment.

Based on two randomized control trials, Bryan (2019) found that ambiguity attitudes lead poor individuals to forgo profitable investments. In the first experiment, ambiguity-averse farmers in Malawi were less inclined to adopt new crop types when doing so required the purchase of rainfall insurance. This requirement increased the ambiguity of the investment, discouraging these farmers from investing, even though the complementarity between rainfall insurance and the new seed type would generate higher returns. In the second experiment, ambiguity-averse farmers in Kenya displayed a similar reluctance to adopt new crop types, even when credit was made available. Suggesting that the farmers' reluctance to adopt new technology is driven by ambiguity attitudes rather than credit constraints.

Finally, Li (2017) demonstrated that poor rural adolescents in China exhibit greater ambiguity aversion and a-insensitivity compared to their poor urban counterparts. Given that the rural group is poorer, these findings suggest that ambiguity attitudes intensify as poverty worsens. This evidence aligns closely with the predictions of the model.

D. Reference Dependence

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This appendix incorporates reference dependence in the model. To that end, I characterize risk preferences with Cumulative Prospect Theory (Tversky and Kahneman, 1992) (CPT henceforth). According to this model, the individual compares future wealth to her reference point, $RP \geq 0$. Wealth levels that fall below the individual's reference point are classified as losses while wealth levels above that point are evaluated as gains.

The main departure of CPT with respect to EUT and RDU is that the individual can exhibit different risk preferences for gains and losses. This is captured with two ingredients. First, wealth enters the agent's utility differently depending on whether they are classified as gains or losses, a property that is captured by the following assumption on the agent's utility:

Assumption 6. *The agent's value function is the piece-wise function*

$$V(w,r) = \begin{cases} u(b(x_0,z) - RP) & \text{if } b(x_0,z) \geq RP, \\ -\lambda u(RP - b(x_0,z)) & \text{if } b(x_0,z) < RP. \end{cases}$$

where $\lambda > 1$, $RP > 0$, and u satisfies the properties of Assumption 3.

In words, utility is assumed to be convex for losses, which generates risk seeking attitudes, and concave for gains, which generates risk aversion. Furthermore, Assumption 6 introduces loss aversion which means that losses loom larger than commensurate gains. This property is captured by the parameter $\lambda > 1$.

The second ingredient is that the probability weighting function is defined separately over gains and losses. Probabilities associated with gains are transformed by the probability weighting function w, introduced in Assumption 4. On the other hand, probabilities associated with losses are transformed with a probability weighting function which I denote by w^- that applies transformations to cumulative probabilities, $F(z|e)$ rather than to decumulative probabilities.

I simplify the problem by assuming that w^- adopts the properties of w.

Assumption 7. *A probability weighting function for losses is a function $w^{-} : [0,1] \to [0,1]$ that satisfies the duality condition $w^{-}(F(z|e)) = 1 - w\big(1 - F(z|e)\big)$ for all z.*

Throughout, I assume that the reference point, RP, is exogenous to the alternatives faced by the decision maker. Specifically, it is assumed that the reference point is the status quo or the individuals' initial wealth x_0. This reference-point rule which has received recent empirical support (Baillon et al., 2020).

Assumption 8. *The reference point is the individual's initial wealth $RP = x_0$.*

The problem faced by the CPT agent is the same as in the main body of the paper: she must choose $e \in [0,1]$ to allocate consumption today against investing to derive expected utility in the future. Accordingly, the utility of an agent with CPT preferences when

$$\begin{aligned} CPT(z,e) =& u\big((1-e)x_0\big) + \delta \int_{b(x_0,z)\geq x_0} u\Big(b(x_0,z) - x_0\Big) \mathrm{d}\Big(w\big(1 - F(z|e)\big)\Big) - \\ & \delta \int_{b(x_0,z)<x_0} v\Big(x_0 - b(x_0,z)\Big) \mathrm{d}\Big(w^{-}\big(F(z|e)\big)\Big), \end{aligned} \tag{D.1}$$

We present the solution to the investment problem when the individual exhibits reference-dependent preferences. It turns out that the result that individuals forgo profitable investments stated in Proposition 3— which is the basis for the poverty trap in Proposition D1— holds under similar conditions as compared to the setting in which the agent exhibits RDU preferences. Intuitively, loss aversion, $\lambda > 1$, does not restore the convexity of the problem and thus does not alter the result that investment is at the corners of $[0,1]$. Moreover, the other component that was introduced in this framework, the negative utility of losses, simply rescales utility levels in the loss domain without changing the curvature of the objective in e.

Proposition D1. *Suppose assumptions 1-8 hold. If the probability weighting function $w(\cdot)$ exhibits optimism or likelihood insensitivity (Definitions 1-3), then there exists a threshold $\hat{x}_0 \in [\underline{x}, \bar{x}]$ such that:*

$$e_c^* = \begin{cases} 0, & x_0 < \hat{x}_0, \\ 1, & x_0 > \hat{x}_0, \end{cases}$$

where $\hat{x}_0$ is strictly increasing in the degree of optimism or likelihood insensitivity.

Proof. Using Assumption 7 and Assumption 8 , rewrite (D.1) as:

$$\begin{aligned} CPT(z,e) =& u\big((1-e)x_0\big) + \delta \int_{\bar{x}}^{x_0} u\Big(b(x_0,z) - x_0\Big)\mathrm{d}w\big(1-F(z|e)\big) \\ & - \delta \int_{x_0}^{\underline{x}} \lambda u\Big(x_0 - b(x_0,z)\Big)\mathrm{d}\Big(1 - w(1-F(z|e))\Big), \end{aligned} \tag{D.2}$$

Using integration by parts, rewrite (D.2) as

$$\begin{aligned} CPT(z,e) =& u\big((1-e)x_0\big) + \delta \int_{x_0}^{\bar{x}} u'\Big(b(x_0,z) - x_0\Big)b_z(x_0,z)w\big(1-F(z|e)\big)\mathrm{d}z \\ & - \delta \int_{\underline{x}}^{x_0} \lambda u'\Big(x_0 - b(x_0,z)\Big)b_z(x_0,z)\Big(1 - w\big(1-F(z|e)\big)\Big)\mathrm{d}z, \end{aligned} \tag{D.3}$$

Define the difference in probability weights between full and zero investment:

$$\Delta W(z) := w\big(1 - F(z|1)\big) - w\big(1 - F(z|0)\big).$$

The net utility gain from investing $e = 1$ rather than $e = 0$ is:

$$\begin{aligned} \Delta U(x_0) :=& -u(x_0) + \delta \int_{x_0}^{\bar{x}} u'\Big(b(x_0,z) - x_0\Big)\, b_z(x_0,z)\, \Delta W(z)\, dz \\ & + \delta \int_{\underline{x}}^{x_0} \lambda\, u'\Big(x_0 - b(x_0,z)\Big)\, b_z(x_0,z)\, \Delta W(z)\, dz. \end{aligned} \tag{D.4}$$

Let

$$V(x_0) := \delta \int_{x_0}^{\bar{x}} u'\Big(b(x_0,z) - x_0\Big)\, b_z(x_0,z)\, \Delta W(z)\, dz + \delta \int_{\underline{x}}^{x_0} \lambda\, u'\Big(x_0 - b(x_0,z)\Big)\, b_z(x_0,z)\, \Delta W(z)\, dz. \tag{D.5}$$

The optimal investment rule when $e \in \{0,1\}$ satisfies

$$e_c^*(x_0) = \begin{cases} 1, & V(x_0) \geq u(x_0), \\ 0, & V(x_0) < u(x_0). \end{cases}$$

Step 1 (Corner solutions). Under optimism or likelihood insensitivity, $w''(p) < 0$ over a nontrivial interval of $p \in (0,1)$. Since $\mathrm{CPT}(z,e)$ depends linearly on $w(1-F(z|e))$, this concavity of w induces non-convexity in e. Thus, interior solutions are dominated by the corners $e \in \{0,1\}$.

Step 2 (Monotonicity of $V(x_0)$). Differentiating $V(x_0)$ with respect to x_0 gives

$$V_{x_0}(x_0) = \delta \int_{\underline{x}}^{\bar{x}} \Big[u''(y)\, b_z b_{x_0} + u'(y)\, b_{x_0 z} \Big] \Delta W(z)\, dz,$$

where

$$y = \begin{cases} b(x_0, z) - x_0 \text{ if } b(x_0, z) \geq x_0, \\ x_0 - b(x_0, z) \text{ if } b(x_0, z) < x_0. \end{cases}$$

By Assumption 3 (curvature upper bound) and Assumption 2 (complementarity $b_{x_0 z} > 0$), we have $V_{x_0}(x_0) > 0$. Hence, $V(x_0)$ is strictly increasing in initial wealth.

Step 3 (Boundary behavior). Since $b(\underline{x}, z) = 0 \leq \underline{x}$ and $b_{x_0} > 0$ is continuous, there exists $\varepsilon > 0$ such that for all $x_0 \in (\underline{x}, \underline{x} + \varepsilon)$ and all $z \in [\underline{x}, \bar{x}]$ it holds that $b(x_0, z) < x_0$. Thus, the gains region is empty at those levels of x_0 and the decision to invest is given by:

$$V(x_0) - u(x_0) = -u(x_0) + \delta \int_{\underline{x}}^{\bar{x}} \lambda\, u'\big(x_0 - b(x_0, z)\big)\, b_z(x_0, z)\, \Delta W(z)\, dz.$$

The first term is strictly negative, and the integral term is bounded and continuous. Therefore, for x_0 sufficiently close to $\underline{x}$, $V(x_0) - u(x_0) < 0$, so $e_c^* = 0$.

At high wealth, Assumption 1 ensures strict FOSD in e: there exist $\eta > 0$ and $\lambda_w > 0$ such that $\int_H \Delta W(z)\, dz \geq \lambda_w \eta$ for some $H \subset [\underline{x}, \bar{x}]$. By Assumption 2, there exists $\kappa > 1$ with $b(\bar{x}, z) \geq \kappa \bar{x}$ for all $z \in H$. Then

$$V(\bar{x}) \geq \delta\, \lambda_w \eta\, u'(\kappa \bar{x} - \bar{x}) \min_{z \in H} b_z(\bar{x}, z).$$

If the above inequality holds, then $V(\bar{x}) > u(\bar{x})$ and hence $e_c^* = 1$ for sufficiently high x_0.

Step 4 (Existence and uniqueness of the threshold). We have $V(\underline{x}) < u(\underline{x})$ and $V(\bar{x}) \geq u(\bar{x})$ if $\delta\, \lambda_w \eta\, u'(\kappa \bar{x} - \bar{x}) \cdot \min_{z \in H} b_z(\bar{x}, z) > u(\bar{x})$, while $V'(x_0) > 0$. By continuity, there exists a unique $\hat{x}_0 \in (\underline{x}, \bar{x}]$ such that $V(\hat{x}_0) = u(\hat{x}_0)$. Hence, $e_c^* = 0$ for $x_0 < \hat{x}_0$ and $e_c^* = 1$ for $x_0 > \hat{x}_0$.

Step 5 (Comparative statics). Let i be less optimistic (or less likelihood insensitive) than j. Define

$$\Delta W_{ij}(z) := \Big[w_i(1-F(z|1)) - w_i(1-F(z|0))\Big] - \Big[w_j(1-F(z|1)) - w_j(1-F(z|0))\Big].$$

Lemma 1 implies $\int \Delta W_{ij}(z)\, dz < 0$. Since $V(x_0)$ is linear in $\Delta W(z)$, then $V_i(x_0) - V_j(x_0) < 0$. Because $V_{x_0} > 0$ (Step 2), the implicit function theorem yields:

$$\frac{d\hat{x}_0}{d(\text{bias})} = -\frac{V_{\text{bias}}(\hat{x}_0)}{V_{x_0}(\hat{x}_0)} > 0.$$

Thus, the wealth threshold $\hat{x}_0$ increases with the degree of optimism or likelihood insensitivity. ∎

While loss aversion does not alter the fact that the optimal solution lies at the boundaries of the investment set $[0,1]$, it does affect the location of the threshold $\hat{x}_0$ from Proposition D1. The following corollary shows that higher loss aversion increases this threshold.

Corollary C1. *The threshold level of initial wealth from Proposition D1 is strictly increasing in λ: $\frac{d\hat{x}_0}{d\lambda} > 0$.*

Proof. Let

$$\begin{aligned}\Phi(x_0;\lambda) :=& \delta \int_{x_0}^{\bar{x}} u'\big(b(x_0,z) - x_0\big)\, b_z(x_0,z)\, w\big(1 - F(z \mid 1)\big)\, dz \\ &- \delta \int_{\underline{x}}^{x_0} \lambda\, u'\big(x_0 - b(x_0,z)\big)\, b_z(x_0,z)\, \big(1 - w\big(1 - F(z \mid 1)\big)\big)\, dz - u(0). \end{aligned} \tag{D.6}$$

By the envelope/monotonicity argument in Step 1 (the proof of Proposition D1), we have $\Phi_{x_0}(x_0;\lambda) > 0$ at the cutoff: the gain component rises with x_0 by $b_{x_0 z} > 0$, and the curvature bound $-\frac{u''}{u'} < \frac{b_{zx_0}}{b_z b_{x_0}}$ guarantees that this complementarity dominates the dampening from concavity of u; the loss component's x_0-effect is (weakly) smaller in magnitude and does not overturn positivity.

Differentiating Φ with respect to λ (holding x_0 fixed) only affects the loss integral:

$$\Phi_\lambda(x_0;\lambda) = -\delta \int_{\underline{x}}^{z^\dagger(x_0)} u'\big(x_0 - b(x_0,z)\big)\, b_z(x_0,z)\, \big(1 - w(1 - F(z \mid 1))\big)\, dz < 0,$$

since $u' > 0$, $b_z > 0$, and $1 - w(\cdot) \in (0,1)$.

The cutoff $\hat{x}_0(\lambda)$ is defined by $\Phi(\hat{x}_0(\lambda); \lambda) = 0$. By the implicit function theorem,

$$\frac{d\hat{x}_0}{d\lambda} = -\frac{\Phi_\lambda(\hat{x}_0(\lambda); \lambda)}{\Phi_{x_0}(\hat{x}_0(\lambda); \lambda)} \; > \; 0,$$

because $\Phi_\lambda < 0$ and $\Phi_{x_0} > 0$ at the cutoff. ■

Loss aversion thus deepens the behavioral poverty trap from Proposition 5, extending it to individuals with higher initial wealth. Intuitively, loss aversion amplifies the disutility from outcomes where future wealth falls short of the initial endowment ($b(x_0, z) < x_0$). These states matter most when wealth is low, since even small investment risks translate into reductions in future wealth. As a result, the low-wealth region in which individuals optimally choose not to invest expands, making more individuals more vulnerable to the adverse consequences of probability weighting.

E. Additional Empirical Analyses.

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Table 7: The Relationship between Prelec (1998)'s Probability Weighting Function and Income or Wealth

Variable y_i	(1) Financial Wealth	(2) Financial Wealth	(3) Return Stock	(4) Return Stock	(5) Family Income	(6) Family Income	(7) Housing Wealth	(8) Housing Wealth
Inverse-S	-1.532***	-1.282***	-1.653***	-1.257***	-0.254***	-0.185***	-0.280	-0.187
	(0.363)	(0.325)	(0.395)	(0.371)	(0.060)	(0.055)	(0.193)	(0.171)
Optimism/Pessimism	-0.004	-0.005	-0.008	-0.007	-0.000	-0.000	0.000	-0.000
	(0.011)	(0.012)	(0.010)	(0.011)	(0.002)	(0.002)	(0.006)	(0.006)
Utility Curvature	0.010	0.010	0.007	0.009	0.001	0.001	0.005	0.005
	(0.013)	(0.014)	(0.014)	(0.014)	(0.002)	(0.002)	(0.007)	(0.008)
Constant	5.900***	2.127	4.207***	-3.416***	10.827***	9.829***	3.302***	-3.210***
	(0.185)	(1.314)	(0.198)	(1.260)	(0.031)	(0.247)	(0.097)	(0.743)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
R^2	0.014	0.216	0.012	0.129	0.008	0.153	0.002	0.233
N	1902	1901	2245	2244	2629	2628	1921	1920

This table presents OLS estimates of the model $\ln(y_i + 1) = b_0 + b_1$Inverse-S$_i + b_2$ Opt./Pess.$_i + b_3$U.curv$_i$.+Controls$_i'\Gamma + \varepsilon_i$. The variable y_i captures the respondent's i self-reported income and wealth. It can be one of the following variables: "Financial Wealth", "Return Stock", "Family Income", or "Housing Wealth". "Inverse-S" is the respondent i's index of likelihood insensitivity obtained from an estimation of Prelec (1998)'s probability weighting function. "Opt./pess." is the respondent's i's index of optimism and pessimism obtained from an estimation of Prelec (1998)'s probability weighting function. "U.curv" is the respondent i's curvature of the utility function obtained from an estimation of a CRRA utility. . Robust standard errors are presented in parentheses. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Table 8: The Relationship between Chateauneuf et al. (2007)'s Probability Weighting Function and Income or Wealth

Variable y_i	(1) Financial Wealth	(2) Financial Wealth	(3) Return Stock	(4) Return Stock	(5) Family Income	(6) Family Income	(7) Stock Wealth	(8) Stock Wealth
Inverse-S	-1.872***	-1.475***	-2.229***	-1.744***	-0.305***	-0.219***	-0.483**	-0.290*
	(0.363)	(0.325)	(0.388)	(0.369)	(0.062)	(0.059)	(0.192)	(0.170)
Optimism/Pessimism	-2.266***	-1.384**	-1.297*	-0.138	-0.409***	-0.209*	-0.758**	-0.189
	(0.673)	(0.621)	(0.697)	(0.672)	(0.117)	(0.111)	(0.361)	(0.326)
Utility Curvature	0.037	0.020	-0.050	-0.055	-0.006	-0.005	0.004	-0.010
	(0.040)	(0.038)	(0.042)	(0.041)	(0.006)	(0.005)	(0.022)	(0.019)
Constant	6.414***	2.624**	4.195***	-3.642***	10.918***	9.883***	3.441***	-3.190***
	(0.288)	(1.338)	(0.305)	(1.297)	(0.046)	(0.256)	(0.154)	(0.756)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
R^2	0.017	0.214	0.014	0.129	0.013	0.154	0.005	0.232
N	1902	1901	2245	2244	2629	2628	1921	1920

This table presents OLS estimates of the model $\ln(y_i + 1) = b_0 + b_1$Inverse-S$_i + b_2$ Opt./Pess.$_i + b_3$U.curv$_i$.+Controls$_i'\Gamma + \varepsilon_i$. The variable y_i captures the respondent's i self-reported income and wealth. It can be one of the following variables: "Financial Wealth", "Return Stock", "Family Income", or "Housing Wealth". "Inverse-S" is the respondent i's index of likelihood insensitivity obtained from an estimation of Chateauneuf et al. (2007)'s probability weighting function. "Opt./pess." is the respondent's i's index of optimism and pessimism obtained from an estimation of Chateauneuf et al. (2007)'s probability weighting function. "U.curv" is the respondent i's curvature of the utility function obtained from an estimation of a CRRA utility. Robust standard errors are presented in parentheses. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Table 9: The Relationship between Chateauneuf et al. (2007)'s Probability Weighting Function and Income or Wealth

Variable y_i	(1) Financial Wealth	(2) Financial Wealth	(3) Return Stock	(4) Return Stock	(5) Family Income	(6) Family Income	(7) Housing Wealth	(8) Housing Wealth
Inverse-S	-1.867***	-1.471***	-2.222***	-1.740***	-0.303***	-0.218***	-0.480**	-0.289*
	(0.362)	(0.325)	(0.388)	(0.368)	(0.062)	(0.058)	(0.192)	(0.170)
Optimism/Pessimism	-2.273***	-1.383**	-1.267*	-0.105	-0.404***	-0.204*	-0.752**	-0.181
	(0.674)	(0.623)	(0.699)	(0.674)	(0.117)	(0.111)	(0.362)	(0.326)
Utility Curvature	0.037	0.020	-0.051	-0.056	-0.006	-0.005	0.004	-0.010
	(0.040)	(0.038)	(0.042)	(0.041)	(0.006)	(0.005)	(0.022)	(0.019)
Constant	6.419***	2.621*	4.188***	-3.656***	10.917***	9.881***	3.441***	-3.193***
	(0.289)	(1.338)	(0.306)	(1.297)	(0.046)	(0.256)	(0.154)	(0.756)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
R^2	0.017	0.214	0.014	0.129	0.013	0.154	0.005	0.232
N	1902	1901	2245	2244	2629	2628	1921	1920

This table presents OLS estimates of the model $\ln(y_i+1) = b_0 + b_1\text{Inverse-S}_i + b_2\,\text{Opt./Pess.}_i + b_3\text{U.curv}_i.+\text{Controls}_i'\Gamma + \varepsilon_i$. The variable y_i captures the respondent's i self-reported income and wealth. It can be one of the following variables: "Financial Wealth", "Return Stock", "Family Income", or "Housing Wealth". "Inverse-S" is the respondent i's index of likelihood insensitivity obtained from an estimation of Chateauneuf et al. (2007)'s probability weighting function. "Opt./pess." is the respondent's i's index of optimism and pessimism obtained from an estimation of Chateauneuf et al. (2007)'s probability weighting function. "U.curv" is the respondent i's curvature of the utility function obtained from an estimation of a CRRA utility. Robust standard errors are presented in parentheses. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Table 10: The Relationship between Prelec (1998)'s Probability Weighting Function and Income or Wealth

Variable y_i	(1) Financial Wealth	(2) Financial Wealth	(3) Return Stock	(4) Return Stock	(5) Family Income	(6) Family Income	(7) Housing Wealth	(8) Housing Wealth
Inverse-S	-0.436***	-0.370***	-2.867***	-2.176***	-0.170***	-0.127***	-0.235	-0.176
	(0.122)	(0.110)	(0.731)	(0.686)	(0.038)	(0.035)	(0.145)	(0.129)
Optimism/Pessimism	-0.006	-0.022	-0.014	-0.150	-0.001	-0.005	0.013	-0.015
	(0.029)	(0.026)	(0.193)	(0.186)	(0.010)	(0.009)	(0.039)	(0.035)
Utility Curvature	0.004**	0.003*	0.028**	0.025**	0.001	0.001	0.004	0.003
	(0.002)	(0.002)	(0.011)	(0.011)	(0.001)	(0.001)	(0.003)	(0.002)
Constant	1.412***	0.668*	6.902***	-8.247***	2.735***	2.112***	2.370***	-2.482***
	(0.076)	(0.389)	(0.465)	(2.096)	(0.025)	(0.148)	(0.093)	(0.572)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
R^2	0.010	0.200	0.011	0.134	0.009	0.142	0.003	0.211
N	1902	1901	2245	2244	2629	2628	1921	1920

This table presents OLS estimates of the model $(y_i)^{1/4} = b_0 + b_1$Inverse-S$_i + b_2$ Opt./Pess.$_i + b_3$U.curv$_i$.+Controls$_i'\Gamma + \varepsilon_i$. The variable y_i captures the respondent's i self-reported income and wealth. It can be one of the following variables: "Financial Wealth", "Return Stock", "Family Income", or "Housing Wealth". "Inverse-S" is the respondent i's index of likelihood insensitivity obtained from an estimation of Prelec (1998)'s probability weighting function. "Opt./pess." is the respondent's i's index of optimism and pessimism obtained from an estimation of Prelec (1998)'s probability weighting function. "U.curv" is the respondent i's curvature of the utility function obtained from an estimation of a CRRA utility. Robust standard errors are presented in parentheses. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Table 11: The Relationship between Chateauneuf et al. (2007)'s Probability Weighting Function and Income or Wealth

	(1) Financial Wealth	(2) Financial Wealth	(3) Return Stock	(4) Return Stock	(5) Family Income	(6) Family Income	(7) Housing Wealth	(8) Housing Wealth
Inverse-S	-0.577***	-0.456***	-3.775***	-2.879***	-0.191***	-0.139***	-0.376***	-0.237*
	(0.117)	(0.106)	(0.718)	(0.679)	(0.038)	(0.036)	(0.144)	(0.128)
Optimism/Pessimism	-0.582***	-0.337*	-2.145*	0.028	-0.253***	-0.133**	-0.602**	-0.189
	(0.206)	(0.190)	(1.255)	(1.210)	(0.072)	(0.068)	(0.280)	(0.255)
Utility Curvature	0.009	0.003	-0.082	-0.103	-0.004	-0.003	0.002	-0.008
	(0.013)	(0.012)	(0.076)	(0.075)	(0.004)	(0.004)	(0.017)	(0.015)
Constant	1.509***	0.742*	6.890***	-8.840***	2.793***	2.146***	2.508***	-2.455***
	(0.093)	(0.393)	(0.555)	(2.167)	(0.029)	(0.153)	(0.124)	(0.573)
R^2	0.014	0.199	0.012	0.133	0.013	0.143	0.005	0.210
N	1902	1901	2245	2244	2629	2628	1921	1920

This table presents OLS estimates of the model $(y_i)^{1/4} = b_0 + b_1$Inverse-S$_i + b_2$ Opt./Pess.$_i + b_3$U.curv$_i$.+Controls$'_i\Gamma + \varepsilon_i$. The variable y_i captures the respondent's i self-reported income and wealth. It can be one of the following variables: "Financial Wealth", "Return Stock", "Family Income", or "Housing Wealth". "Inverse-S" is the respondent i's index of likelihood insensitivity obtained from an estimation of Chateauneuf et al. (2007)'s probability weighting function. "Opt./pess." is the respondent's i's index of optimism and pessimism obtained from an estimation of Chateauneuf et al. (2007)'s probability weighting function. "U.curv" is the respondent i's curvature of the utility function obtained from an estimation of a CRRA utility. The estimates presented in Columns 1-4 do not include additional control variables, and the estimates presented in Columns 5-8 do include them. Robust standard errors are presented in parentheses. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Table 12: The Effects of Payday on the Probability of deviating from Expected Utility

	(1) RDU	(2) RDU	(3) RDU	(4) RDU	(5) RDU	(6) RDU	(7) RDU	(8) RDU
Low Expenditures	0.363***	0.281**	0.287**	0.295***				
	(0.124)	(0.131)	(0.117)	(0.108)				
Low Checkings Balance					0.308**	0.313*	0.512***	0.302*
					(0.144)	(0.166)	(0.155)	(0.163)
$\hat{\gamma}_i$	-1.058***	-0.902***	-0.894***	-1.018***	-1.103***	-0.976***	-0.976***	-1.065***
	(0.224)	(0.227)	(0.212)	(0.245)	(0.208)	(0.230)	(0.209)	(0.236)
Varian Index	-5.701***	-4.685***	-5.771***	-4.286***	-5.769***	-4.814***	-5.864***	-4.280***
	(1.750)	(1.396)	(1.445)	(1.414)	(1.680)	(1.391)	(1.423)	(1.471)
Accuracy Stroop Test	0.083**	0.096*	0.113**	0.099**	0.082**	0.090*	0.099**	0.094**
	(0.041)	(0.050)	(0.048)	(0.042)	(0.042)	(0.051)	(0.049)	(0.043)
Constant	0.174	0.308	0.246	0.290	0.135	0.242	0.063	0.274
	(0.467)	(0.498)	(0.574)	(0.566)	(0.468)	(0.506)	(0.576)	(0.582)
Subgroup	Income < 20,000	Caloric Crunch	Lives Check by Check	Liquidity Constrained	Income < 20,000	Caloric Crunch	Lives Check by Check	Liquidity Constrained
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-281.427	-333.785	-335.821	-361.638	-283.273	-334.383	-332.586	-362.724
N	456	534	537	571	456	534	537	571

This table presents probit estimates of the model $\text{RDU}_i = b_0 + b_1\text{Low Financial Circumstances}_i + b_2\hat{\gamma}_i + b_3\text{Before Payday}\times\hat{\gamma}_i + \text{Controls}_i'\Gamma + \varepsilon_i$. The dependent variable "RDU$_i$" is a binary variable that takes a value 1 if respondent i's preferences are classified as Rank-Dependent Utility and 0 otherwise. In Columns (1) and (2) the variable "Low Expenditures" is a binary variable that takes a value of 1 if respondent i has lower than median expenditures in the past 7 days and 0 otherwise. In Columns (3) and (4) the variable "Low Cash Holdings" is a binary variable that takes a value of 1 if respondent i has lower than median cash holdings and 0 otherwise. In Columns (5) and (6) the variable "Low Checking Balance" is a binary variable that takes a value of 1 if respondent i has lower than median checking and savings balances and 0 otherwise. The variable $\hat{\gamma}_i$ captures subject's i utility curvature. "Varian Index" captures the extent to which participant's i responses are consistent with the maximization of a non-satiated utility function. Accuracy Stroop Test captures the performance of respondent i on the Stroop test. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Table 13: The Effects of Payday on the Probability of deviating from Expected Utility

	(1) RDU	(2) RDU	(3) RDU	(4) RDU	(5) RDU	(6) RDU	(7) RDU	(8) RDU
Before Payday	-0.107	-0.563**	0.112	-0.497**	0.023	-0.583***	-0.006	-0.502**
	(0.121)	(0.276)	(0.113)	(0.249)	(0.125)	(0.226)	(0.121)	(0.223)
$\hat{\gamma}_i$	-1.063***	-1.574***	-1.074***	-1.720***	-1.072***	-1.744***	-0.798***	-1.289***
	(0.203)	(0.314)	(0.246)	(0.351)	(0.211)	(0.320)	(0.218)	(0.332)
Before Payday$\times\hat{\gamma}_i$		0.842**		1.216***		1.214***		0.993**
		(0.390)		(0.447)		(0.447)		(0.428)
Varian Index	-8.181***	-8.286***	-5.875***	-5.973***	-5.729***	-5.762***	-5.161***	-5.338***
	(1.794)	(1.829)	(1.397)	(1.370)	(1.676)	(1.736)	(1.470)	(1.436)
Accuracy Stroop test	0.086	0.081	0.042	0.034	0.086**	0.074*	0.058*	0.049
	(0.055)	(0.057)	(0.045)	(0.045)	(0.042)	(0.044)	(0.035)	(0.035)
Constant	0.175	0.466	0.519	0.868*	0.342	0.768*	0.239	0.547
	(0.639)	(0.650)	(0.472)	(0.485)	(0.468)	(0.461)	(0.503)	(0.510)
Subgroup	Lower than median expenditures	Lower than median expenditures	One Payment	One Payment	Income < 20,000	Income < 20,000	Lower than median credit limit	Lower than median credit limit
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-329.862	-327.118	-368.413	-362.293	-285.428	-280.684	-346.365	-342.648
N	540	540	582	582	456	456	536	536

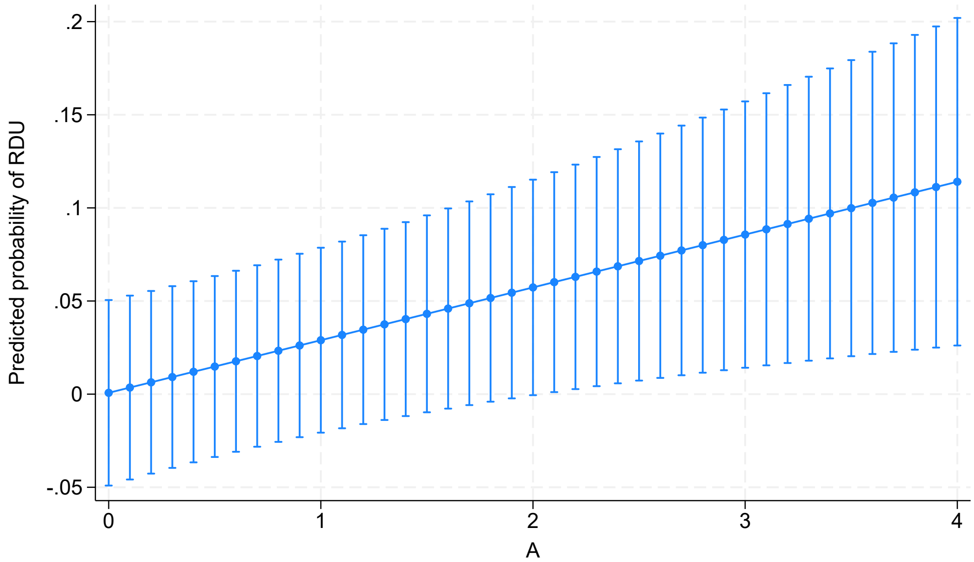
This table presents probit estimates of the model $\text{RDU}_i = b_0 + b_1\text{Before Payday}_i + b_2\hat{\gamma}_i + b_3\text{Before Payday}\times\hat{\gamma}_i + \text{Controls}_i'\Gamma + \varepsilon_i$. The dependent variable RDU_i is a binary variable that takes a value of 1 if respondent i is classified as Rank-Dependent Utility maximizer and 0 otherwise. "Before Payday" is a binary variable that takes a value of 1 if respondent i is assigned to the group that completed the survey before payday and 0 otherwise. The variable $\hat{\gamma}_i$ captures subject's i utility curvature. "Varian Index" captures the extent to which participant's i responses are consistent with the maximization of a non-satiated utility function. Stroop Test Accuracy captures the accuracy of respondent i on the Stroop test questions. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Table 14: The effects of Payday and Utility curvature on being unbiased

	(1) RDU	(2) RDU	(3) RDU	(4) RDU	(5) RDU	(6) RDU
Before Payday	0.014	-0.020	0.024	-0.008	0.031	0.002
	(0.075)	(0.077)	(0.076)	(0.078)	(0.077)	(0.079)
$\hat{A}_i$	-0.013	-0.040***	-0.019	-0.046***	-0.023	-0.051***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
Before Payday$\times\hat{A}_i$		0.071**		0.068**		0.074**
		(0.035)		(0.035)		(0.034)
Varian Index			-1.099	-1.014	-1.131	-1.040
			(0.759)	(0.762)	(0.799)	(0.800)
Time Stroop test			0.023	0.022	-0.001	-0.003
			(0.028)	(0.028)	(0.030)	(0.030)
Constant	0.176***	0.188***	0.093	0.105	-0.362	0.227
	(0.054)	(0.055)	(0.183)	(0.183)	(0.346)	(0.449)
Controls	NO	NO	NO	NO	YES	YES
Log-likelihood	-772.400	-770.465	-759.143	-757.411	-744.241	-742.340
N	1131	1131	1131	1131	1114	1114

This table presents probit estimates of the model $\text{RDU}_i = b_0 + b_1\text{Before Payday}_i + b_2\hat{A}_i + b_3\text{Before Payday}\times\hat{A}_i + \text{Controls}_i'\Gamma + \varepsilon_i$. The dependent variable RDU_i is a binary variable that takes a value of one if respondent i is classified as Rank-Dependent Utility maximizer and zero otherwise. "Before Payday" is a binary variable that takes a value of one if respondent i is assigned to the group that completed the survey before payday and zero otherwise. The variable $\hat{A}_i$ is captures subject's i utility curvature. " Varian Index" captures participant's i consistency with the maximization of a non-satiated utility function. Time Stroop Test captures the accuracy of respondent i on the Stroop test. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, * denotes significance at the 0.1 level.

Figure 6: Marginal Effects of treatment by different levels of A



Note: 95% confidence intervals