Poverty and Uncertainty Attitudes: Theory and Experimental Evidence*

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Abstract

This paper shows that well-established biases in decision making under uncertainty generate poverty traps. A theoretical framework is developed to show that the biases of probability weighting and ambiguity attitudes can lead individuals to forgo profitable investments. The model further predicts that poverty increases the likelihood of such investment errors. As a result, these biases disproportionately discourage investment among poor individuals, thereby contributing to the persistence of poverty. The existence of this poverty trap is empirically validated using data from two experiments conducted on representative samples of American households.

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1. Introduction

The poor often forgo opportunities that could help them escape poverty. 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 of education (Jensen, 2010, Nguyen, 2008). These patterns persist even when credit, liquidity, and information constraints are relaxed (Duflo et al., 2011, Dupas and Miguel, 2017, Suri and Udry, 2022). This evidence suggests that poverty perpetuates through mechanisms beyond material constraints that are rooted in the behavioral and psychological consequences of poverty.

This paper offers an explanation for these patterns of behavior grounded in how individuals perceive uncertainty. It proposes that well-established biases in decision making under uncertainty—*probability weighting* and *ambiguity attitudes*—can generate poverty traps. These biases distort the perceived return to investments, causing individuals to systematically undervalue opportunities that are, in expectation, profitable. Moreover, poverty amplifies these distortions. Consequently, poor individuals become more prone to these perceptual errors, which discourages investment, lowers expected future earnings, and reinforces poverty.

I formalize this 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 the trade-offs between risk and returns objectively, and choose a level of investment that maximizes utility in the absence of bias.

To understand how mistaken perceptions of uncertainty perpetuate poverty, I introduce *probability weighting* into the model (Quiggin, 1982, Tversky and Kahneman, 1992, Abdellaoui, 2000). Under probability weighting, an individual's preferences between risky alternatives are not linear with respect to probabilities. A large body of empirical evidence shows that individuals, when making decisions under risk, systematically misperceive probabilities in this way (see Fehr-Duda and Epper (2011) and Wakker (2010, p. 204)).[1]

A key prediction of the model is that probability weighting induces underinvestment relative to the expected-utility benchmark. This occurs because, under this

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

bias, individuals assign disproportionate weight to the probabilities of extreme returns while underweighting other probabilities. As a consequence, investments that raise the probability of favorable but moderate outcomes are undervalued, even when they are profitable on average. Importantly, certain types of probability weighting generate extreme underinvestment, leading individuals not to invest at all. In particular, when probability weighting induces risk-seeking attitudes, investments with non-extreme returns become unappealing, and individuals optimally choose to forgo investment entirely.

In the model, rich and poor individuals exhibit the same degree of probability weighting—they are equally accurate (or inaccurate) in evaluating probabilities. However, the poor face additional constraints that magnify the consequences of these misperceptions. Specifically, I assume that initial wealth and investment are complementary in generating future wealth. This captures the idea that poorer individuals must invest more to achieve the same improvement as the rich, owing to limited market access, lower capital, or weaker networks. Under this assumption, the gains from investment rise with initial wealth, and the poor are therefore more exposed to the extreme underinvestment induced by probability weighting. Because their investments generate modest gains, distorting the perceived probabilities of success has a first-order effect on their evaluation of these investments. For the rich, by contrast, the gains from investment are large enough such that the influence of probability weighting becomes negligible.

To understand the long-run consequences of this investment behavior, I extend the model to a dynamic setting in which the individual repeatedly chooses how much to invest each period. The results reveal a self-reinforcing dynamic between biased perceptions of risk and economic disadvantage. When wealth is low, probability weighting leads individuals to forgo profitable investments, limiting subsequent wealth accumulation. Low future wealth, in turn, further reduces the perceived gains from investing, strengthening the behavioral distortion and sustaining low investment. By contrast, wealthier individuals, who experience higher gains and whose probability distortions matter less in relative terms, continue to invest and accumulate wealth. The model therefore provides a behavioral foundation for poverty traps: even without credit, information, or market frictions, misperceptions 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 of the model arises because the behavioral poverty trap keeps biased and poor individuals persistently poor, while those who are less biased and less externally constrained can escape poverty. The analyses show that, on average, respondents display a probability weighting function with an inverse-S shape, meaning that the probabilities of extreme outcomes are overweighted while the probabilities of intermediate outcomes are underweighted. This shape of probability weighting generates risk seeking attitudes for high monetary outcomes. More importantly, I find that both family income and financial wealth are significantly and negatively 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 support the model's predictions, they are also open to alternative interpretations. Specifically, one could argue that causality runs in the opposite direction: individuals who are most affected by probability weighting may become poor as a 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) using the GfK Knowledge Panel. In this study, respondents were randomly assigned to complete an incentivized survey shortly before or after their monthly payday, generating exogenous variation in financial resources. I use this design to test whether individuals with fewer resources—those surveyed before payday—are more prone to underinvest in an experimental task due to probability weighting. Although average underinvestment does not differ significantly across treatment groups,the difference becomes pronounced among before-payday respondents who also exhibit sufficiently concave utility. Intuitively, the poverty trap mechanism operates for participants whose marginal utility of consumption is steep: these individuals experience a sharper decline in the value of consumption before payday and thus become more susceptible to the distortions induced by probability weighting. This evidence provides a causal test of the theory and supports its core prediction for the subgroup of respondents with high curvature in their utility function.

The paper concludes by extending the model to incorporate misperceptions of *subjective probabilities*, commonly referred to as *ambiguity attitudes* (Trautmann and van de Kuilen, 2015). In this extension, the investment project is assumed to be ambiguous, that is its return distribution is unknown to the decision maker. To model preferences in such environments, 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. The extended model shows that the behavioral poverty trap identified under risk persists under ambiguity: ambiguity attitudes further distort the perceived attractiveness of investment, reinforcing extreme underinvestment among the poor. Moreover, the threshold level of initial wealth required to avoid the poverty trap becomes higher under ambiguity, implying that even individuals who would escape poverty under risk may remain trapped when facing ambiguous opportunities. Thus, 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 persistent poverty through mechanisms 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 decision-making under uncertainty. Whereas previous behavioral models largely abstract from uncertainty, this paper highlights how poverty and distorted perceptions of uncertainty interact. Specifically, I show theoretically and empirically that probability weighting and ambiguity attitudes—two empirically robust biases—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. In particular, it uses the distinction emphasized by (Wakker, 2010) between *pessimism and 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). The model and empirical results demonstrate that only the latter, the cognitive limitations to accurately perceive probabilities, can generate poverty traps. Thus, in contrast to existing work, the framework identifies a purely *cognitive* channel that alone can generate persistent poverty. Another tool borrowed from the literature of decision theory is the distinction between probability weighting caused by risk and that caused by ambiguity, which is conceptualized by the theory of Baillon et al. (2025). This difference is crucial to easily incorporate ambiguity attitudes in the model, and shows that under a more realistic setting of ambiguity, the poverty trap emerges and affects individuals with higher initial wealth. This implies that in real-world settings where ambiguity is pervasive, such behavioral poverty traps are easier to sustain and more economically consequential.

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 perception 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.

The remainder of the paper is organized as follows. Section 2 presents a stylized model that serves as an example to introduce the intuition of the theoretical framework. Section 3 focuses only on risk and shows that the results from Section 2 can be extended to a more general setting. Sections 4 and 5 show that the model's predictions are empirically validated by data from two experiments. Finally, Section 6 discusses extensions of the model, such as the extension to ambiguity.

2. Motivating Example

To illustrate the mechanism through which probability weighting can generate underinvestment and, ultimately, poverty traps, consider the following simple two-period setup. An individual begins with initial wealth level $x_0 \geq 0$ and decides to invest a share $e \in [0,1]$ of her wealth in a risky project, consuming the remainder $(1-e)x_0$ immediately. If the project succeeds, next-period wealth is given by a Cobb-Douglas technology:

$$x_0^{\mu} z^{1-\mu},$$

where $\mu \in (0,1)$ measures the complementarity between initial wealth and the return $z > 1$. If the project fails, next-period wealth is equal to 0. It will be assumed that the probability of success increases proportionally with the share invested: $p(\text{success}|e) = e$.

Suppose that the individual distorts probabilities according to the probability weighting function

$$w(e) = e^{\beta}, \text{ with } \beta \in [1,2).$$

When $\beta > 1$, probabilities are misperceived, and when $\beta = 1$, probabilities are perceived accurately. For analytical convenience, consumption utility is assumed to follow the CRRA specification: $u(x) = x^{1-\gamma}$, with $0 < \gamma < 1$.

Biased individual. Consider first the case $\beta > 1$. The optimization problem is

$$\underset{e\in[0,1]}{\text{argmax}} \left[e^{\beta} \cdot \left(x_0^{\mu} z^{1-\mu}\right)^{1-\gamma} + (1-e^{\beta}) \cdot \left(0\right)^{1-\gamma}\right] + \left((1-e) \cdot x_0\right)^{1-\gamma}. \tag{1}$$

Let e_r^* denote the optimal investment level. For an interior optimum, the first-order condition is

$$\beta (e_r^*)^{\beta-1} \left(x_0^{\mu} z^{1-\mu}\right)^{1-\gamma} - x_0(1-\gamma)\left((1-e_r^*) \cdot x_0\right)^{-\gamma} = 0. \tag{2}$$

The first expression in the equation above represents the marginal benefit of investment, which depends on the probability weighting parameter β. The second expression captures the marginal utility cost of reducing present consumption.

Under $\beta > 1$, the objective may be non-concave, and corner solutions must therefore be considered.[2] To investigate when a corner solution is relevant, evaluate (2) as $e_r^* \to 0^+$:

$$\lim_{e\to 0^+} \left[\beta (e_r^*)^{\beta-1} (x_0^{\mu} z^{1-\mu})^{1-\gamma} - x_0(1-\gamma)\left((1-e_r^*) \cdot x_0\right)^{-\gamma}\right] = -x_0(1-\gamma)\left(x_0\right)^{-\gamma} < 0. \tag{3}$$

Thus, for sufficiently small e, the perceived marginal benefit of investment is lower than the marginal cost of reduced consumption; investing a small amount is never optimal. Hence, $e_r^* = 0$ is optimal. Moreover, as $e_r^* \to 1^-$ the marginal cost of sacrificing the last unit of consumption explodes; the upper boundary cannot be optimal. Because the Cobb–Douglas technology $x_0^{\mu} z^{1-\mu}$ features complementarity between initial wealth and returns, the marginal benefit of investment rises with x_0 and large investment levels become attractive when x_0 becomes sufficiently large. Consequently, for $\beta > 1$, $e_r^* = 0$ is optimal at low wealth, while a positive and interior level of investment becomes optimal once initial wealth exceeds a threshold $\hat{x}_0 > 0$. Therefore,

$$e_r^* = \begin{cases} 0, & \text{if } x_0 < \hat{x}_0, \\ \in (0,1) & \text{if } x_0 \geq \hat{x}_0. \end{cases} \tag{4}$$

At low wealth levels, probability weighting leads the individual to perceive investment as insufficiently rewarding relative to foregone consumption, resulting in complete underinvestment.

[2]The second order condition of the problem is given by :

$$x_0^{1-\gamma}\Big[-\gamma(1-\gamma)(1-e)^{-\gamma-1} + \beta(\beta-1)(x_0^{\mu} z^{1-\mu})^{1-\gamma} e^{\beta-2}\Big].$$

Unbiased individual. For comparison, consider the case of accurate probability perception. Let e_u^* denote the optimal investment level. Solving (2) for $\beta = 1$ yields the closed-form solution

$$e_u^* = 1 - \left(\frac{1-\gamma}{\left(x_0^{\mu} z^{1-\mu}\right)^{1-\gamma}} \right)^{\frac{1}{\gamma}}. \tag{5}$$

The second order condition corroborates that in this case the problem is globally strictly concave and admits a unique maximizer given by e_u^*.[3] Moreover, investment increases with initial wealth since:

$$\frac{de_u^*}{dx_0} = \frac{1-\gamma}{\gamma}(1-\gamma)^{\frac{1}{\gamma}} z^{-\frac{(1-\gamma)}{\gamma}} x_0^{-\frac{(1-\gamma)}{\gamma}-1} > 0 \tag{6}$$

Under unbiased probability perception, poorer individuals invest less because returns are smaller when x_0 is low. The crucial difference is that the unbiased poor always invest *something*, whereas the biased poor invest *nothing* when $x_0 < \hat{x}_0$. Probability weighting causes poor individuals to mistakenly forgo profitable investments.

Takeaway. If this investment decision were repeated over time, the poor and biased individual would start the next period with an endowment of 0, further reducing her incentive to invest. A wealthier but otherwise identical individual would accumulate wealth, which strengthens the incentive to continue investing. This perpetuation of the wealth gap arises even though, under accurate probability perception, both individuals would invest and converge to similar wealth levels.

This simple example captures the core mechanism of the poverty trap developed in the paper. While individuals from all income levels misperceive probabilities to the same extent, the consequences of these biases fall disproportionately on the poor. Because the potential gains from investment are lower for the poor, they are more susceptible to passing on opportunities due to probability misperceptions. In contrast, wealthier individuals—though equally biased—may still perceive investment worthwhile. These asymmetric behavioral responses reinforce poverty: the poor do not invest, earn lower expected returns, and thus remain trapped in a state of economic disadvantage.

[3] At $e = e_u^*$ and $\beta = 1$ the second derivative equals $-x_0^2(1-\gamma)\big((1-e_u^*)\cdot x_0\big)^{-\gamma-1} < 0$.

3. Theoretical Framework

This section analyzes decision making under risk, that is when the distribution of returns is objectively known. It shows that the mechanism illustrated in the motivating example extends to a general theoretical setting. 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 study the dynamic implications for wealth accumulation and the emergence of poverty traps.

3.1. 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 future wealth at $t = 1$.

Let z denote the stochastic return to investment. At the time the individual chooses e, the realization of z is uncertain and may take any value in the bounded interval $[\underline{x}, \bar{x}]$. The effect of investment on the distribution of returns is captured by the conditional cumulative distribution function $F(z|e)$, which satisfies the following properties:

Assumption 1. *The cumulative distribution function $F(z|e)$ is twice continuously differentiable in e, 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).

An immediate implication of Assumption 1 is that when the individual chooses the lowest investment level, $e = 0$, obtaining a high return is unlikely but still possible. This corresponds to an economic environment in which individuals may improve their outcomes even with a negligible investment. Such a feature may be viewed as unrealistic, as it rules out threshold effects, i.e. situations in which a minimum level of investment is required before improvements become feasible (Dasgupta and Ray, 1986, Galor and Zeira, 1993, Bowles et al., 2011b). In Appendix B, I introduce an alternative specification of the cumulative distribution function that captures these thresholds. Importantly, the main result of the paper—the emergence of a poverty trap driven by probability weighting—continues to hold in that more realistic setting.

Future wealth 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* $H \subset [\underline{z}, \bar{z}]$ *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 realized return on investment. In addition, the wealth production function 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 a given realization of z, richer individuals achieve higher final wealth. This complementarity captures the idea that initial wealth amplifies the gains from successful investment because richer individuals own more capital, face lower barriers to access markets, or have more influential networks. In fact, the normalization at the lower boundary ensures that individuals with the lowest initial wealth cannot generate future wealth. Finally, the top-region gain condition guarantees that investment is on expectation profitable at high 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:

$$\mathbb{E}\big(u(z, e)\big) = u\big(x_0(1 - e)\big) + \delta \int_{\underline{x}}^{\bar{x}} u\Big(b(x_0, z)\Big) \mathrm{d}F(z|e). \tag{7}$$

The first expression in (7) 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.

The consumption utility function, u, is assumed to satisfy 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 implies diminishing marginal utility of consumption. Under expected utility (henceforth EU), this property implies that the individual is risk averse. Moreover, 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). Hence, individuals with lower initial wealth experience smaller increases in consumption utility from a given investment return compared to wealthier individuals. This assumption is standard in related models, e.g. in Dalton et al. (2016), and is satisfied by common functional forms. For instance, with CRRA utility $u(b) = b^{1-\gamma}$ and Cobb–Douglas technology $b(x_0, z) = x_0^{\mu} z^{1-\mu}$, the condition reduces to $\gamma < 1$.

3.2. Probability Weighting Functions and Rank-Dependent Utility

The standard assumption that individuals perceive 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. *Let* $p \in [0, 1]$. *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:*** *For some* $\tilde{p} \in [0, 1]$, $w''(p) < 0$ *if* $p < \tilde{p}$ *and* $w''(p) > 0$ *if* $p > \tilde{p}$;

(iv) ***Certainty Effect:*** *if* $\tilde{p} = 0$, $\lim_{p\to 0} w'(p) > 1$ *and* $\lim_{p\to 1} w'(p) < 1$;

(v) ***Possibility Effect:*** *if* $\tilde{p} = 1$, $\lim_{p\to 1} w'(p) > 1$ *and* $\lim_{p\to 0} w'(p) < 1$;

(vi) ***Certainty and Possibility Effects:*** *if* $\tilde{p} \in (0, 1)$, $\lim_{p\to 1} w'(p) > 1$ *and* $\lim_{p\to 0} w'(p) > 1$; *and*

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

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. $p = 1$. Moreover, $w(p)$ can have three possible shapes: concave, convex, or inverse-S, which are determined by the location of the inflection point $\tilde{p} \in [0, 1]$. It is worth emphasizing that 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):

$$RDU\big(u(z, e)\big) = u\big(x_0(1 - e)\big) + \delta \int_{\underline{x}}^{\bar{x}} u\Big(b(x_0, z)\Big) \mathrm{d}\Big(w\big(1 - F(z|e)\big)\Big). \tag{8}$$

RDU generalizes expected utility by applying probability weighting to the decumulative function $1 - F(z|e)$. Thus, for a given return level $Z \in [\underline{x}, \bar{x}]$ and investment level $e' \in [0, 1]$, the individual considers the *rank* or probability of obtaining a higher level of return, given by $1 - F(Z|e')$. This probability is perceived through the weighting function by $w\big(1 - F(Z|e')\big)$. In other words, decumulative probabilities are transformed using the function w with the properties as described in Assumption 4.

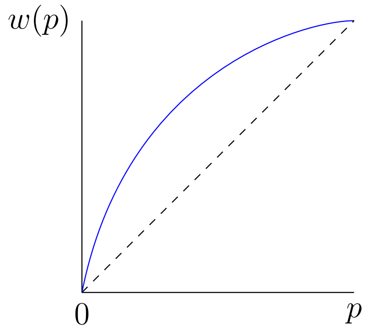
Accordingly, a return infinitesimally lower than Z changes the perceived rank by $\mathrm{d}\Big(w\big(1 - F(Z|e')\big)\Big)$, which represents the differential of the integral in (8). Hence, in the RDU framework, the utility derived from obtaining a return Z, denoted $u(b(\cdot, Z))$, is weighted by its contribution to the perceived rank $\mathrm{d}\Big(w\big(1 - F(Z|e')\big)\Big)$, and these weighted utilities are integrated over all possible returns $z \in [\underline{x}, \bar{x}]$.

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.

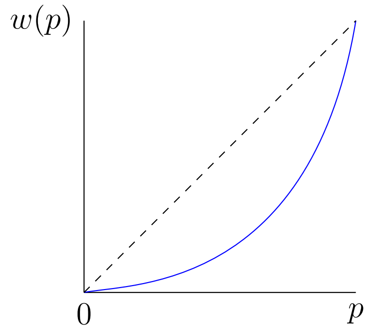
3.3. Motivational and Cognitive Factors of Probability Weighting

To comprehensively investigate the relationship between poverty and probability weighting, I follow Wakker (2010) in distinguishing between two distinct types of probability weighting. The first stems from pessimism and optimism. This type of probability weighting 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, we examine how the severity of probability weighting, 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.

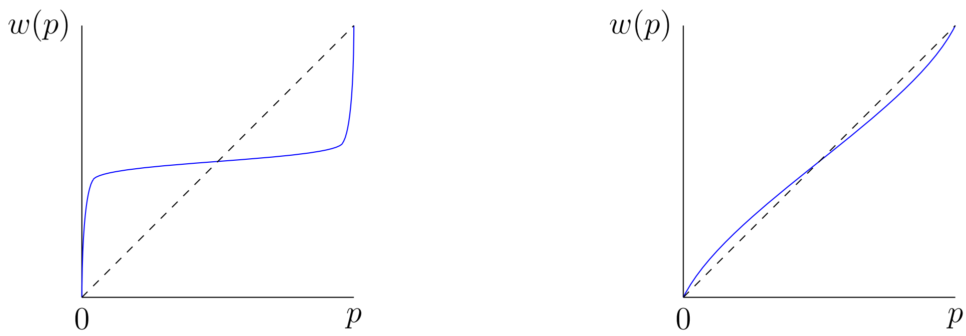
Definition 2. *An agent i with weighting function $w_i(p)$ is more optimistic (pessimistic) than an agent with weighting function w_j if $w_i(p) = \theta\big(w_j(p)\big)$ where the function $\theta : [0,1] \to [0,1]$ is twice continuously differentiable with $\theta' > 0$ and $\theta'' < 0$ ($\theta''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

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) leads to more (less) risk aversion.*

The second type of probability weighting is driven by likelihood insensitivity (Tversky and Wakker, 1995, Wakker, 2010). It captures the idea that individuals misperceive 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 probability weight to the probabilities of extreme returns and insufficient weight to the probabilities of intermediate returns.



(a) Extreme likelihood insensitivity

(b) Moderate likelihood insensitivity

Figure 2: Examples of likelihood insensitivity

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 crude perception of these probabilities as being close to "50-50"—either the event under consideration happens or it won't.

It is useful for the analysis 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 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 distribution is left-skewed, the same bias 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 a given investment level e, stronger pessimism, stronger optimism, or stronger likelihood insensitivity generates a larger set of probabilities for which the probability weighting function satisfies $w'(p) < 1$.*

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

To understand the intuition underlying this result, consider an individual who becomes more pessimistic. This increased pessimism raises the weight assigned to the probability of the lowest return. Because the average slope of the probability weighting function must equal one—since $w(0) = 0$ and $w(1) = 1$— we have

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

Such greater overweighting of the worst outcome necessarily reduces the weights assigned to other outcomes. Consequently, the set of probabilities receiving insufficient weight, that is less weight than under EU, expands. In this case, this expansion affects the probabilities of intermediate and high returns. A similar reasoning applies when an individual becomes more optimistic or more likelihood insensitive. Under stronger optimism, underweighting extends to low and intermediate probabilities, while under stronger likelihood insensitivity it primarily affects intermediate probabilities.

3.4. Probability Weighting and Investment Choice

We are now in a position to examine how probability weighting influences the investment decision. 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). The optimal investment level chosen by the RDU individual, e_r^*:*

(i) is unique, interior in the set $[0, 1]$, and increasing in x_0;

(ii) if the individual is more pessimistic than a unique threshold level of pessimism (in the sense of Definition 2), then $e_r^* < e_u^*$.

The RDU individual with sufficiently strong pessimism underinvests relative to an EU individual with otherwise identical preferences and initial wealth. 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, thereby reducing her willingness to invest in the risky project. The degree of pessimism required to generate underinvestment depends on how productive the investment is. When investment only modestly increases the probability of favorable outcomes, even moderate pessimism suffices to reduce optimal investment. In contrast, when investment substantially improves these probabilities, only sufficiently pronounced 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 the poor individual chooses not to invest at all even when the investment is objectively profitable.

Proposition 3. *Assume that Assumptions 1–4 hold and that the individual exhibits optimism (Definition 1) or likelihood insensitivity (Definition 3). There exists a threshold level of initial wealth* $\hat{x}_0 \in (\underline{x}, \bar{x}]$ *such that the optimal investment level is:*

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

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

Optimism leads the individual to assign excessive weight to the probability of the best outcome and insufficient weight to all other probabilities. The risk-seeking attitude generated by this misperception 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. The likelihood-insensitive individual misperceives 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 on 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; combined with the risk-seeking distortions induced by optimism or likelihood insensitivity, this makes complete non-investment optimal.

The mathematical rationale behind this result parallels that of the example in Section 2. The concavity of the probability weighting function, whether due to optimism or likelihood insensitivity, introduces non-convexities into the optimization problem. As a result, the optimal solution often lies at one of the boundaries of the feasible set $[0, 1]$. Hence, when an investment is undervalued due to probability weighting, 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 required by Assumption 3—makes individuals with higher initial wealth more susceptible to extreme underinvestment. Greater curvature steepens the marginal utility cost of foregone consumption, thereby expanding the region in which the distorted marginal benefits from investment fail to outweigh its immediate utility cost.

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

3.5. 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 that there are $t = 1, ..., T$ periods. In each period t, the agent is endowed with initial wealth x_t and chooses an optimal level of investment e_t^* to maximize her utility. The stochastic return to the investment made in period t, denoted by z_t, is drawn from the cumulative distribution function $F(z_t|e_t)$ which satisfies the properties in Assumption 1. Moreover, the future wealth of period t is determined by the function $b(x_t, z_t)$ with the properties in Assumption 2. Accordingly, future wealth evolves according to:

$$x_{t+1} = \int_{\underline{x}}^{\bar{x}} b(x_t, z_t) \mathrm{d}F\left(z_t|e_t\right). \tag{9}$$

In words, wealth in $t+1$ is determined by the expected benefits from investment in t.

Throughout, it is assumed that the agent chooses the optimal e_t in each period t to maximize her intertemporal utility over periods t and $t+1$. This framework admits two complementary interpretations. First, the agent can be viewed as myopic, making decisions in each period about current and next-period wealth without explicitly considering subsequent periods. This assumption is consistent with the notion of isolation, 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). 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 changes the way they evaluate future risks (Karni and Safra, 1990, Gilboa and Schmeidler, 1993, Sarin and Wakker, 1998). Alternatively, the framework can be interpreted in an overlapping-generations (OLG) setting, in which each generation lives for a single period, transfers its accumulated wealth to the next, and derives utility from this bequest. In this interpretation, investment represents the share of resources allocated to descendants—or equivalently, to the productive capital stock of the next generation.

We turn to characterize the long-run equilibrium when the evolution of wealth follows the law of motion given in (9). The following proposition shows that under EU there is 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 initial wealth (Proposition 1). Since higher initial wealth raises the marginal return to investment, through the complementarity $b_{x_0,z} > 0$, next-period wealth increases with x_0. However, at sufficiently high wealth levels, diminishing returns to initial wealth ($b_{x_0,x_0} < 0$) make the wealth-accumulation curve flatten, causing it eventually to grow more slowly than the 45-degree line $x_{t+1} = x_t$. Moreover, the same diminishing returns to initial wealth property, ensures that at low wealth levels, accumulation remains effective enough that expected wealth rises. These two forces together imply that the wealth-transition curve crosses the identity line exactly once, yielding a unique steady state at which expected wealth neither rises nor falls.

Before turning to the long-run equilibria under probability weighting, I introduce an additional assumption that prevents "free-lunch" growth: it ensures that individuals with very low wealth cannot accumulate wealth without investing.

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

$$\int b(x_0, z)\, dF(z \mid 0) \;\leq\; \underline{x} \;+\; k\,(x_0 - \underline{x}).$$

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 $\underline{x}$, expected wealth cannot grow more than proportionally to current wealth. The function b remains fully smooth and concave exactly as specified in the baseline model. The assumption only rules out the knife-edge case in which zero investment would generate automatic wealth increases for very poor individuals.

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

Proposition 5. *Assume that Assumptions 1–5 hold and that the individual exhibits either optimism or likelihood insensitivity. 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 steady state is a corner solution at the lower boundary* $x_r^* = \underline{x}$*;*

(ii) if $x_0 > \tilde{x}_0$*, the steady state is a high-wealth equilibrium* $x_r^* = x_H > \hat{x}_0$*.*

At low levels of wealth, small investments are 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 rises, however, investment becomes more effective due to the complementarity between initial wealth and returns ($b_{x_0 z} > 0$), and since higher investment increases success probabilities in the sense of first-order stochastic dominance. These two forces—excessive underinvestment at low wealth and sharply increasing responsiveness at intermediate wealth—generate an S-shaped wealth transition function $M_r(x)$. This shape implies 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 continued investment sustains long-run prosperity.

Proposition 5 provides an explanation for the empirical regularity that the poor frequently pass up profitable opportunities. They may misperceive the returns to additional schooling as too small to justify the cost (Jensen, 2010, Nguyen, 2008), or exhibit excessive price sensitivity for effective preventive health products (Dupas and Miguel, 2017). In both cases, probability weighting leads them to undervalue investments that would, on average, improve their future economic prospects.

To conclude the model, it is shown that pessimism does not generate a poverty trap. Instead, it leads to a unique steady-state equilibrium at a lower level of wealth than that obtained under expected utility.

Corollary 2. *Under the conditions of Proposition 5, suppose instead that the individual exhibits pessimism (in the sense of Definition 1). 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 expected utility. 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—wealth and investment continue to rise together. This preserves the concavity of the transition map $M_r(x)$, ensuring that wealth dynamics converge to a unique, globally stable steady state. Pessimism therefore reduces long-run 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 probabilities.

4. Correlational Evidence of the Behavioral Poverty Trap

In this section, I use the experimental data from Dimmock et al. (2021) to evaluate the empirical validity of the poverty trap predicted by the theory. The study by Dimmock et al. (2021) implemented an incentivized experiment in the American Life Panel, a representative sample of American households. The original goal of the experiment was to analyze the relationship between household portfolio diversification and probability weighting. These data therefore provide a unique opportunity to investigate whether probability weighting is associated with differences in wealth and income, consistent with the poverty trap mechanism derived in Section 3.

Notably, 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/optimism. To deal with this, I fit the respondent's answers to the questions designed to elicit probability weighting functions 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 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:

$$w(p_{ij}) = \exp\Big(-\beta_i\big(-\ln(p_{ij})\big)^{\alpha_i}\Big), \tag{10}$$

where the index j represents the questions designed to elicit probability weighting. To estimate the parameters α_i and β_i in (10), 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 (10) 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 (10) 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: lower values of $\hat{\beta}_i$ reflect stronger pessimism (if $\hat{\beta}_i < 1$), while higher values denote stronger optimism (if $\hat{\beta}_i > 1$).

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

$$u(x_{ik}) = x_{ik}^{1-\gamma_i}. \tag{11}$$

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 $\hat{\beta}_i$.[4] 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.

The aforementioned findings are further corroborated by analyzing the estimates at the individual level. A majority of respondents, 2012 out of 2640, exhibit $\hat{\alpha}_i < 1$, which indicates likelihood insensitivity. Furthermore, a majority of subjects, 1872 out

[4] It should be emphasized that 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.

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).

Table 1: Estimates of Probability Weighting Functions

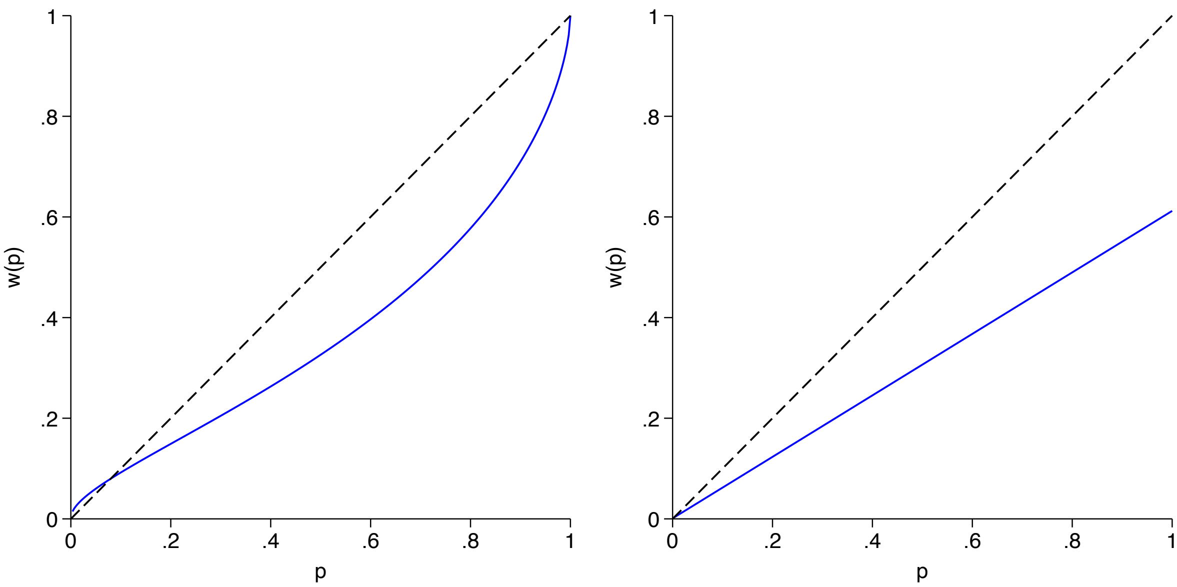
	Prelec (1998)		**Chateauneuf et al. (2007)**	
	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{s}_i$	$\hat{c}_i$
Mean	0.815	1.855	0.594	0.028
25th perc.	0.361	0.932	0.257	-0.118
50th perc.	0.630	1.411	0.611	0.001
75th perc.	0.972	2.329	0.891	0.056
St. Dev.	1.211	1.550	0.358	0.067

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.

A distinct advantage of these data is that, in previous waves of the ALP, the same respondents were asked to report their levels of income and wealth. This allows me to examine the relationship between those responses and the previously discussed indices of insensitivity and pessimism. Specifically, the analysis incorporates the following variables: "Financial 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 self-reported annual income; and "Housing Wealth", capturing the household's reported real estate holdings.

Table 2 presents the descriptive statistics of these variables. All are continuous and expressed in dollars (or thousands of dollars), and in each case the standard deviation exceeds the mean, indicating considerable dispersion. To stabilize this variability, I apply a natural logarithmic transformation, following the approach used by Dimmock et al. (2016b) and Dimmock et al. (2021). Specifically, I use the transformation $ln(y_i + 1)$, where y_i denotes the variable under consideration. This transformation not only reduces the influence of extreme values but also helps mitigate concerns about

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.

selection on non-zero values, which arise due to the presence of multiple zero observations. To assess the robustness of the results to alternative transformations, I also estimate regressions using the quartic-root transformation, i.e. $(y_i)^{1/4}$, as recommended by Thakral and Tô (2023). This transformation also addresses potential biases associated with selection on non-zero values.

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 households 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 of the transformed income and wealth variables is regressed on the indexes of probability weighting. The advantage of running separate regressions, where each variable presented in Table 2 serves as the dependent variable in turn, is that these variables capture different dimensions of income and wealth. Thus, this approach offers insight into the specific contexts where the proposed poverty trap operates. For example, Return Stock captures income with lower liquidity relative to that included in Family Income, and might therefore be less relevant in the case of 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 the respondents' utility curvature to isolate the effect of probabilistic risk attitudes on income and wealth. Thus, an empirically relevant relationship between poverty and probability weighting must emerge above and beyond the average influence of utility curvature. Moreover, in some specifications, I include other control variables that might moderate the relationship between probability weighting and income (or wealth), such as the respondent's age, gender, ethnicity, level of education, state of residence, spoken language, and employment status.

Table 3 presents the OLS estimates of the regressions. These results indicate 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. Moreover, these relationships remain highly significant after the introduction of controls. This empirical finding is consistent with the model's prediction that likelihood insensitivity generates a poverty trap (Propositions 3 and 5). Furthermore, the coefficient on Inverse-S is not significant when Housing Wealth is used as the dependent variable. This 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.[5] Table 10 in Appendix E, shows that these results also hold when quartic-root transformations are applied to the dependent variable. This indicates that these findings are not an artifact of the specific transformation used to stabilize variance, but are robust to alternative transformations.

The estimates presented in Table 3 also indicate that pessimism does not significantly affect the respondents' income and wealth. The same conclusion holds when the quartic-root transformation of the dependent variable is used (see Table 8). This corroborates the prediction of the model that pessimism does not generate a poverty trap (Corollary 2).

The aforementioned lack of support for the theoretical predictions under pessimism/optimism

[5] It must be noted that the same qualitative results are obtained without winsorization (see Table 8 in Appendix E).

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)
Opt./Pess.	-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)
U. Curv	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 $\ln(y_i + 1) = b_0 + b_1\text{Inverse-S}_i + b_2\ \text{Opt./Pess.}_i + b_3\text{U.curv}_i + \text{Controls}_i'\Gamma + \varepsilon_i$. 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 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.

may stem from the fact that the estimate $\hat{\beta}_i$ can be confounded by factors other than pessimism or optimism, such as insensitivity and utility curvature (Gonzalez and Wu, 1999, Abdellaoui et al., 2011, Li et al., 2018). To address this potential identification problem, I repeat the previous analyses using an alternative parametric form of probability weighting that is better suited to disentangle optimism and pessimism. In particular, I assume the neo-additive form proposed by Chateauneuf et al. (2007):

$$w(p_{ij}) = \begin{cases} 0 & \text{if } p = 0, \\ c_i + s_i \cdot p_{ij} & \text{if } p \in (0,1), \\ 1 & \text{if } p = 1. \end{cases} \tag{12}$$

This parametric form is recommended for constructing indexes of pessimism and insensitivity because its parameters have a clean and simple interpretation (Wakker, 2010). I estimate the parameters c_i and s_i in (12) simultaneously with the parameter γ_i in (11) using non-linear least squares.

Columns 3 and 4 in Table 1 present the descriptive statistics of the estimates $\hat{c}_i$

and $\hat{s}_i$.[6] Remarkably, the previous finding that most respondents exhibit insensitivity and pessimism emerges again when this alternative parametric form of probability weighting is used. Specifically, respondents exhibit likelihood insensitivity on average, as indicated by the average estimated value of $\hat{s}_i$, which is less than 1. They also exhibit pessimism on average, since $1 - \hat{c}_i + \hat{s}_i > 0$ holds for the average values of $\hat{c}_i$ and $\hat{s}_i$. Moreover, Figure 3b shows that these conclusions also hold for the median respondent.

Following Wakker (2010) and Abdellaoui et al. (2011), I compute indexes of likelihood insensitivity and pessimism/optimism for each respondent using $\hat{c}_i$ and $\hat{s}_i$. To capture likelihood insensitivity, I use the value $-\hat{s}_i$ if $\hat{s}_i < 1$. I refer to this continuous index of likelihood insensitivity as "Inverse-S." For optimism and pessimism, I use the expression $\frac{2\hat{s}_i + \hat{c}_i}{2}$, which compares how strongly a respondent overweights small probabilities (associated with the best outcomes) to how strongly they underweight large probabilities (associated with the worst outcomes).[7]

Table 4 reports the OLS estimates using alternative indexes of probability weighting as explanatory variables. Consistent with the previous results, higher likelihood insensitivity is associated with lower financial wealth, lower return on stocks, and lower family income. Moreover, the relationship between the pessimism index and the income and wealth measures is also negative and statistically significant, though generally weaker once control variables are introduced. In particular, greater pessimism is associated with lower financial wealth, which is particularly relevant for poor households. For Family Income, I also find a negative and significant relationship; however, this relationship becomes only borderline significant after including controls, suggesting that the influence of pessimism is less robust and may be partially moderated by other socio-demographic factors.

Thus, when I use this alternative parametric form of probability weighting function, I find support for Propositions 3 and 5. Poverty is positively associated with likelihood insensitivity (i.e., higher insensitivity corresponds to lower wealth and income). Table 11 in Appendix E shows that these results also hold when a quartic-root transformation of the dependent variable is used. In addition, Table 9 in Appendix E show that these findings remain robust when a 95% winsorization is applied to the

[6] It should be noted that I did not apply winsorization to these data. When I apply a 95% winsorization 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. Therefore, these data are less likely to produce misleading conclusions due to the presence of outliers.

[7] As p approaches zero, the weighting function becomes $w(p) = c$. In contrast, as p approaches one, it becomes $w(p) \approx 1 = c + s$. Thus, comparing a respondent's level of optimism to her level of pessimism is equivalent to computing the difference $c - (1 - c - s)$. The index $\frac{2\hat{s}+\hat{c}}{2}$ is a linear transformation of that difference (Wakker, 2010).

Table 4: 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	-1.872***	-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)
Opt./Pess.	-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)
U. Curv	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 $\ln(y_i + 1) = b_0 + b_1\text{Inverse-S}_i + b_2\,\text{Opt./Pess.}_i + b_3\text{U.curv}_i + \text{Controls}_i'\Gamma + \varepsilon_i$. 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.

estimate $\hat{c}_i$, which is the analog of $\hat{\beta}_i$ in Prelec (1998)'s parametric specification. Therefore, these results are robust to the choice of data transformation.

Overall, the empirical evidence is consistent with the predictions of the model. Nevertheless, this analysis does not establish causality. The observed correlations could also reflect an alternative mechanism: individuals, regardless of their initial wealth, may fall into poverty if they display sufficiently strong probability distortions. This interpretation contrasts with the model's conjecture, which posits that poverty amplifies the effects of probability weighting, causing poor individuals to make suboptimal investment choices that reinforce their low-wealth status. The next section provides causal evidence to more directly test this prediction.

5. 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. The study by Carvalho et al. (2016) conducted experiments with two panels of representative U.S. households to examine how financial resources influence economic decision-making. In both experiments, respondents were randomly assigned to one of two groups, with each group completing a survey either shortly before or shortly after monthly payday. The survey included a battery of questions eliciting risk and time preferences, as well as measures of decision-making quality.

The elicitation of risk preferences included in Carvalho et al. (2016) does not make it possible to cleanly identify the probability weighting and utility functions. However, I recover these preference components from the questions originally designed to measure decision-making quality. These questions were administered only to participants in the GfK KnowledgePanel; accordingly, the empirical analysis in this section focuses on that sample.

Carvalho et al. (2016) measured decision-making quality using the method of Choi et al. (2007), which requires respondents to allocate an endowment between two risky assets. Specifically, respondents choose the fraction of their endowment to invest in good x_1, with the remaining fraction automatically invested in good x_2. When making this decision, respondents knew that with probability 0.5 only the investment in x_1 would yield a return, and with the complementary probability 0.5, only their investment inx_2 would yield a return. In total, the survey included 25 such allocation problems, which varied in the size of the endowment and the amount of investment that could be afforded in one good relative to the other.[8]

The participants' risk preferences were recovered with the Money Metric Index method of Halevy et al. (2018) (MMI, henceforth). The most important property of this method for the present analysis, is its ability to recover probability weighting and utility functions for a *given level of decision-making quality*. This is because it is based on a theoretical result that separates a participant's consistency of choices with respect to the maximization of a non-satiated utility function, which is Carvalho et al. (2016)'s criterion for decision-making quality, from mispecification, which refers to the goodness-of-fit of the parametric forms that are assumed to recover risk preferences. This separation is advantageous for our purposes since it allows us to safely ignore decision-making quality and focus on risk preferences.

In line with the theoretical model, it is assumed that a participant i makes choices in each of these questions by maximizing the following utility:

$$RDU_i = w_i(0.5) \cdot u_i\big(\max\{x_1, x_2\}\big) + (1 - w_i(0.5)) \cdot u_i\big(\min\{x_1, x_2\}\big). \tag{13}$$

Where $w_i(1/2)$ is assumed to have the following parametric form:

[8] In the jargon of Choi et al. (2007), the relative prices of x_1 and x_2 were varied across questions. Thus, the slope of the budget line in the two-dimensional plane differed across questions, and so was the extent to which one good was cheaper (more expensive) than the other.

$$w_i(1/2) = \frac{1}{2+\beta_i} \text{ with } \beta_i > -1. \quad (14)$$

When $\beta_i > 0$, the probability assigned to the favorable outcome, $\max\{x_1, x_2\}$, is underweighted, that is, perceived as smaller than its objective value of 0.5. In this case, the decision maker underinvests relative to the expected-utility (EU) benchmark due to this misperception of the probability of the favorable outcome. Conversely, when $\beta_i < 0$, the probability of the favorable outcome is overweighted, leading the decision maker to overinvest relative to the EU benchmark. Finally, when $\beta_i = 0$ the decision maker maximizes EU.

Consistent with the previous empirical analysis, I also assume that the consumption utility function belongs to the CRRA family:

$$u_i(z) = \begin{cases} \frac{z^{1-\gamma_i}}{1-\gamma_i} & \text{if } \gamma_i \geq 0 \text{ and } \gamma_i \neq 1, \\ \ln(z) & \text{if } \gamma_i \geq 0 \text{ and } \gamma_i = 1. \end{cases} \quad (15)$$

The parameter γ_i captures risk aversion due to utility curvature. For the sake of robustness, I also estimate an alternative model in which consumption utility is assumed to belong to the CARA family. In that specification, I use the parametric form $u_i(z) = -\exp\big(-A_i z\big)$ where $A_i \geq 0$. I apply the MMI method to estimate the parameters β_i and γ_i for each respondent. I also use this method to estimate the individual-specific parameters β_i and A_i when the model is estimated with CARA utility.

Table 5 provides descriptive statistics of 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, which implies that participants perceived the probability 0.5 to be on average equal to 0.417. This pattern of probability underweighting is also observed when the consumption utility function is assumed to belong to the CARA family. In that case, the probability 0.5 is perceived as 0.390. Thus, subjects on average underweighted the probability of the best outcome and, thus, exhibited underinvestment relative to the EU benchmark.

The theoretical framework developed in this paper predicts that poverty exacerbates the underinvestment arising from probability weighting. To empirically assess this prediction, 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 EU if I cannot reject the null hypothesis $\hat{\beta}_i = 0$; otherwise, the respondent is classified as RDU. This hypothesis test is implemented by constructing 95% confidence inter-

[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.

Table 5: 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 $\beta_i > -1$.

vals for $\hat{\beta}_i$ using a resampling procedure.[10] I find that the majority of respondents in the sample exhibit significant probability weighting and can therefore be classified as RDU. In particular, 622 respondents out of 1131 (55% of the sample) are RDU, while 509 are classified as EU. When assuming a CARA utility function, 682 respondents are classified as RDU (60% of the sample) and 449 as EU.[11]

The first analysis of these data relates the classification of risk preferences to indicators of the respondents' economic circumstances. The primary goal of this analysis is to corroborate the empirical patterns observed in the previous section. Specifically, I examine whether respondents classified as RDU or EU differ in terms of having below-median expenditures during the last seven days, below-median cash holdings, and below-median checking and savings balances Essentially, these variables indicate how the respondent's economic situation relates to that of others in the sample.[12]

The regression estimates reported in Table 6 indicate that individuals facing worse economic circumstances are more likely to be classified as RDU. Specifically, respondents with below-median expenditures and below-median checking and savings balances are, respectively, 6% and 15% more likely to deviate from EU due to proba-

[10] Specifically, I generate 1,000 bootstrap resamples of each individual dataset to construct these confidence intervals, following the approach of Halevy et al. (2018).

[11] It should be emphasized that the probability $p = 1/2$ 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.

[12] The focus on medians follows Carvalho et al. (2016), who report stronger correlations between financial circumstances and the treatment (i.e., completing the survey before payday) when using median regressions.

bility weighting. Moreover, the point estimate of the relationship between below-median cash holdings and being classified as RDU is positive but not statistically significant. Furthermore, the estimates presented 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. One of the examined subgroups includes individuals reporting financial hardship, while another—partially overlapping—subgroup reports experiencing a caloric crunch. Taken together, these results reinforce the findings of the previous section: probability weighting and poverty, as reflected in more constrained economic conditions, are positively associated.

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

	(1) RDU	(2) RDU	(3) RDU	(4) RDU	(5) RDU	(6) RDU
Low Expenditures	0.153**	0.178**				
	(0.077)	(0.082)				
Low Cash Holdings			0.072	0.116		
			(0.078)	(0.084)		
Low Checkings Balance					0.201**	0.223**
					(0.085)	(0.089)
$\hat{\gamma}_i$	-0.790***	-0.812***	-0.785***	-0.810***	-0.798***	-0.828***
	(0.134)	(0.137)	(0.134)	(0.137)	(0.134)	(0.138)
Varian Index	-11.461***	-11.766***	-11.516***	-11.845***	-11.451***	-11.818***
	(2.005)	(2.096)	(1.993)	(2.084)	(1.992)	(2.086)
Time Stroop test		0.001		0.001		0.001
		(0.004)		(0.004)		(0.004)
Constant	0.695***	0.199	0.728***	0.278	0.631***	0.168
	(0.105)	(1.413)	(0.105)	(1.407)	(0.123)	(1.405)
Controls	NO	YES	NO	YES	NO	YES
Log-likelihood	-749.279	-720.490	-750.827	-721.921	-748.411	-719.778
N	1131	1116	1131	1116	1131	1116

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 is classified as Rank-Dependent Utility maximizer and 0 otherwise. In Columns (1) and (2) the variable "Low Financial Circumstances" 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 Financial Circumstances" 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 Financial Circumstances" 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. Time Stroop Test captures the time in seconds that respondent i spent on answering 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.

I now turn to the second part of the analysis, which examines whether the model's predictions can be validated experimentally. 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, relative to respondents in the control group—those surveyed after payday. To this end, I regress the classification of risk preferences on a treatment indicator labeled "Before Payday." In all specifications, I control for utility curvature, captured by the individual estimate $\hat{\gamma}_i$ in the case of CRRA utility. In additional specifications, I include further controls to account for individual heterogeneity: decision-making quality, measured by Varian's Index (Varian, 1982); cognitive ability, proxied by the time spent on the Stroop test (administered to the GfK KnowledgePanel sample); and demographic characteristics, including ethnicity, age, education, gender, employment status, and occupation type.

Table 7 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 result remains robust to the inclusion of control variables. This statistically insignificant relationship is consistent with the results of Carvalho et al. (2016), who show that temporary financial strain does not directly affect risk attitudes. I extend their result by showing that such short-term financial circumstances also do not influence adherence to expected utility.

Recall that the strength of the behavioral poverty trap crucially depends on utility curvature (see Assumption 3 and Corollary 1). I account for 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 resulting estimates are presented in columns (2), (4), and (6) of Table 7. The coefficient of the interaction term Before Payday $\times \hat{\gamma}_i$ indicates that being financially constrained, combined with a more concave utility function, increases the likelihood that investment decisions deviate from the EU benchmark. This conclusion is supported by Figure 4 which presents the average treatment effect for different values of $\hat{\gamma}$. Furthermore, Table 14 and Figure 6 in Appendix D confirm that these results are robust to assuming a CARA specification of consumption utility. Hence, the conclusions are not driven by the particular functional form of utility adopted.

This empirical result is consistent with Corollary 1. It shows that poverty amplifies the underinvestment arising from probability weighting when the utility function is sufficiently concave. Intuitively, the poverty trap manifests among participants for whom the marginal utility of an additional dollar is steep. These individuals experience a substantial decline in consumption utility before payday, making them more susceptible to the adverse effects of probability weighting.

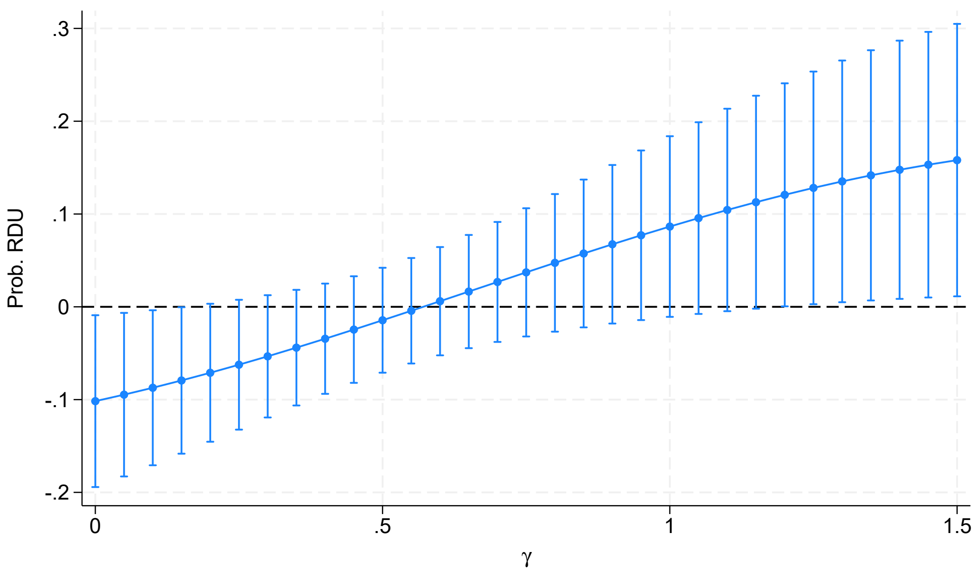
The robustness of this interaction between the treatment and utility curvature is further supported by analyses that restrict the sample to respondents reporting difficult economic circumstances. The estimates presented in Table 13 in Appendix E

Table 7: 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*	-0.026	-0.286**	-0.032	-0.315**
	(0.075)	(0.139)	(0.076)	(0.146)	(0.077)	(0.147)
$\hat{\gamma}_i$	0.385***	0.626***	-0.792***	-1.055***	-0.817***	-1.099***
	(0.114)	(0.166)	(0.135)	(0.184)	(0.137)	(0.185)
Before Payday $\times\hat{\gamma}_i$		-0.460**		0.494**		0.553**
		(0.229)		(0.236)		(0.238)
Varian Index			-11.440***	-11.535***	-11.736***	-11.983***
			(2.018)	(2.031)	(2.059)	(2.084)
Time Stroop test			0.001	0.001	0.000	0.001
			(0.003)	(0.003)	(0.004)	(0.004)
Constant	-0.338***	-0.465***	0.433	0.406	0.615	0.278
	(0.080)	(0.101)	(1.226)	(1.225)	(1.345)	(1.404)
Controls	NO	NO	NO	NO	YES	YES
Log-likelihood	-772.598	-770.595	-741.266	-739.040	-726.804	-720.158
N	1131	1131	1116	1116	1116	1116

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 a 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. Time Stroop Test captures the time in seconds that respondent i spent on answering 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.

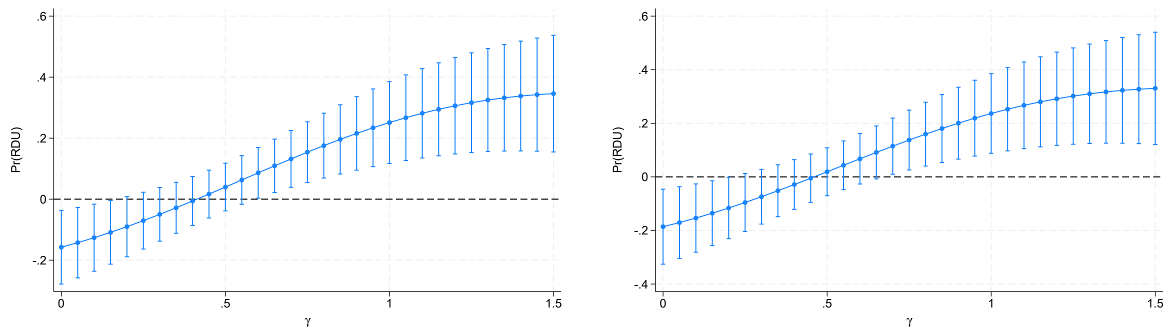
Figure 4: Marginal effects of Payday for different levels of γ



Note: Bars represent 95% confidence intervals.

reveal a heterogeneous treatment effect among these subgroups: participants with sufficiently concave utility functions exhibit a stronger response to the treatment. Notably, the degree of curvature required for the treatment effect to reach significance is, for some subgroups, lower than in the full-sample analysis. Figures 5a and 5b illustrate this pattern for respondents reporting having annual incomes below $20,000 and receiving a single monthly payment. These findings support the interpretation that the treatment is more pronounced when participants experience a sharper decline in utility before payday. For individuals facing harsher economic circumstances, a large utility drop can occur even with less utility curvature, making the treatment effect detectable at lower levels of utility curvature.

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.

6. Extensions

6.1. Reference Dependence and Poverty Traps

There is substantial empirical 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 perceived 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 C. 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 reason 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 3 and do not impede poor and biased individuals from forgoing profitable investments.

Moreover, the extension also shows that loss aversion increases the threshold $\hat{x}_0$ (Proposition 3). Thus, under reference-dependent preferences individuals with higher initial wealth will be trapped in a vicious dynamic of low investment and low wealth accumulation. This result is driven by the assumption that the individual's reference point corresponds to the *status quo* or initial wealth (Terzi et al., 2016, Baillon et al., 2020). As a result, any positive investment reduces current consumption and is therefore evaluated as a loss. Since loss aversion amplifies the disutility from these losses, the low-wealth region in which individuals with optimism or insensitivity do not invest expands.

6.2. Ambiguity Attitudes and Poverty Traps

The theoretical framework developed in Section 3 can be readily extended to incorporate ambiguity attitudes. To do so, I consider a setting in which the probabilities of returns are ambiguous. In this context, an individual may exhibit either aversion or preference toward 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 under ambiguity is more convex than her weighting function under risk. 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 D. Importantly, 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 under ambiguity than under risk, 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 perceived as ambiguous, perhaps due to limited familiarity or because it involves technological innovation, the poor are more likely to forgo it, thereby reinforcing their condition of poverty.

6.3. Other models of Risk and Ambiguity

Rank-Dependent Utility was chosen to characterize risk preferences because it accounts for probability weighting, and because it provides a flexible framework that easily allows for extensions to reference dependence (Appendix C) and ambiguity (Appendix D). However, there are other available models of risk that can account for probability misperception. For example, disappointment aversion (Gul, 1991), disappointment aversion without priors (Kőszegi and Rabin, 2006), and prospect reference theory (Viscusi, 1989). Remarkably, RDU and these models are equivalent for two outcomes (Wakker, 2010). Therefore, the conclusion of our motivating example in Section 2 can also be understood under the lens of those theories. [13]

Another reason for choosing RDU is that it has a close relation to other theories of decision making under ambiguity. Choquet Expected Utility (Schmeidler, 1989), which is the cornerstone of Source Theory, coincides for the case of binary outcomes with the multiple priors model (Gilboa and Schmeidler, 1989) and with the α max-min model (Ghirardato et al., 2004, Chateauneuf et al., 2007). Hence, the result presented in Appendix C that ambiguity attitude deepens the behavioral poverty trap, also arises in the case of binary outcomes when those models are assumed.

7. Conclusion

I introduced a novel poverty trap generated by the individuals' tendency to misperceive objective and ambiguous probabilities. Due to these biases, profitable opportunities are not evaluated accurately, which explain why poor individuals often fail to exploit investments that would improve their condition. I also demonstrated that the consequences of these misperceptions are stronger among the poor. Thus, because of their vulnerable position, they suffer more from their mistakes. The modern approach

[13] Accordingly, stronger elation seeking, in the model of Gul (Gul, 1991), or stronger gain seeking, in the model of (Kőszegi and Rabin, 2006), can get in the way of evaluating profitable opportunities and, subsequently, perpetuate poverty.

of behavioral economics, and in particular, the tools provided by decision theory have provided useful for further understanding this behavioral poverty trap.

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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 (8) 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:

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

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. *An interior solution to the RDU individual's problem of maximizing investment is guaranteed under pessimism.*

Proof. The second derivative of (A.6) with respect to e gives

$$u''\big(x_0(1-e)\big)x_0^2 + \int_{\underline{x}}^{\bar{x}} u'\big(b(x_0,z)\big)b_z(x_0,z)\Big(w_j'\big(1-F(z|e)\big)F_{ee}(z|e) - w_j''\big(1-F(z|e)\big)(F_e(z|e))^2\Big)\mathrm{d}z \tag{A.13}$$

A sufficient and necessary condition for an interior solution is that (A.13) is negative. Since $b_z(x_0, z) \geq 0$ (Assumption 2), $u' \geq 0$, and $u'' < 0$ (Assumption 3), equation (A.13) indicates that for an interior solution it suffices that:

$$\int_{\underline{x}}^{\bar{x}} w_j'\big(1 - F(z|e)\big)F_{ee}(z|e)\mathrm{d}z < \int_{\underline{x}}^{\bar{x}} w_j''\big(1 - F(z|e)\big)(F_e(z|e))^2\mathrm{d}z. \tag{A.14}$$

Since $w_j'\big(1 - F(z|e)\big) > 0$ for all r and e (Assumption 4) and $F_{ee}(z|e) > 0$ for all z and e (Assumption 1), the inequality given in (A.14) holds under pessimism, which implies $w''\big(1 - F(z|e)\big) > 0$ for all z and e. ■

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 (7) 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:

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

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

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

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):

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

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:

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

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

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

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

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

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

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

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, $[\underline{x}, \bar{x}] \backslash \{\underline{x}\}$. 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 $-\frac{u''\big(b(x_0,z)\big)}{u'\big(b(x_0,z)\big)} < \frac{b_{z,x_0}(x_0,z)}{b_z(x_0,z)b_{x_0}(x_0,z)}$ 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 j with probability weighting function w_j, and let her exhibit optimism (Definition 1) or likelihood insensitivity (Definition 2). According to Lemma A2, an interior investment level may not be optimal because $w_j''(p) < 0$ for some $p \in [0, 1]$. Hence, $e_r^* \in \{0, 1\}$.

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

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

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

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

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 $e_u^*(x_0)$ 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, $b_{x_0x_0} \le 0$ (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 $\partial_{x_0x_0}H \le 0$ by concavity of $H(\cdot; e)$. Under strict first-order stochastic dominance, $F_{ee} \ge 0$ implies $\partial_{ee}H = -\int b(x_0, z)\, dF_{ee}(z \mid e) \le 0$. Finally, Assumption 2 (complementarity $b_{x_0z} > 0$) implies $\partial_{x_0e}H = -\int b_{x_0}(x_0, z)\, dF_e(z \mid e) \le 0$ because $F_e \le 0$. Hence, we have $M_u''(x_0) \le 0$: 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),

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

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:

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

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

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

Hence,

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

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 $G(\underline{x}) \le 0$ 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. From Proposition 3, 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 45° 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 45° 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 $M_r(x_0') \geq x_0'$. Moreover, for sufficiently large x_0 sdiminishing returns in initial wealth ($bx_0x_0 \leq 0$) 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. ■

Proposition 6

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 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 agent derives utility solely 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 3.

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 3. The utility of the individual is identical to that presented in the main text (equation (8)), 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 from 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. 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

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

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 C1— 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 C1. *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 (C.1) as:

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

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

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

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:

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

Let

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

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 C1. The following corollary shows that higher loss aversion increases this threshold.

Corollary 3. *The threshold level of initial wealth from Proposition C1 is strictly increasing in* λ*:* $\frac{d\hat{x}_0}{d\lambda} > 0$.

Proof. Let

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

By the envelope/monotonicity argument in Step 1 (the proof of Proposition C1), 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.

D. 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.

D.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 :

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

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

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

The preferences in (D.1) and (D.2) imply an *aversion* to betting on events generated by the ambiguous project that violate the normative model of subjective expected utility (Savage, 1954).[14] This *ambiguity averse* behavior has been documented in promi-

[14]Formally, assume without loss of generality that $u(0) = 0$. Under subjective expected utility, the preference in (D.1) implies $P(E_1) \cdot u(M) < p \cdot u(M) \Leftrightarrow P(E_1) < p$ and the preference in (D.2) implies

nent 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.

D.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:

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

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.[15]

The main problem of modeling ambiguity attitudes using the model in (D.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 "extra probability weighting."

D.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

$P(E_2) < 1-p$. Note that the inequalities $P(E_1) < p$ and $P(E_2) < 1-p$ violate probability laws.

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

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:

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

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

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

where integration is over the cumulative distribution of $P(E|e)$ transformed by the source function w_s. Notice that equation (D.5) is analogous to (8) 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 (D.5) to the same individual's investment in the risky good. Proposition D1 states that ambiguity attitudes, regardless of its type, exacerbates the poverty trap described in Proposition 5.

Proposition D1. *Assume that Assumptions 1-4 hold and that individual preferences under ambiguity are characterized by Source Theory (eq.(D.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.

D.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.

E. Additional Empirical Analyses.

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Table 8: 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)
Opt./Pess.	-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)
U. curv	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 $\ln(y_i + 1) = b_0 + b_1\text{Inverse-S}_i + b_2\ \text{Opt./Pess.}_i + b_3\text{U.curv}_i. + \text{Controls}_i'\Gamma + \varepsilon_i$. 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 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 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)
Opt./Pess.	-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)
U.curv.	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)
Opt./Pess.	-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)
U.curv.	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 $(y_i)^{1/4} = b_0 + b_1\text{Inverse-S}_i + b_2\ \text{Opt./Pess.}_i + b_3\text{U.curv}_i.{+}\text{Controls}_i'\Gamma + \varepsilon_i$. 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 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)
Opt./Pess.	-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)
U.curv.	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 $(y_i)^{1/4} = b_0 + b_1\text{Inverse-S}_i + b_2\ \text{Opt./Pess.}_i + b_3\text{U.curv}_i. + \text{Controls}_i'\Gamma + \varepsilon_i$. 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. 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
IHS (Expenditures)	-0.129**	-0.172***	-0.129**	-0.142**	-0.143**	-0.121**
	(0.051)	(0.061)	(0.056)	(0.056)	(0.058)	(0.052)
Before Payday	0.084	-0.007	0.007	0.008	-0.033	-0.040
	(0.117)	(0.131)	(0.122)	(0.133)	(0.124)	(0.119)
$\hat{\gamma}_i$	-1.159***	-0.902***	-0.903***	-1.127***	-1.043***	-0.988***
	(0.210)	(0.228)	(0.208)	(0.236)	(0.219)	(0.210)
Varian Index	-12.920***	-9.438***	-13.258***	-13.708***	-10.459***	-9.207***
	(3.067)	(3.479)	(3.137)	(3.492)	(2.749)	(2.956)
Time Stroop test	-0.001	-0.001	0.002	-0.004	-0.001	0.003
	(0.005)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Constant	1.419	2.345	1.100	1.881	1.278	0.891
	(1.890)	(2.556)	(2.502)	(2.203)	(2.444)	(2.065)
Subgroup	One payment	Financial Hardship	I live from paycheck to paycheck	Income < 20,000 USD	Caloric Crunch	Could not raise 2000 for emergency.
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	547	426	503	425	498	529
Log-Likelihood	-339.646	-270.015	-309.805	-261.732	-306.583	-334.629

This table presents probit estimates of the model $\text{RDU}_i = b_0 + b_1\text{IHS(Expenditures)}+b_2\text{Before Payday}_i + b_3\hat{\gamma}_i + b_4\text{Before Payday}\times\hat{\gamma}_i+\text{Controls}_i'\Gamma + \varepsilon_i$. The dependent variable RDU $_i$ is a binary variable that takes a value of 1 if respondent i is classified as a Rank-Dependent Utility maximizer and 0 otherwise. "IHS(Expenditures)" is the Inverse Hyperbolic Sine transformation of the variable Total Expenditures, which captures the self-reported expenditures of the household in the last seven days. "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. Time Stroop Test captures the time in seconds that respondent i spent on answering 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 13: The Effects of Payday on the Probability of deviating from Expected Utility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RDU	RDU	RDU	RDU	RDU	RDU	RDU	RDU
Before Payday	-0.067	-0.524**	0.112	-0.523**	0.056	-0.606**	0.013	-0.481**
	(0.129)	(0.251)	(0.110)	(0.206)	(0.125)	(0.237)	(0.113)	(0.216)
$\hat{\gamma}_i$	-0.914***	-1.432***	-1.006***	-1.685***	-1.004***	-1.729***	-0.703***	-1.194***
	(0.224)	(0.328)	(0.198)	(0.279)	(0.224)	(0.324)	(0.208)	(0.286)
Before Payday$\times\hat{\gamma}_i$		0.848**		1.264***		1.318***		0.991***
		(0.395)		(0.353)		(0.402)		(0.362)
Varian Index	-16.595***	-16.708***	-12.222***	-12.399***	-12.625***	-12.614***	-10.512***	-10.707***
	(3.669)	(3.667)	(2.842)	(2.865)	(3.259)	(3.239)	(2.989)	(3.022)
Time Stroop test	-0.007	-0.006	0.003	0.004	-0.003	-0.002	-0.003	-0.002
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Constant	3.280	2.988	0.273	0.090	1.642	1.417	1.788	1.830
	(2.226)	(2.225)	(1.733)	(1.668)	(2.084)	(2.020)	(1.796)	(1.758)
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	-284.016	-281.702	-368.961	-362.379	-288.826	-283.214	-350.309	-346.552
N	459	459	582	582	456	456	536	536

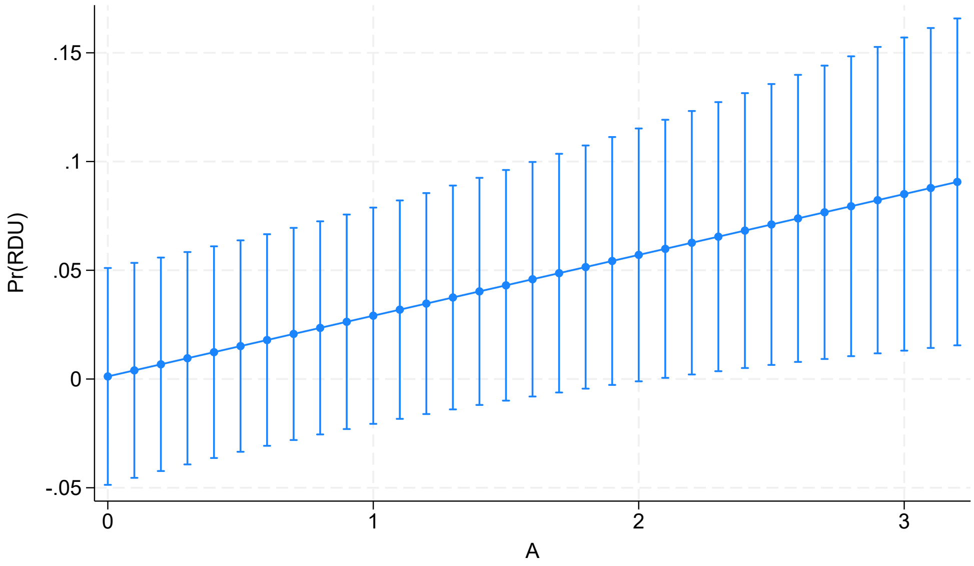
This table presents probit estimates of the model $\text{RDU}_i = b_0 + b_1\text{Before Payday}_i + b_2\hat{\gamma}_i + b_3\text{Before Payday}\times\hat{\gamma}_i + \text{Controls}_i'\Gamma + \varepsilon_i$. The dependent variable RDU_i is a binary variable that takes a value of 1 if respondent i is 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. Time Stroop Test captures the time in seconds that respondent i spent on answering 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	0.015	-0.018	0.038	0.003
	(0.075)	(0.077)	(0.075)	(0.077)	(0.077)	(0.079)
$\hat{A}_i$	-0.013	-0.040***	-0.016	-0.043***	-0.018	-0.046***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Before Payday$\times\hat{A}_i$		0.071**		0.069**		0.073**
		(0.035)		(0.035)		(0.034)
Varian Index			-2.077	-1.916	-1.722	-1.576
			(1.540)	(1.546)	(1.638)	(1.641)
Time Stroop test					-0.006*	-0.006*
					(0.004)	(0.004)
Constant	0.176***	0.188***	0.217***	0.226***	2.007	2.011
	(0.054)	(0.055)	(0.062)	(0.063)	(1.326)	(1.321)
Controls	NO	NO	NO	NO	YES	YES
Log-likelihood	-772.400	-770.465	-771.496	-769.700	-746.210	-744.160
N	1131	1131	1131	1131	1116	1116

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 responent 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 time in seconds that respondent i spent on answering the questions of 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

F. Overlapping Generations Model

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Consider a small open economy in which there is a constant population of agents with unit mass. Each agent lives for two periods and belongs to a dynasty of overlapping generations connected through capital transfers. Each parent has one parent and one child, inheriting capital from the former and bequesting capital to the later. Each agent is a potential capital investor when young, and a producer and consumer when old.

Agents exhibit preferences defined over old-age consumption, x_{t+1}, from which they derive a lifetime utility $u_t = u(x_{t+1})$. Under EUT the agent's objective is to maximize $\mathbb{E}\big(u(x_{t+1})\big)$. I consider instead a setting in which the agent distorts probabilities through the probability weighting function from Assumption 4.

In the first period of life, the agent makes a decision about a level of investment e. As in the motivating example, I consider two levels of investment e_H and e_L such that $e_H > e_L$. I assume that there is a fixed cost of investment $c(e)$. For simplicity, it is assumed that only the high investment level generates a cost, so $c(e_H) = c$ and $c(e_L) = 0$ where $c > 0$.

Since all agents are endowed with zero resources, choosing to invest has to be financed with borrowing. Whatever decision is made about investment, I assume that an agent accumulates capital k_{t+1} according to

$$k_{t+1} = \beta + p(e)Hk_t + \big(1 - p(e)\big)Lk_t, \tag{F.1}$$

where $p(e)$ is a probability that exhibits $p(e_H) > p(e_L)$, $\beta > 0$, and $1 > H > L > 0$. Equation (F.1) shows that the agent is more likely to accumulate higher capital when an investment is made. Note, however, that a high investment does not guarantee higher capital accumulation. The model incorporates uncertainty about the agents' future income through uncertainty about productive efficiency.

In the second period, the agent produces output y_{t+1} using capital according to:

$$y_{t+1} = Ak_{t+1}. \tag{F.2}$$

where $A > 0$. The agent realizes a final income of x_{t+1} which determines final consumption and utility. This level of consumption depends on the agent's past actions. If she abstained from capital investment by choosing $e = e_L$, then she consumes all realized output. However, if investment was performed, $e = e_H$, she needs to pay back lenders their return on the loan c. Throughout, I assume that agents have access to competitive financial intermediaries which have access to a perfectly elastic supply of funds at the world interest rate of r. Since competition between intermediaries drives their profits to zero, the rate of interest is equal to the intermediaries own cost of borrowing. All in all, the consumption profile of agents is:

$$x_{t+1} = \begin{cases} A\big[\beta + k_t(H-L)p(e_L) + Lk_t\big] & \text{if } e = e_L \\ A\big[\beta + k_t(H-L)p(e_L) + Lk_t\big] - c(1+r) & \text{if } e = e_L \end{cases} \tag{F.3}$$

Finally, I discuss the agent's utility. When there is no investment, the agent's utility is given by

$$RDU(e_L) = A\beta + A(H-L)k_t w(p(e_L)) + Ak_t L. \tag{F.4}$$

Under investment, the agent's utility is given by

$$RDU(e_H) = A\beta + Ak_t(H-L)w(p(e_H)) + A[k_t L] - (1+r)c \tag{F.5}$$

Thus, the RDU agent will decide to invest as long as

$$RDU(e_H) \geq RDU(e_L) \Leftrightarrow A(H-L)k_t\big(w(p(e_H)) - w(p(e_L))\big) \geq (1+r)c. \tag{F.6}$$

The following Proposition characterizes a threshold capital level $\hat{k}$such that the agent invests whenever her inherited capital surpasses is larger. I provide such capital level for the RDU agent and also for her EU counterpart.

Proposition E1. *There exist unique capital levels $\hat{k}_r > 0$ and $\hat{k}_e > 0$ such that the RDU agent invests if $k_t > \hat{k}_r$ and the EUT agent invests if $k_t > \hat{k}_e$. These capital levels are such that $k_e < \hat{k}_r$ whenever $w(p(e_H)) - w(p(e_L)) < p(e_H) - p(e_L)$.*

Proof. Fix c. Note that the expression $A(H-L)k_t\big(w(p(e_H)) - w(p(e_L))\big)$ smoothly increases in k_t over the domain $[0, +\infty)$. Moreover, the expression $(1+r)c$ is constant in capital. Therefore, there exists a unique capital level such that (F.6) holds with equality. Denote by $\hat{k}_r$ the capital level that satisfies the following equality:

$$A(H-L)\hat{k}_r\big(w(p(e_H)) - w(p(e_L))\big) = (1+r)c. \tag{F.7}$$

Given that the $A(H-L)k_t\big(w(p(e_H)) - w(p(e_L))\big)$ is increasing in k_t, any capital level such that $k_t > \hat{k}_r$ implies $RDU(e_H) \geq RDU(e_L)$; the individual engages in investment.

Under expected utility, the benefit from capital investment becomes $A(H-L)k_t\big((p(e_H)) -$

$(p(e_L))\big)$, which also smoothly increases in k_t over $[0, +\infty)$. Therefore, there also exists a unique capital level $\hat{k}_e$ such that

$$A(H - L)\hat{k}_r\big(p(e_H - p(e_L)\big) = (1 + r)c. \tag{F.8}$$

Suppose that $p(e_H) - p(e_L) > w(p(e_H)) - w(p(e_L))$. Then, using (F.8) it must be that

$$(1 + r)c = A(H - L)\hat{k}_e\big(p(e_H) - p(e_L)\big) > A(H - L)\hat{k}_e\big(w(p(e_H)) - w(p(e_L))\big). \tag{F.9}$$

Hence, the capital level $\hat{k}_e$ that guarantees (F.7) must exhibit $\hat{k}_r > \hat{k}_e$.

■

The decision to invest in capital is affected by the agent's probability weighting. When probabilities are underweighted, the decision to invest is made when capital is sufficiently high. This behavior generates a behavioral poverty trap: at levels $k \in (\hat{k}_e, \hat{k}_r)$ the decision maker erroneously believes that returns to investment are lower than they actually are and refrains from investing even though she would choose to invest if she did not suffer from probability weighting.

Next, I show that stronger deviations from expected utility due to optimism, pessimism, or insensitivity decrease the threshold level $\hat{k}_r > 0$. Therefore, the segment under which the agent does not invest due to irrationalities, $k \in (\hat{k}_e, \hat{k}_r)$, becomes larger and the behavioral poverty trap happens for a wider range of capital levels.

Corollary D1. *Stronger pessimism, optimism, and likelihood insensitivity leads to a lower $\hat{k}_r$. It also enlarges the segment in which $w(p(e_H)) - w(p(e_L)) < p(e_H) - p(e_L)$ holds.*

Proof. Lemma 1 shows that stronger optimism, likelihood insensitivity, or pessimism lead to a larger segment in which $w'(p) < 1$. In this outcome environment, that condition implies that $\int_{p(e_L)}^{p(e_H)} w'(s)\mathrm{d}s < \int_{p(e_L)}^{p(e_H)} \mathrm{d}s \Leftrightarrow w(p(e_H)) - w(p(e_L)) < p(e_H) - p(e_L)$ for a wider range of values of $p(e_H)$ and $p(e_L)$.

Since $A(H - L)k_t\big(w(p(e_H)) - w(p(e_L))\big)$ is increasing in k_t, then it must be that stronger optimism, likelihood insensitivity, and pessimism, through their influence on reducing the difference $w(p(e_H)) - w(p(e_L))$, lead to a lower value k_r such that (F.7) holds.

■

Given the above, the intergenerational evolution of capital for an individual dynasty satisfies.

$$k_{t+1} = \begin{cases} \beta + p(e_H)Hk_t + \big(1 - p(e_H)\big)Lk_t & \text{if } k \geq \hat{k}_r \\ \beta + p(e_L)Hk_t + \big(1 - p(e_L)\big)Lk_t & \text{if } k < \hat{k}_r. \end{cases} \tag{F.10}$$

Each of these lineage transition equations correspond to a stable stochastic difference equation. The intersections with the 45 degree line are given by the stationary points:

$$k^{**} = \frac{\beta}{(1 - p(e_H)(H - L) - L)}, \tag{F.11}$$

$$k^{*} = \frac{\beta}{(1 - p(e_L)(H - L) - L)}. \tag{F.12}$$

The transition equations are drawn under the restrictions $\beta < 1 - p(e_H)(H - L) - L$, which makes the analysis non-trivial.

The long-run distribution of capital in the economy is such that only investors with capital accumulation are those agents who are endowed with capital levels $k_0 > \hat{k}_r$. These agents converge to the high steady-state equilibrium. All other agents who start off with $k_0 < \hat{k}_r$ remain forever as non-investors. Note that agents with $\hat{k}_e > k_0 > \hat{k}_r$ will not engage in investment even though they would end-up in the high steady state if they had an accurate perception of probabilities.