Why Don't Farmers Buy Insurance? Estimating Competing Models of Agricultural Insurance Decision-Making

Colter Hoffman

Department of Economics, University of California, Davis, 1 Shields Ave, Davis, CA 95616, USA

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Abstract

Using data from a randomized intervention among smallholder hog farmers in Sichuan, China, we estimate alternative models of insurance demand under neoclassical, present-biased, and reference-dependent decision rules. The neoclassical specifications include a baseline model, one with liquidity constraints, and one with imperfect trust. The reference-dependent model provides the best in-sample fit. Allowing heterogeneity through mixture specifications shows that approximately 90 percent of farmers are reference dependent, while the remaining population share is best described by a neoclassical rule; present bias, liquidity constraints, and distrust do not add explanatory power once heterogeneity is allowed. We evaluate out-of-sample predictions from our structural estimations with machine learning algorithms and find that models incorporating reference dependence remain competitive. Machine learning, however, can help identify likely adopters.

1 Introduction

Many studies have shown that uninsured risk is largely responsible for the failure of small-scale farmers to profit maximize in developing countries. However, take-up of index insurance has been extremely low at market price, with high subsidies required for widespread adoption.

Some neoclassical reasons why we might see low levels of insurance are basis risk (Clarke, 2016), liquidity constraints (Cole et al., 2013), and doubts about receiving insurance payouts (Liu et al., 2020). Potential behavioral reasons for this phenomenon include present bias (Casaburi and Willis, 2018), a preference for certainty (Serfilippi et al., 2020), compound-risk aversion (Elabed and Carter, 2015), and loss aversion (Lampe and Würtenberger, 2020; Shin et al., 2022).

Understanding which behavioral factors are most responsible for low take-up of insurance is important for at least three reasons. First, doing so will assist in designing policy aimed at correcting underconsumption of insurance by designing contracts and policies that better align with farmers' preferences and decision-making processes. Recent work highlights the broader relevance of this approach: in Germany, Dalhaus et al. (2020) demonstrate that modifying index insurance to better match decision-makers' prospect-theoretic preferences can raise its perceived value without requiring subsidies. Similarly, Andreoni et al. (2023) show that tailoring incentives based on elicited behavioral preferences boosts participation in polio vaccination campaigns in Pakistan.

Second, it will help determine if we *should* try to increase take-up. Many papers in this literature frame policies aimed at boosting take-up of insurance in developing countries as obviously welfare improving. This is certainly the case if liquidity constraints or behavioral biases are causing underconsumption of insurance. However, if non-standard preferences are responsible for low take-up, policies may distort individuals' decisions without providing sufficient benefit to justify doing so. Indeed, Harrison et al. (2020) show that some behavioral interventions to promote index insurance can increase purchase rates while reducing average welfare.

Despite growing evidence that behavioral factors matter in the context of insurance for smallholder farmers, it remains unclear which mechanisms are most relevant.

Distinguishing among competing explanations is essential for understanding demand and for designing more effective insurance products.

In this paper, we use data from a randomized insurance intervention among smallholder hog farmers in Sichuan, China to estimate and compare structural models of insurance demand. We develop a discrete choice framework that accommodates neoclassical, present-biased, and reference-dependent decision rules. Within the neoclassical family, we estimate a baseline model of expected utility, a version with liquidity constraints captured by a parameter for liquid wealth, and a third that incorporates imperfect trust. Each model is jointly estimated using observed insurance take-up as well as responses to risk and time preference tasks. The benchmark results show that the reference-dependent model provides the best fit to the data, outperforming neoclassical and present-biased specifications.

To relax the assumption that all individuals follow a single decision rule, we estimate a set of mixture models in which the population consists of two distinct types. These models allow for heterogeneity by estimating the share of individuals who are reference-dependent versus those who follow alternative decision rules. The results consistently indicate that between 88 and 93 percent of the population is best characterized as reference dependent. For the remaining share, the estimated parameters of the alternative model converge to the neoclassical case, suggesting that present-biased and low-trust variants do not improve explanatory power once heterogeneity is allowed.

Our estimations consistently favor models that incorporate reference dependence, while alternatives fall short in explaining observed take-up. Intuitively, this suggests that farmers may evaluate insurance not only in terms of expected consumption, but also through the lens of premiums as losses and payouts as gains.

Finally, we benchmark the best-fitting structural model against a suite of machine learning algorithms trained to predict insurance take-up. These include logistic regression, random forests, gradient-boosted trees (XGBoost), and neural networks. The machine learning models perform slightly better than the structural model, particularly when given access to additional covariates. However, the structural model delivers strong out-of-sample performance despite being tightly grounded in economic theory. We also show that machine learning models can be tuned to identify likely insurance adopters, which may support more targeted outreach or subsidy efforts.

This paper makes contributions to a variety of interrelated literatures. First, there is a growing literature on the behavioral determinants of agricultural insurance demand in developing countries. Several recent studies point to present bias as an important barrier to agricultural insurance uptake in low-income settings. Casaburi and Willis (2018), Belissa et al. (2019), and Liu et al. (2020) find that allowing farmers to delay premium payments increases demand, consistent with models of present-biased preferences. Baillon et al. (2022) and Belissa et al. (2025) provide further evidence of present bias in insurance choice.

Other studies emphasize the role of reference dependence in shaping insurance decisions. A number of studies elicit individual-level preferences, assign individuals a loss aversion parameter under specific assumptions, and then regress insurance uptake or willingness to pay on this measure (Lampe and Würtenberger, 2020; Shin et al., 2022; Mishra et al., 2023; and Cecchi et al., 2024). Other work involving reference dependence in the context of agricultural insurance includes Pétraud et al. (2015), McIntosh et al. (2019), and Manganyi et al. (2024). Evidence from other agricultural contexts in China suggests that loss aversion shapes a range of decisions, including adoption of an improved cotton variety (Liu, 2013) and crop residue management (Huang et al., 2025).

Related work shows that ambiguity aversion can amplify the negative effect of basis risk on insurance demand (Elabed and Carter, 2015; Bryan, 2019; Belissa et al., 2020; and Cecchi et al., 2024). The hog insurance examined in our study is not index-based, so basis risk is not a relevant concern here.

Serfilippi et al. (2020) show that a preference for certainty lowers insurance demand: framing both costs and benefits as uncertain with a premium rebate increases willingness to pay. Their insurance contract introduces uncertainty in costs, whereas the contracts in our setting require fixed, known payments.[1]

[1] Under imperfect trust, the cost of a delayed premium contract may be uncertain if the insurer fails to pay out and the insured is therefore not required to pay the premium.

Compared to the existing literature on behavioral factors that dampen insurance demand among smallholder farmers, this study makes three main contributions. First, we directly compare two leading behavioral theories of insurance decision-making alongside three neoclassical models. Some studies consider multiple behavioral factors (for example, Cecchi et al., 2024 examine both ambiguity aversion and loss aversion in an insurance game), while others contrast a single behavioral explanation with standard economic factors (as in Casaburi and Willis, 2018). However, to the best of our knowledge, no existing study spans such a set of both behavioral and neoclassical frameworks within a unified empirical design. Second, we take seriously the economic and behavioral foundations of each model, structurally estimating the behavioral primitives that shape insurance decisions. To our knowledge, this is the only study within this literature to do so. Lastly, we use machine learning methods to benchmark the predictive accuracy of our structural models, demonstrating that our best-fitting model reliably captures out-of-sample variation in insurance choices.

We also contribute to the literature on structural behavioral economics (reviewed by DellaVigna, 2018 and Barseghyan et al., 2018). Our approach is methodologically similar to DellaVigna et al. (2017), who model job search behavior in Hungary using behavioral and neoclassical preferences. Other related work includes structural analyses of U.S. insurance markets (Barseghyan et al., 2013; Handel and Kolstad, 2015).

We also contribute to work using machine learning to assess the empirical performance of economic models. Fudenberg and Liang (2019) show that machine learning can reveal systematic patterns missed by structural models, while Ellis (2025) find comparable performance between the two approaches in a risky choice experiment.

A number of studies in the broader literature on agricultural insurance in developing countries are relevant to this project, most of which focus specifically on index insurance. For a review of such studies, see Carter et al. (2017). Resoundingly, this literature has found low levels of demand for standard insurance products in the absence of large subsidies or other interventions (Giné et al., 2008; Giné and Yang, 2009; Cole et al., 2013). While many solutions to this issue have been proposed, none seem to have been consistently successful in a way that can be repeated outside of experimental settings.

The gains from reducing risk are large, though. Farmers that insure risk are able to mitigate both its ex-ante effects on investment and its ex-post effects on consumption. Although some studies do not find such benefits (Giné and Yang, 2009), the majority do. Findings range from increased investment in Mali, Ghana, and Bangladesh to improved household coping in Kenya (Giné and Yang, 2009; Elabed and Carter, 2018; Karlan et al., 2014; Hill et al., 2019; Janzen and Carter, 2019). Evidence from China shows that swine insurance improves productive efficiency by reducing risk and enabling more efficient resource allocation (Feng et al., 2025).

This paper proceeds as follows. Section 2 describes the study context and data. Section 3 outlines the structural models and estimation strategy. Section 4 presents results without heterogeneity, while Section 5 reports results from the mixture model. Section 6 covers the machine learning analysis. Section 7 concludes.

2 Data and Setting

The empirical setting for this study is the market for hog insurance among smallholder farmers in Sichuan, China. Livestock earnings, particularly from hogs, represent a crucial source of income in this region. The insurance program is implemented through a partnership in which the provincial government oversees policy design and premium collection, while the state-owned People's Insurance Company is responsible for issuing contracts and processing claims. Our analysis is based on data from a randomized controlled trial (RCT) conducted by Liu et al. (2020).

As part of the RCT, insurance was offered to farmers during an enrollment period that ran from late June to the end of September 2011. Farmers in the treatment group had access to a delayed premium payment contract, under which the premium (plus interest) was not due at the time of enrollment but instead at the end of the insurance period, in contrast to the standard up-front payment required of the control group. All households in the treatment group and half of those in the control group received a household visit providing information about the insurance product.

Treated households additionally received a voucher that enabled delayed premium payment, along with information about how the deferred payment arrangement would function.

The insurance contract covered the death of enrolled hogs during the fattening period. Farmers received compensation equal to 70 percent of the hog's market value, less a deductible, up to a maximum payout of RMB 500 (approximately USD 83). The market price was fixed across all breeds, and compensation was determined by the hog's weight at death. Farmers were required to insure either all of their eligible hogs or none at all. Two policy durations were available: a four-month policy with a premium of RMB 6 (approximately USD 1), and a six-month policy with a premium of RMB 7.5 (approximately USD 1.25). These premia reflect a 70 percent government subsidy, with farmers paying less than the actuarially fair price of coverage. Take-up was 16 percent under the delayed premium contract and 5 percent under the standard up-front payment, levels that remain surprisingly low given the heavily subsidized cost of coverage.

A baseline household survey was also carried out in December 2010. Selected variables from these data serve as key inputs to our structural estimation. Decisions designed to elicit risk and time preferences are used to support the joint identification of our structural parameters. Risk preferences were measured via choices among five lotteries following Binswanger (1980), while time preferences were measured using binary intertemporal choices between a smaller, sooner, and a larger, later monetary reward. We also incorporate survey data on income from hogs and other sources.

2.1 Simulation of Income and Insurance Payouts

Although we observe summary income measures for each farmer, we do not observe the full distribution of potential income realizations and insurance payouts. Recovering these distributions is necessary for expected utility calculations in the estimation procedure. To do so, we run Monte Carlo simulations to model hog mortality, and obtain the resulting income and insurance payout distributions.

The simulations draw hog mortality rates from a beta distribution centered on the empirical mean of 3.5 percent over a six-month period.[2] In Appendix A, we show that our chosen scale parameter of $s = 1$ yields a distribution consistent with reported three-year death rates, and in Appendices F.1 and F.2 we show that our main results are robust to alternative values of this parameter. For each distinct number of hogs observed in the data, we run 100,000 simulations. In each simulation, we draw a death rate and then simulate mortality timing for all hogs using that rate. The simulated month of death determines whether the pig survives, its market weight at death if it does not, and the resulting income, including insurance payouts when applicable. Full details of this procedure can be found in Appendix A.

3 Models and Estimation

We structurally estimate three families of models: these include reference-dependent, present-biased, and neoclassical models. The neoclassical family includes a baseline model as well as extensions that incorporate imperfect trust and liquidity constraints. The goal of these estimations is to conduct a horse-race among models to identify which best fits the observed data. In doing so, we aim to shed light on the underlying decision-making mechanisms driving insurance uptake in this context. This is similar to the methodology of DellaVigna et al. (2017) in their study of job search in Hungary, and stands in contrast to the more typical focus on counterfactual welfare and policy analysis in structural estimation.

Subjects make three sets of decisions that we leverage to jointly estimate the structural parameters of each model. These include insurance take-up, as well as responses in the risk and time preference elicitation tasks. We begin by modeling the insurance decision.

3.1 Insurance Choice

We estimate a two-period model in which insurance decisions are made and premiums are paid, where applicable, in period 0. In period 1, hogs are sold, insurance payouts

[2] Liu et al. (2020) report the death rate to be 6 to 8 percent per year.

are received, and the premium (plus interest) is paid if the farmer purchased insurance under the delayed premium contract.[3]

In period 0, farmers begin with an endowment, interpreted as savings carried over from the previous, unmodeled period. Because we do not observe household savings, we model this endowment as a fraction of $\bar{I}_i$, household income per capita reported in the survey. Specifically, we define the endowment as $\omega \bar{I}_i$, where ω is a model parameter that captures the proportion of annual income available as liquid wealth at the start of the fattening period. This parameter is intended to reflect potential liquidity constraints farmers face when making insurance purchase decisions. When ω is not estimated, we set it to 0.25, though we examine the robustness of our results to alternative values in Appendices F.3 and F.4.

If a farmer insures, they pay a premium $p(N_i, D_j)$, determined by the number of hogs owned N_i and the insurance choice D_j (insure for six months, insure for four months, or not insure). This premium is RMB 6 per hog for the four-month policy and RMB 7.5 per hog for the six-month policy. We observe the number of hogs per farmer in the baseline survey. If the premium is paid at harvest, interest is added according to gross rate R_j^c. Liu et al. (2020) report a prevailing annual net interest rate of 18 percent, which translates to 9 percent for the six-month policy and 6 percent for the four-month policy, assuming simple interest accrual.

Any income not consumed in period 0 is carried over to period 1 with gross interest rate R^s, which we assume to be zero under our main specification (reflecting informal savings).[4] Farmers also receive baseline non-hog income B_i in period 1. We observe each farmer's per capita income $\bar{I}_i$ and the share of income derived from hogs. We define B_i as $(1 - \text{hog income share}) \times \bar{I}_i$.

Finally, hog-related income $\pi(N_i, D_j, \theta, \tau)$ is received in period 1, which consists of revenue from selling hogs and any insurance payouts. Pigs that survive the entire fattening period are sold for the market price of 1,000 RMB reported by Liu et al. (2020). Hogs that die earlier generate insurance payouts if covered. Under this

[3]This simplified model does not capture all potential benefits of insurance, such as encouraging investment Karlan et al. (2014) or protecting vulnerable households from falling into poverty Janzen et al. (2021). Models that incorporate these additional benefits would deepen the puzzle of low take-up.

[4]We include a robustness check of our main results using an interest rate of 5% on savings in Appendix F.5.

government-designed insurance contract, payouts are based on the hog's weight at death, equal to 70 percent of the estimated market value minus a deductible of 100 RMB, and are capped at 500 RMB. The perceived distribution of $\pi(N_i, D_j, \theta, \tau)$ is determined by θ, which is a random shock affecting hog mortality, and by τ, which captures the perceived probability of receiving an insurance payout when one is owed. Simulation of the distribution of θ is described in Section 2.1, with further details provided in Appendix A. To incorporate τ into the model, we augment the distribution of mortality shocks, θ, by splitting each realization into two states: one in which the insurance payout is received with probability τ, and one in which it is not with probability $1 - \tau$. In the survey, farmers were directly asked about their perceived probability of receiving an insurance payout when due (τ). When this parameter is not estimated, we use these surveyed, farmer-specific τ values in our estimations.[5]

Given this set up, under the neoclassical model, expected utility associated with the insurance decision for individual i under insurance contract j is:

$$EU_{ij,insurance} = \max_{c_{ij}^0, c_{ij}^1} \; u(c_{ij}^0) + \delta E\left[u(c_{ij}^1)\right] \tag{1}$$

where c_{ij}^0 is consumption in period 0, c_{ij}^1 is consumption in period 1, and δ is the discount factor. We assume constant relative risk aversion (CRRA): $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$.

The budget constraints for farmers in the control group, who are required to pay the insurance premium up front, are as follows:

$$c_{i0} \leq \omega \bar{I}_i - p(N_i, D_j) \tag{2}$$

$$c_{i1} = R^s \cdot (\omega \bar{I}_i - p(N_i, D_j) - c_{i0}) + B_i + \pi(N_i, D_j, \theta, \tau) \tag{3}$$

Farmers in the treatment group are instead allowed to delay premium payment until the end of the contract period. Their budget constraints are:

[5] In Appendix F.6, we show our main findings are robust to the assumption of full trust, which involves setting $\tau = 1$ for all subjects.

$$c_{i0} \leq \omega \bar{I}_i \tag{4}$$

$$c_{i1} = R^s \cdot (\omega \bar{I}_i - c_{i0}) + B_i + \pi(N_i, D_j, \theta, \tau) - R_j^c \cdot p(N_i, D_j) \tag{5}$$

In addition to the standard neoclassical model, in which γ and δ are estimated, we consider two extensions. First, to capture perceived payout beliefs, we estimate τ. This allows us to test whether respondents' reported probabilities understate their true pessimism and whether incorporating this parameter improves the model's ability to explain observed variation in insurance uptake. Lower values of τ translate into lower insurance demand, as reduced confidence in payouts diminishes the product's perceived value. Second, we estimate ω, which captures the role of liquidity constraints. This extension enables us to examine whether limited liquidity helps explain muted demand for insurance in our setting. Smaller ω values constrain liquidity, amplifying the burden of paying premiums.

We next move on to the behavioral models of insurance demand. For the present-biased agent, expected utility is instead given by:

$$EU_{ij,insurance} = \max_{c_{ij}^0, c_{ij}^1} \; u(c_{ij}^0) + \beta\delta E\left[u(c_{ij}^1)\right] \tag{6}$$

where β is the present-bias parameter. Lower β values indicate increased levels of impatience. Because standard insurance requires an up-front premium and provides only a delayed payout, greater impatience makes this product less attractive.

Under the model of reference dependence, expected utility is:

$$EU_{ij,insurance} = \max_{c_{ij}^0, c_{ij}^1} \; u(c_{ij}^0) + \eta v(w_{ij}^0 | r_i^0) + \delta E\left[u(c_{ij}^1) + \eta v(w_{ij}^1 | r_i^1)\right] \tag{7}$$

$$\text{where:} \qquad v(w|r) = \begin{cases} u(w - r) & \text{if } w \geq r \\ -\lambda u(w - r) & \text{if } w < r \end{cases}$$

In addition to consumption utility derived from $u(\cdot)$, gain–loss utility is derived from $v(\cdot)$, weighted by η, with λ capturing the degree of loss aversion.[6] Wealth levels in periods 0 and 1 are denoted by w_{ij}^0 and w_{ij}^1, while r_i^0 and r_i^1 represent the corresponding reference wealth levels. Following Schmidt (2016), Lampe and Würtenberger (2020), and Shin et al. (2022), we adopt a "no insurance" reference point, in which outcomes are evaluated relative to the counterfactual scenario without coverage.[7] With this framework in mind, gains and losses are measured as deviations in wealth due to the insurance purchase decision. In every period and state of the world, individuals compare their wealth to what it would have been had they not purchased insurance. We calculate wealth according to the right-hand side of the budget constraints defined in Equations 2–5.[8]

There are two mechanisms through which reference dependence can dampen insurance uptake. First, since premiums are experienced as losses, while payouts are experienced as gains, loss aversion implies that the pain of paying premiums outweighs the pleasure of receiving payouts of similar size. Second, diminishing sensitivity implies that the frequent, small premium losses near the reference point are felt more acutely than the rare, large payouts, whose marginal utility is muted once they push wealth far from the reference point.

Because η and λ are not separately identified given the variation in our data, we fix the value of λ. In one specification, we set $\lambda = 1.6$, consistent with the estimate from Dupas (2014). In an alternative specification, we fix $\lambda = 1$, implying reference dependence without loss aversion.

[6] Notice that because $u(\cdot)$ is retained alongside $v(\cdot)$, agents continue to value the risk-hedging benefits of insurance even while evaluating gains and losses relative to a reference point. This is in contrast to Lampe and Würtenberger (2020), who model agents with gain–loss utility alone, and use this framework to account for observed insurance behavior.

[7] Schmidt (2016) provides a theoretical treatment of insurance demand under prospect theory, proposing "no insurance" as one of two possible reference points. Lampe and Würtenberger (2020) and Shin et al. (2022) find empirical support for this reference point. While Schmidt and Shin et al. refer to it as the "status quo" reference point, they explicitly define the status quo as the absence of insurance coverage.

[8] One might object that this measure corresponds to cash on hand rather than total wealth, since non-liquid assets (hogs) are not included. However, because gain–loss utility is defined over *deviations* in wealth, the results are invariant to whether hogs are included in wealth. By period 1, all hogs have either died or been sold and are therefore liquid. In period 0, including hogs in the wealth measure does not affect deviations attributable to the insurance decision.

3.2 Risk and Time Preferences

In addition to insurance choices, we incorporate responses from the risk and time preference elicitation tasks to jointly estimate the structural parameters of each model. These choices provide additional information on each subject's utility curvature, time discounting, and behavioral features including present bias and weight on gain–loss utility. We now describe how these decisions are modeled.

For the risk preference module, subjects choose between five options: four are binary lotteries with probabilistic payouts, and one is a degenerate lottery offering a certain payout. The binary lotteries involve a high and low payout, denoted x^a_{ij} and x^b_{ij}, respectively. These lotteries are detailed in Appendix B. The expected utility for individual i choosing lottery j is given by:

$$EU_{ij,risk} = p[u(x^a_{ij}) + \eta v(x^a_{ij}|r)] + (1-p)[u(x^b_{ij}) + \eta v(x^b_{ij}|r)] \tag{8}$$

where p is the probability of the high payout (equal to 1 in the certain option). We make the standard assumption of $r = 0$ for this task.[9] To estimate neoclassical or present-biased models, we set η to 0.

For the time preference module, subjects make a series of choices (c) between a smaller amount tomorrow (option $j = 1$) and a larger amount in one month (option $j = 2$). These choices are detailed in Appendix B. Individual i's expected utility from option j in choice c is:

$$EU_{ijc} = \beta^{\mathbf{1}\{j>\phi\}}\delta^{\frac{1}{6}(j-1)}[u(x_{ijc}) + \eta v(x_{ijc}|r)] \tag{9}$$

As above, we assume $r = 0$. The agent discounts the later payout ($j = 2$) by one month using $\delta^{\frac{1}{6}}$, where δ is the discount factor over a six-month horizon. When estimating the neoclassical model, we set $\beta = 1$ and $\eta = 0$. For the present-biased model, we set $\eta = 0$ and estimate β alongside the other parameters. For the reference-dependent model, we set $\beta = 1$ and estimate η instead.

We consider three reasonable specifications for present bias, governed by the

[9]An alternative assumption is that subjects anchor on the certain payout in the risk elicitation task and on the constant, early payout in the time elicitation task. We show our results are robust to this assumption in Appendix F.7.

cutoff parameter ϕ. The most natural specification applies β only to the later payoff, setting $\phi = 1$. However, since the sooner option is delivered tomorrow, an agent may still treat it as a future outcome. In that case, both payoffs are scaled by β, and we set $\phi = 0$. Finally, to give the present-biased model maximum flexibility to compete with alternative specifications, we remove β from this module entirely by setting $\phi = 2$. In this case, β is no longer disciplined by behavior in the time preference task and is instead free to adjust to best explain insurance choices.

3.3 Estimation Procedure

With the decision environment fully specified for each model, we now turn to the estimation procedure. We adopt the random utility framework, in which total utility for individual i, choosing alternative j in choice c, is given by expected utility plus an idiosyncratic error term ε_{ijc}:

$$TU_{ijc} = EU_{ijc} + \varepsilon_{ijc} \tag{10}$$

We assume that ε_{ijc} follows an i.i.d. Type I extreme value distribution with scale parameter σ_c. Then the probability of agent i choosing alternative k when making choice c is:

$$P_{ikc} = \frac{e^{EU_{ikc}/\sigma_c}}{\sum_j e^{EU_{ijc}/\sigma_c}} \tag{11}$$

Let $\boldsymbol{\psi}$ denote the vector of parameters to be estimated, and let $\mathbf{x}$ represent the observed characteristics that enter the utility function. For each individual i, alternative k, and choice situation c, let y_{ikc} be an indicator equal to 1 if individual i chooses alternative k in choice c, and 0 otherwise. The log-likelihood of observing the vector of decisions that are actually made is equal to:

$$\log \mathcal{L}(\boldsymbol{\psi} \mid \mathbf{y}, \mathbf{x}) = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{c=1}^{C} y_{ikc} \log P_{ikc} \tag{12}$$

Maximizing this function with respect to the vector of parameters $\boldsymbol{\psi}$ yields our maximum likelihood estimates.

Since each subject makes only one insurance decision and one risk decision, but multiple time preference decisions, we apply weights to the time module so that it contributes equally to log-likelihood. Specifically, we scale the log-likelihood from each time choice so that the total weight of the time module matches that of the insurance and risk modules. This ensures that all three decision types are given equal influence in the parameter estimation, despite differences in the number of observed choices.

We fix the scale parameter in the risk and time preference modules to $\sigma_{\text{elicit}} = 10$ to improve identification.[10] For the insurance module, we estimate the scale parameter σ_{insure} under the baseline neoclassical model and hold it fixed at that value across all other model specifications.[11] Appendix C discusses the rationale and mechanics of these assumptions in further detail. We show that our main results are robust to alternative scale assumptions in Appendices F.8 and F.9.

For each model specification, we conduct a two-stage optimization procedure. We begin with 50 estimations from randomly drawn initial values over wide parameter bounds. We then refine the search by running 10 additional estimations using jittered starting values drawn from a tighter range around the best initial estimate. We select the final estimate as the one with the highest log-likelihood across all runs. We note that parameter estimates are highly stable across initializations.

4 Estimates with No Heterogeneity

Table 1 presents our benchmark estimates. The estimated coefficients for risk aversion (γ) and the discount factor (δ) are fairly stable and precisely estimated across model specifications.[12] As columns (1) and (2) indicate, the weight on gain–loss utility (η) is small, though precisely estimated.[13] When we fix $\lambda = 1$, η is estimated to be slightly

[10] This prevents utilities from being over-scaled relative to the error term under the standard normalization of $\sigma = 1$, yielding stable and well-identified estimates.

[11] We estimate σ_{insure} as a multiple of the fixed elicitation scale: $\sigma_{\text{insure}} = \chi \cdot \sigma_{\text{elicit}}$. We estimate $\chi = 8.8$ under the baseline neoclassical model. In models with more parameters, χ is not separately identified, so we hold it fixed at 8.8 across all specifications.

[12] However, when other parameters such as β or τ are not precisely identified, we lose joint identification. In particular, when a parameter is estimated near the boundary of the parameter space, the likelihood surface can be flat, reducing precision for both that parameter and other jointly estimated parameters.

[13] This small magnitude is intuitive. Gain–loss utility is evaluated around a reference point of zero, where the utility function is steep. In contrast, consumption utility reflects changes in consumption levels that are typically far from zero, where the utility function is flatter due to diminishing marginal utility. To make the two utility components comparable, a smaller weight on gain–loss utility is necessary.

larger than when $\lambda = 1.6$, reflecting the fact that with less sensitivity to losses, the model increases η to compensate by placing more overall weight on gain–loss utility to fit the observed choices. Among all specifications, the reference-dependent model with $\lambda = 1.6$ provides the best fit, as indicated by the highest log-likelihood and the lowest values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Table 1: Estimates with no Heterogeneity

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9272	0.9271	0.9259	0.9253	0.9252	0.9259	0.9252	0.9266
	(0.0057)	(0.0062)	(11.4513)	(0.0017)	(2.5099)	(0.0036)	(0.0985)	(0.0024)
δ	0.9704	0.9703	0.9669	0.9833	0.9685	0.9669	0.9685	0.9680
	(0.0089)	(0.0057)	(7.8741)	(0.0097)	(2.9862)	(0.0056)	(0.4624)	(0.0283)
η	0.0020	0.0012	-	-	-	-	-	-
	(0.0002)	(0.0001)	-	-	-	-	-	-
β	-	-	1.0000	0.6146	0.0000	-	-	-
	-	-	(2.5846)	(0.0164)	(2.2727)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(0.7344)	-
ω	-	-	-	-	-	-	-	0.1036
	-	-	-	-	-	-	-	(0.0242)
Log-Likelihood	-3053.5	-3050.6	-3295.0	-3284.3	-3243.3	-3295.0	-3243.3	-3256.6
Log-Likelihood (Insurance)	-729.6	-726.0	-1467.9	-1403.0	-1312.3	-1467.9	-1312.3	-1352.8
AIC	79397.7	79320.8	85676.3	85397.0	84330.7	85674.3	84330.7	84677.9
BIC	79413.7	79336.8	85692.3	85412.9	84346.6	85685.0	84346.6	84693.8
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

The present-biased specification that best fits the data is shown in column (5), where β is not disciplined by decisions in the time preference module. The estimated value of zero is clearly unrealistic, as it would imply that farmers place no value on future utility. When β only applies to the later payout, we are not able to separately identify β and δ. However, when β applies to both the payout tomorrow and the payout one month from now, we obtain a precisely estimated coefficient that aligns with values commonly found in the literature.[14]

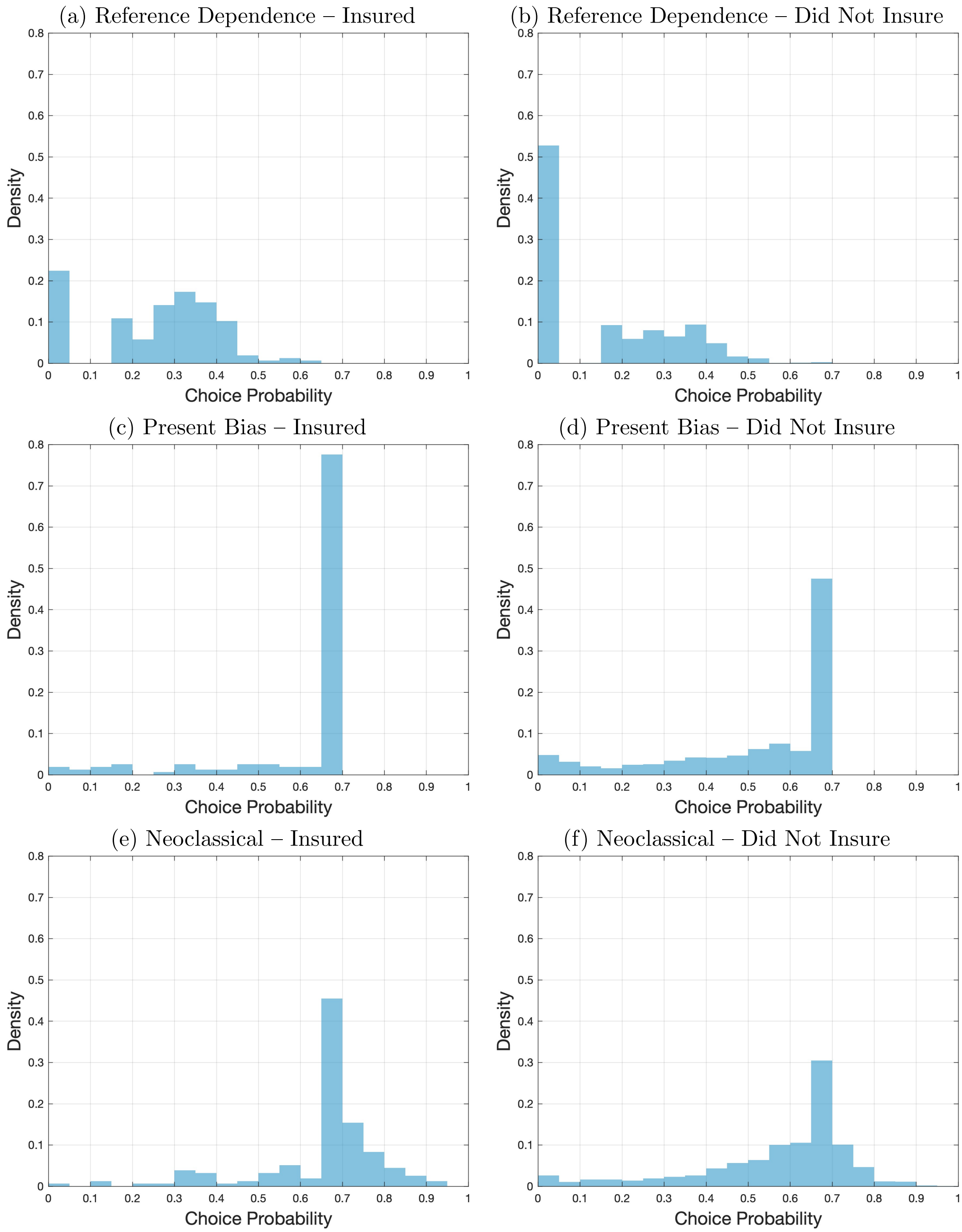
Next, we turn to different specifications of the neoclassical model. When we estimate the trust parameter τ alongside γ and δ, the model implies that individuals assign a zero probability to receiving an insurance payout when one is due. This result is clearly unrealistic, especially given that the average reported value of τ in the survey was 0.732. Under the estimated parameters, this specification and the present-biased model in which β applies only to the insurance decision are observationally equivalent in terms of predicted choices and model fit.[15] However, the unrealistic parameter values suggest that both models miss key elements of how individuals evaluate insurance. The neoclassical model with liquidity constraints estimates that households hold approximately 10 percent of their average annual income in liquid assets at the time the insurance decision is made. For poor households, this constraint likely binds, suppressing demand for insurance. This concern should be ameliorated by the delayed premium contract offered to households in the treatment group. This model provides the best fit among non-reference-dependent models with reasonable parameter estimates. Under the standard neoclassical model without liquidity constraints or imperfect trust, demand is primarily driven by risk and time preferences, with limited ability to account for low take-up among poorer households.

The previous discussion of model fit focused on overall fit across all decision modules. However, we can also isolate model performance by examining the log-likelihood for insurance decisions specifically. When we do so, the advantage of the reference-dependent model becomes even more pronounced: the absolute value of its log-likelihood is roughly half that of the next-best-fitting model. These results highlight that the reference-dependent model provides a substantially better fit than all alternative specifications, making it the most credible explanation for the observed variation in insurance decisions.

[14] DellaVigna et al. (2017) estimate $\beta = 0.58$ in the context of job search in Hungary and note that this is consistent with other empirical findings.

[15] For the risk and time preference modules, neither β nor τ enter the utility specification. For the insurance decision, under standard insurance, both $\beta = 0$ and $\tau = 0$ imply no benefit from the future payout while still requiring an up-front premium. Under the delayed premium contract, both $\beta = 0$ and $\tau = 0$ imply no utility costs (or benefits) of insurance. Under different values of β and τ, however, these models are clearly not identical.

Figure 1: Predicted Choice Probabilities by Model and Observed Insurance Choice



Notes: Choice probabilities are computed according to Equation 11. The reference-dependent model fixes λ at 1.6. In the present-biased model, β applies only to the insurance decision. The neoclassical model corresponds to the baseline specification. These correspond to the best-fitting specification within each model family, with the exception of the neoclassical model (under the estimated parameter values, the best-fitting neoclassical model is observationally equivalent to the best-fitting model of present bias).

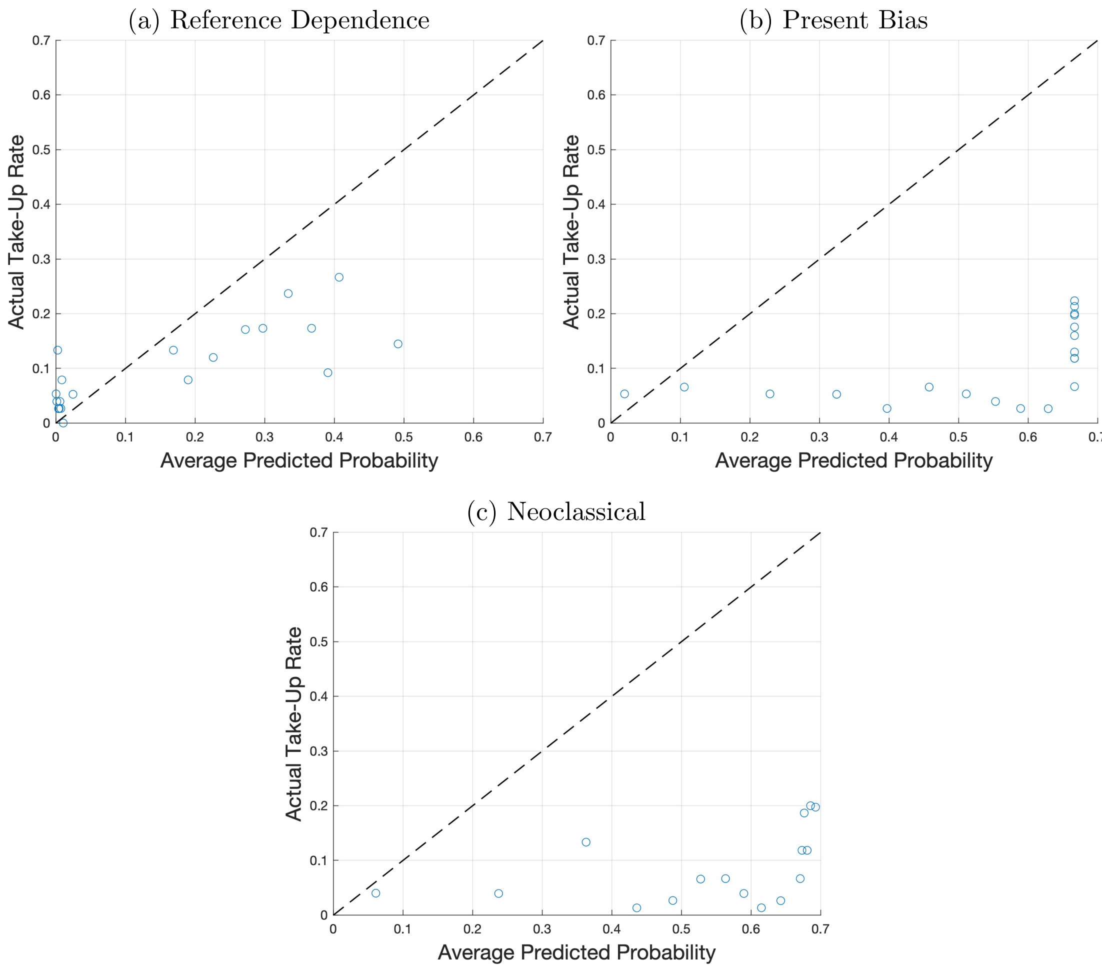
We can examine how the models achieve their fit by visualizing predicted choice probabilities for insurance take-up (calculated according to Equation 11).[16] Figure 1 presents histograms of these probabilities across three model specifications, shown separately for individuals who actually purchased insurance and those who did not. We show the best-fitting specification for the models of reference dependence (with $\lambda = 1.6$) and present-bias (with β applying only to the insurance decision). As noted previously, the best-fitting present-biased model is observationally equivalent to the best-fitting neoclassical model (in which imperfect trust, τ, is estimated), so we do not reproduce figures for the latter. We do, however, present the baseline neoclassical model as a benchmark.

The reference-dependent model assigns near-zero choice probabilities to all individuals offered standard insurance, and probabilities between roughly 0.15 and 0.7 to those offered the delayed premium option. Many more individuals offered standard insurance choose not to insure than to insure, and among those who do insure, the model assigns non-zero (though modest) choice probabilities. The present-biased and neoclassical models show a wide dispersion in predicted choice probabilities for individuals offered standard insurance, including many with relatively high probabilities despite not insuring. Those offered the delayed premium option are generally predicted to have high take-up, regardless of whether they actually insured. This lack of separation across take-up groups suggests that the non-reference-dependent models are less responsive to variation in observed behavior.

Figure 2 divides predicted choice probabilities into 20 bins, each containing 75 or 76 observations, and plots the average predicted probability against the actual take-up rate within each bin. The reference-dependent model slightly underestimates take-up among individuals offered standard insurance. While actual take-up rates in these bins are below 10 percent, the model assigns many individuals near-zero choice probabilities. In contrast, the model slightly overestimates demand among those offered the delayed premium contract. The present-biased and neoclassical models consistently overpredict take-up, assigning choice probabilities that are high

[16] The actual decisions and estimation procedure involve three options: no insurance, four-month insurance, and six-month insurance. For visualization purposes, we group the two insurance products together.

Figure 2: Binned Take-Up Predictions vs. Actual Rates by Model



Notes: Choice probabilities, computed according to Equation 11, are grouped into 20 bins, each containing 75-76 observations. The reference-dependent model fixes λ at 1.6. In the present-biased model, β applies only to the insurance decision. The neoclassical model corresponds to the baseline specification. These correspond to the best-fitting specification within each model family, with the exception of the neoclassical model (under the estimated parameter values, the best-fitting neoclassical model is observationally equivalent to the best-fitting model of present bias).

relative to actual take-up rates for the vast majority of individuals.

5 Mixture Model

While the benchmark models provide insight into the mechanisms driving insurance uptake, the assumption that the entire population follows a single decision-making framework is ultimately unsatisfying. To address this limitation, we estimate a series of two-type mixture models in which a fraction of the population is reference-dependent, while the remainder is assumed to follow an alternative specification. These alternatives include each of the non-reference-dependent specifications estimated in Section 4. The estimation jointly recovers the parameters of both specifications and the population share associated with each decision rule. This procedure is similar to that of Harrison et al. (2010), who estimate a mixture model allowing some individuals to be best described by expected utility theory and others by prospect theory, using experimental choice data from incentivized lottery tasks conducted in Ethiopia, India, and Uganda.

5.1 Estimation

As usual, let i index individuals, k index alternatives, and c index choice contexts. Let the population share associated with the reference-dependent model be π_η, the expected utility under the reference-dependent model be $EU_{ikc}^{(\eta)}$, and expected utility under the alternative model be $EU_{ikc}^{(\neg\eta)}$. Then, the mixture choice probability is:

$$P_{ikc} = \pi_\eta \cdot \frac{e^{EU_{ikc}^{(\eta)}/\sigma_c}}{\sum_j e^{EU_{ijc}^{(\eta)}/\sigma_c}} + (1-\pi_\eta) \cdot \frac{e^{EU_{ikc}^{(\neg\eta)}/\sigma_c}}{\sum_j e^{EU_{ijc}^{(\neg\eta)}/\sigma_c}} \tag{13}$$

These choice probabilities enter Equation 12, and the resulting log-likelihood is maximized to recover the parameters of the mixture model.

5.2 Results

Table 2 presents the mixture model results in which the population is split between reference dependence and present bias, estimated under a variety of specifications.

The six specifications reflect all combinations of two reference-dependent models ($\lambda = 1$ and $\lambda = 1.6$) and three present-biased models, which differ based on the period(s) to which β is applied in the time preference module.

Table 2: Mixture Model Estimates – Reference Dependence & Present Bias

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9269	0.9269	0.9269	0.9267	0.9267	0.9267
	(0.0104)	(0.0073)	(0.0030)	(0.0010)	(0.0035)	(0.0044)
δ	0.9696	0.9695	0.9695	0.9694	0.9694	0.9694
	(0.0069)	(0.0049)	(0.0079)	(0.0069)	(0.0129)	(0.0276)
η	0.0038	0.0038	0.0038	0.0024	0.0024	0.0024
	(0.0005)	(0.0005)	(0.0005)	(0.0003)	(0.0009)	(0.0009)
β	0.9999	1.0000	1.0000	0.9999	1.0000	1.0000
	(0.0061)	(0.0674)	(0.0377)	(0.0057)	(4.2334)	(0.0388)
π_η	0.8976	0.8976	0.8976	0.8889	0.8889	0.8889
	(0.0249)	(0.0251)	(0.0293)	(0.0236)	(0.0970)	(0.0701)
Log-Likelihood	-3020.4	-3020.4	-3020.4	-3017.2	-3017.2	-3017.2
Log-Likelihood (Insurance)	-618.7	-618.7	-618.7	-618.2	-618.2	-618.2
AIC	78540.3	78540.3	78540.3	78456.6	78456.6	78456.6
BIC	78566.9	78566.9	78566.9	78483.2	78483.2	78483.2
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table 3 presents the results from the mixture model in which the population is split between reference-dependent and neoclassical decision-makers. We estimate six specifications, reflecting all combinations of the two reference-dependent models ($\lambda = 1$ and $\lambda = 1.6$) and the three neoclassical models: standard, with trust, and with liquidity constraints.

Across all mixture model specifications, approximately 89 to 93 percent of the population is estimated to be reference-dependent, as indicated by the point estimates for π_η, which are precise across all specifications. Despite the flexibility of the models in allowing for present bias, liquidity constraints, or distrust, the non-reference-dependent population is consistently estimated to follow purely neoclassical behavior. That is, the β and τ estimates are equal to 1 in the specifications in which they are

Table 3: Mixture Model Estimates – Reference Dependence & Neoclassical

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9269	0.9267	0.9268	0.9267	0.9267	0.9265
	(0.0023)	(0.0005)	(0.0044)	(0.0148)	(0.0009)	(0.1836)
δ	0.9695	0.9694	0.9695	0.9694	0.9693	0.9692
	(0.0059)	(0.0043)	(0.0400)	(0.0186)	(0.0047)	(0.0055)
η	0.0038	0.0024	0.0037	0.0024	0.0034	0.0021
	(0.0007)	(0.0007)	(0.0012)	(0.0005)	(0.0003)	(0.0049)
τ	-	-	1.0000	1.0000	-	-
	-	-	(0.0446)	(0.0064)	-	-
ω	-	-	-	-	7.9840	7.9554
	-	-	-	-	(0.0388)	(32.2752)
π_η	0.8976	0.8889	0.9030	0.8948	0.9292	0.9255
	(0.0573)	(0.0723)	(0.1656)	(0.0507)	(0.0211)	(0.1963)
Log-Likelihood	-3020.4	-3017.2	-3019.8	-3016.6	-3010.7	-3007.9
Log-Likelihood (Insurance)	-618.7	-618.2	-617.0	-616.6	-591.8	-592.2
AIC	78538.3	78454.6	78524.2	78441.3	78287.7	78214.8
BIC	78559.6	78475.9	78550.8	78467.9	78314.3	78241.4
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

estimated. This is because allowing some portion of the population to benefit from insurance purchases allows the model to better fit the data, and such benefits are best captured by the neoclassical framework. Indeed, ω is estimated to be around 8, implying large benefits from insurance for the 7 percent of our sample that is classified as neoclassical under this specification. By contrast, the reference-dependent model on its own struggles to rationalize the 5 percent of farmers that do purchase standard insurance. Mixing between reference-dependent and neoclassical types yields slightly better in-sample fit than the benchmark reference-dependent model, as reflected in improvements to the log-likelihood, AIC, and BIC.

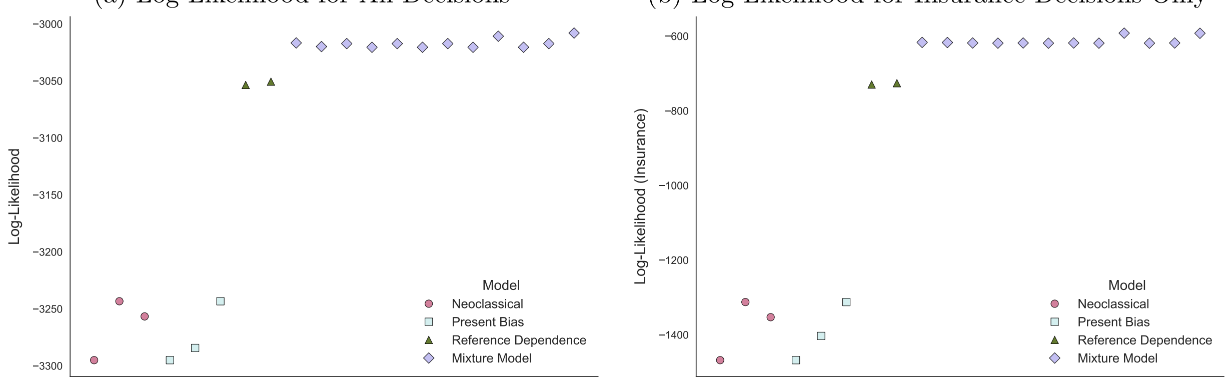
5.3 Summarizing Results across Models

Figure 3 summarizes model fit across the full set of specifications estimated in this paper. Panel (a) visualizes log-likelihood values for the full set of decisions, while panel (b) isolates fit based on insurance decisions only. The results show that models incorporating reference dependence consistently deliver a substantially better fit than those without it, underscoring the central role of reference-dependent preferences in explaining behavior. Mixture specifications yield an additional, though much more modest, improvement by capturing the minority of households that do purchase insurance. We also observe that the improvement in overall model fit is attributable entirely to insurance choices.

Figure 3: Summary of Model Fit across All Specifications

(a) Log-Likelihood for All Decisions

(b) Log-Likelihood for Insurance Decisions Only



Notes: Log-likelihood values correspond to results reported in Tables 1, 2, and 3. Neoclassical model estimates are given in columns (6)–(8) of Table 1; present bias estimates in columns (3)–(5); and reference dependence estimates in columns (1)–(2). Mixture model estimates are presented in Tables 2 and 3.

6 Machine Learning

Our structural estimation was designed to shed light on the mechanisms underlying insurance decisions. The best-fitting specification was a mixture model in which a share of the population is reference dependent, while the remainder follow a neoclassical decision rule, with elevated liquidity levels estimated for the latter. We assessed in-sample fit using log-likelihood, the conventional metric used to evaluate how well discrete choice models explain observed choices. Next, we turn to out-of-sample prediction of insurance take-up to compare the performance of our structural models against a set of machine learning algorithms. We also use these models to address a key policy question: how to predict which individuals are most likely to take up insurance.

6.1 Machine Learning Models

We briefly introduce the machine learning models used for prediction. The full set of hyperparameter grids for each model is provided in Appendix D.

Logistic regression models the log-odds of insurance uptake as a penalized linear function of covariates. We tune the regularization strength and consider both L1 and L2 penalties, as well as alternative class weighting schemes.

Random forests are ensembles of decision trees trained on bootstrapped samples. We tune the number of trees, maximum tree depth, minimum samples per leaf, and the number of covariates considered at each split.

XGBoost implements gradient-boosted decision trees by sequentially fitting new trees to the residual errors from previous iterations. Hyperparameters include the number of boosting rounds, tree depth, and learning rate.

Neural networks are feedforward architectures with ReLU activation functions, dropout regularization, and sigmoid output layers. We tune the number of hidden units, learning rate, and dropout rate, and train each network using the Adam optimizer with mini-batch gradient descent.

6.2 Out-of-sample Fit

Machine learning models excel at detecting patterns and making accurate predictions. If they substantially outperform a structural model, this suggests that the structural specification may be missing key sources of variation in the data. Here, we evaluate the out-of-sample predictive accuracy of our best-fitting structural model and the machine learning algorithms described above, in the spirit of Fudenberg and Liang (2019) and Ellis (2025).

We assess out-of-sample performance using 5-fold cross-validation. The dataset is divided into five equal parts; for each iteration, we fit the model on four folds and generate predictions for the held-out fold. After all five iterations, we combine the predictions for each held-out fold to obtain out-of-sample predictions and performance metrics for the entire dataset. Importantly, we apply the same cross-validation procedure to the structural model. While it was previously estimated on the full dataset (Section 5), we now re-estimate it within each training fold to ensure a fair comparison with the machine learning models.

We evaluate each machine learning model under two settings. In the first, models are trained using the full set of available variables, including those not used in the structural estimation. In the second setting, models are restricted to the same subset of covariates used by the structural model, as defined in Section 3. This allows for a more direct comparison of predictive performance when both approaches are operating with the same informational inputs.

Table 4 summarizes the out-of-sample performance of each model. We report both accuracy and the Brier Score, which in this binary prediction context is equivalent to mean squared error. While accuracy reflects the share of correctly classified outcomes, it ignores the confidence of predictions. In contrast, the Brier Score incorporates the full predicted probability, penalizing models more heavily when they assign low probabilities to outcomes that occur. As such, we place greater emphasis on the Brier Score as a more informative and continuous measure of predictive quality.

When restricted to the same variables used in the structural estimation, the machine learning models perform slightly better than the structural model. Among them, the random forest model achieves the lowest Brier Score at 0.0870, compared to 0.0922 for the best-fitting mixture model. This suggests that the structural model captures much of the predictive signal in the data, even when evaluated strictly on out-of-sample fit. When given access to the full set of covariates, machine learning models improve marginally. XGBoost performs best in this setting, reaching a Brier Score of 0.0838. While this represents the best predictive performance overall, the gains relative to the best-fitting structural model remain modest, indicating that the structural model is well-specified for capturing the core determinants of insurance

Table 4: Model Performance on Insurance Uptake Prediction

Model	**Brier Score**	**Accuracy**
ML: All Variables		
Logistic Regression	0.0863	0.8961
Random Forest	0.0848	0.8967
XGBoost	0.0838	0.8961
Neural Network	0.0866	0.8967
ML: Structural Variables		
Logistic Regression	0.0899	0.8960
Random Forest	0.0870	0.8967
XGBoost	0.0880	0.8967
Neural Network	0.0885	0.8960
Structural Models		
Mixture Model	0.0922	0.8960
Reference Dependence	0.1057	0.8854
Present Bias	0.2953	0.3834
Neoclassical	0.3393	0.3166

Notes: Brier Score and Accuracy are computed from out-of-sample predictions using 5-fold cross-validation. Models in the first panel are trained on the full set of covariates, while those in the second panel are limited to the subset of variables used in the structural estimation. Structural models in the third panel correspond to the best-fitting specification within each model family, with the exception of the neoclassical model, for which baseline results are shown (under the estimated parameter values, the best-fitting neoclassical model is observationally equivalent to the best-fitting model of present bias).

uptake.

6.3 Predicting Likely Insurance Purchasers

The machine learning models above exhibit strong overall predictive accuracy, but they tend to classify most individuals as non-purchasers, reflecting the empirical distribution of insurance uptake. While accurate on average, such predictions are of limited value for policy targeting. In many applications, the goal is to identify individuals likely to purchase insurance in order to inform contract design, subsidy allocation, or outreach efforts. In this subsection, we illustrate how machine learning models can be used to support such targeted policies.

We train the same machine learning models as in Subsection 6.2, but now optimize them for F1 score, which balances precision and recall. The F1 score is defined as:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

where precision is the proportion of predicted purchasers who actually purchase, and recall is the proportion of actual purchasers who are correctly identified. In this context, recall reflects our ability to identify individuals who are likely to insure, which is often the primary policy objective. However, maximizing recall alone can result in high type I error rates. The F1 score accounts for this tradeoff and provides a more balanced criterion for targeting.

To improve model performance in predicting insurance take-up, we apply class weighting during model training so that misclassifying insurance purchasers is penalized more heavily. We then select the classification threshold that maximizes the F1 score based on out-of-sample predictions. Apart from these modifications, the models are trained using the same procedures and data as in Subsection 6.2.

Table 5 reports accuracy, recall, precision, and F1 score for each model. The highest F1 score comes from the random forest model with access to all covariates. It correctly identifies over half of those who purchase insurance, but its precision is low: just over one in four individuals predicted to purchase actually do. These results highlight the difficulty of the task. Insurance uptake is rare, and even well-tuned models struggle to identify likely purchasers without generating a high number of false positives. Nonetheless, the exercise remains valuable from a policy perspective, as even imperfect predictions can improve the targeting of subsidies or outreach efforts.

7 Conclusion

This paper set out to understand insurance decisions among smallholder hog farmers in Sichuan, China by estimating and comparing structural models grounded in different decision rules. We considered neoclassical, present-biased, and reference-dependent models, using a discrete choice framework estimated on insurance take-up, as well as risk and time preference tasks. Among these, the reference-dependent model consistently provided the best fit. We then allowed for heterogeneity by

Table 5: Model Performance on Identifying Insurance Purchasers

Model	**Accuracy**	**Recall**	**Precision**	**F1 Score**
ML: All Variables				
Logistic Regression	0.7895	0.5290	0.2523	0.3417
Random Forest	0.8061	0.5806	0.2848	0.3822
XGBoost	0.8221	0.5097	0.2926	0.3718
Neural Network	0.8068	0.4774	0.2615	0.3379
ML: Structural Variables				
Logistic Regression	0.6947	0.5513	0.1803	0.2717
Random Forest	0.7245	0.6474	0.2186	0.3269
XGBoost	0.6954	0.6731	0.2043	0.3134
Neural Network	0.7854	0.4487	0.2273	0.3017

Notes: Metrics are computed from out-of-sample predictions using 5-fold cross-validation. Models in the first panel are trained on the full set of covariates, while those in the second panel are limited to the subset of variables used in the structural estimation. Models are tuned to optimize for F1 Score.

estimating mixture models, and found that most individuals were best described as reference dependent, with little evidence that present bias, imperfect trust, or liquidity constraints explained additional variation.[17] To assess how well our models predicted behavior, we compared the structural estimates to a set of machine learning algorithms trained on the same data. The machine learning models performed slightly better, especially when allowed to use additional covariates, but the structural model remained competitive and captured much of the signal.

Ultimately, our findings suggest that reference dependence is widespread and plays a central role in shaping the low levels of insurance uptake observed in the data. Reference dependence discourages farmers from purchasing insurance because good states of the world, which occur most of the time, are experienced as losses.[18] This insight can help inform contract design. Future efforts to improve insurance products might follow Dalhaus et al. (2020), who show that designing index insurance with reference dependence in mind can increase a contract's perceived value to farmers.[19]

[17]Other factors undoubtedly influence insurance decisions, but incorporating present bias, imperfect trust, or liquidity constraints into our structural framework does not improve explanatory power beyond what reference dependence provides.

[18]As discussed in Section 3.1, this follows from two features of our model of reference dependence: loss aversion makes premium payments more painful than equivalent gains, and diminishing sensitivity amplifies the impact of repeated small losses relative to infrequent large gains.

[19]Specifically, Dalhaus et al. (2020) examine insurance contracts that insure small losses by removing deductibles and introduce stochastic multiyear premium payments. They find that only the latter increases valuation for reference-dependent farmers.

One important limitation of our analysis is that we take the reference point as given. We follow prior work in assuming that individuals evaluate outcomes relative to a "no insurance" reference point. While this may reasonably characterize the modal individual in our sample, it is unlikely to hold universally or remain fixed over time. Reference points likely evolve with experience and exposure to insurance. Lampe and Würtenberger (2020) confirm this, showing that loss aversion is associated with lower insurance take-up among individuals who did not receive an insurance education module, but with higher take-up among those who did.

Other studies point to learning processes that extend beyond reference dependence. Janzen et al. (2021) find that participating in an insurance game increases subsequent take-up, suggesting that experiential learning can shape future choices. Similarly, Boucher et al. (2024) show that households who have previously received an insurance payout are more likely to purchase insurance again. While these findings are not explicitly about reference dependence, they point to a broader learning process in which individuals come to better understand and internalize what it means to be insured, which may in turn shift the reference point.

Subsidies may help accelerate this process by encouraging initial uptake and giving individuals the opportunity to form this experience. This idea is supported by Cai et al. (2020) and Arteaga et al. (2023), who show that subsidies boost initial insurance uptake and that demand remains elevated even after subsidies are withdrawn.

Future work should aim to better understand how reference points related to insurance are formed and how they evolve with experience. Gaining insight into this process is essential for understanding insurance decisions and designing products and policies that promote sustained uptake and effective risk mitigation.

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A Simulation of Income and Insurance Payouts

We use Monte Carlo simulations to construct income and insurance payout distributions for structural estimation. Hog death is modeled as a discrete event that can occur in any of the six months following insurance enrollment, or not at all. In each simulation, we draw a death rate from a Beta distribution centered on the empirical mean of 3.5 percent over six months, consistent with the annual mortality rate of 6 to 8 percent reported by Liu et al. (2020). This distribution is given by:

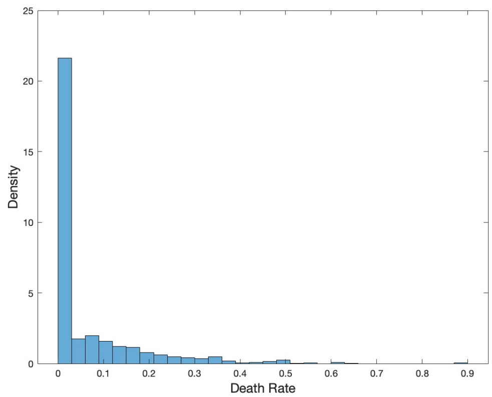
$$deathrate \sim \mathrm{Beta}(\alpha, \beta), \quad \text{with} \quad \alpha = s \cdot \mu, \quad \beta = s \cdot (1 - \mu) \tag{15}$$

where $\mu = 0.035$ is the empirical average death rate and $s > 0$ is a scale parameter that governs dispersion. To calibrate the scale parameter s, we use the empirical average three-year death rate observed in our sample from 2008 to 2010. Figure A1 compares these empirical rates (panel (a)) to distributions of simulated death rates generated from the Beta distribution under different values of s. For our main results, we set $s = 1$, which yields a distribution of death rates consistent with the observed three-year mortality data. As shown in Appendices F.1 and F.2, our findings are robust to alternative choices of s.

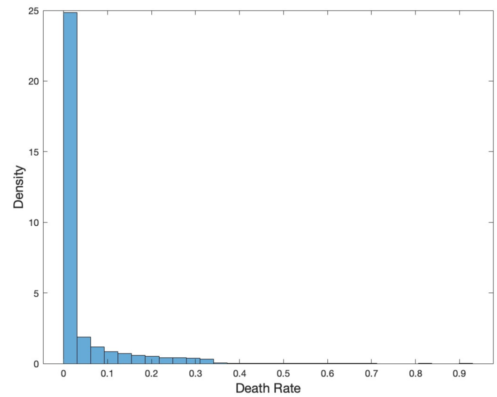
For each unique number of pigs observed in the data, we simulate 100,000 draws. In each draw, a death rate is pulled from the Beta distribution, which defines a probability mass function over the seven possible outcomes (death in months 1 through 6, or survival). Hog death is then simulated according to this distribution. Month of death determines the weight of the pig, under the assumption of linear growth from 20 percent to 100 percent of market weight over the six-month period. Pigs that survive the full six months are sold for the market price of 1,000 RMB reported by Liu et al. (2020). Hogs that die earlier generate insurance payouts if covered. Payouts are based on the hog's weight at death, equal to 70 percent of the estimated market value minus a deductible of 100 RMB, and are capped at 500 RMB. We run separate simulations for each insurance scenario: no insurance, four-month

Figure A1: Simulated and Empirical Hog Mortality Distributions

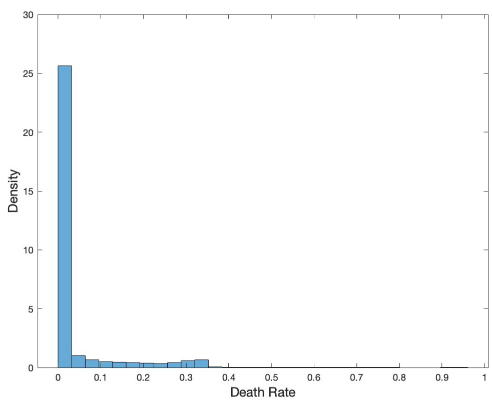
(a) Empirical death rate (2008–2010)



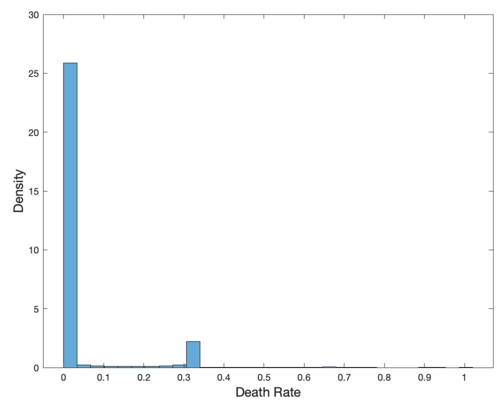
(b) Three-Year Beta Distribution ($s = 1$)



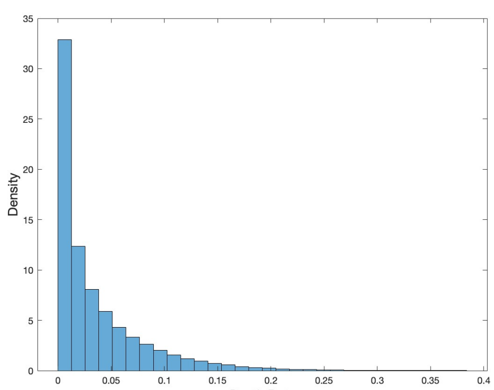
(c) Three-Year Beta Distribution ($s = 0.5$)



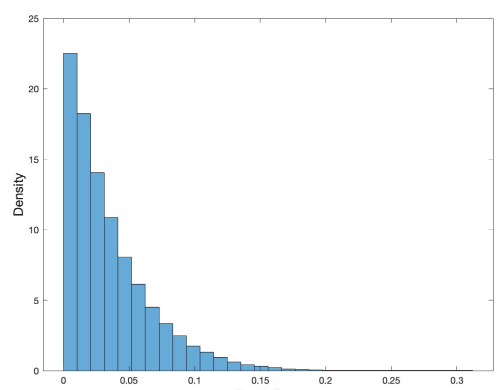
(d) Three-Year Beta Distribution ($s = 0.1$)



(e) Three-Year Beta Distribution ($s = 5$)



(f) Three-Year Beta Distribution ($s = 10$)



Notes: Empirical and simulated hog mortality distributions under Equation 15. Panel (a) shows the observed three-year mortality rate from 2008–2010, while panels (b)–(f) display simulated three-year distributions with alternative values of the scale parameter s. Smaller values of s generate more dispersed death rates, and larger values yield distributions concentrated around the empirical mean of 3.5 percent.

coverage (months 3–6), and six-month coverage (any month). Resulting income distributions are discretized onto a 25-point grid and used for expected utility and certainty equivalent calculations.

B Risk and Time Elicitation Modules

For the risk preference module, participants were asked to respond to the following questions:

Do you prefer:

A. 1000 RMB for sure

B. 50% chance of 900 RMB and 50% chance of 1200 RMB

C. 50% chance of 800 RMB and 50% chance of 1400 RMB

D. 50% chance of 400 RMB and 50% chance of 2000 RMB

E. 50% chance of 0 RMB and 50% chance of 3000 RMB

For the time preference module, participants were asked to respond to the following questions:

Do you prefer:

1. 100 RMB tomorrow or 110 RMB in one month?
2. 100 RMB tomorrow or 120 RMB in one month?
3. 100 RMB tomorrow or 130 RMB in one month?
4. 100 RMB tomorrow or 140 RMB in one month?
5. How much (in minimum) would you have to be paid to wait?

The final question was open-ended and asked respondents to report the minimum amount they would require in one month to prefer it over receiving 100 RMB tomorrow. For estimation purposes, we treat these responses as discrete choices drawn from the set of observed answers, which includes the following 11 delayed payment amounts: 100, 110, 120, 130, 140, 150, 160, 170, 180, 200, and 250 RMB.

For reference-dependent estimation, our main results made the standard assumption that the reference point for these tasks is zero. However, an alternative assumption is that participants anchor on the certain payout of 1000 RMB for the risk preference module, and on the early, certain payout of 100 RMB for the time preference module. We show that our results are robust to this alternative assumption in Appendix F.7.

C Scale Assumptions for Estimation

In this appendix, we clarify and document the assumptions regarding scale in our estimation procedure. Recall from Equation 11 that choice probabilities are given by:

$$P_{ikc} = \frac{e^{EU_{ikc}/\sigma_c}}{\sum_j e^{EU_{ijc}/\sigma_c}}$$

where σ_c is the scale parameter for choice c, capturing the variance of the unobserved error term. As is typical in logit estimation, utility coefficients and scale cannot be separately identified, and a normalization is required. Because real-world insurance decisions and laboratory-style elicitation tasks are different in nature, these choices are likely subject to different levels of noise. We therefore allow for two scale parameters: σ_{insure} for the insurance choice and σ_{elicit} for the elicitation tasks.

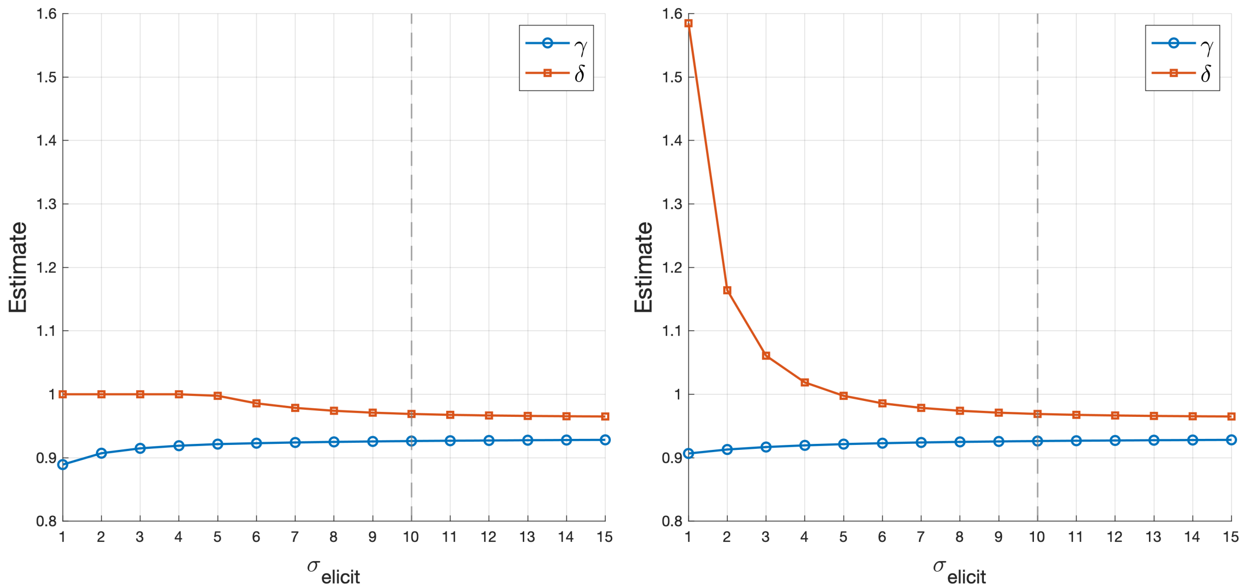
We fix the elicitation scale at $\sigma_{\text{elicit}} = 10$. The standard normalization sets this value to 1, implying that the idiosyncratic error term follows an i.i.d. Type I extreme value distribution with variance $\pi^2/6$.[20] However, in our case, at low values of σ_{elicit}, utilities are over-scaled relative to the error term, destabilizing the likelihood and driving parameter estimates such as δ to implausible values. Figure C1 reports estimates of γ (CRRA) and δ (discount factor) across different values of σ_{elicit}, using only the risk and time elicitation data. The results in the main text impose an upper bound of 1 on δ, reflecting the fact that values greater than 1 are unreasonable because they imply negative discounting. Panel (a) maintains this assumption for comparison. However, when this restriction is relaxed in panel (b), δ rises to nearly

[20] More generally, the variance is given by $\frac{\pi^2}{6}\sigma_c^2$.

1.6 with scale fixed at 1. When we increase σ_{elicit}, estimated parameters quickly converge, and remain stable thereafter. Our interest is not in γ or δ themselves, but in obtaining reasonable estimates of these parameters to facilitate identification of our parameters of interest.

Figure C1: Sensitivity of γ and δ to Elicitation Scale

(a) Estimates with $\delta \leq 1$ (b) Estimates with δ Unconstrained



Notes: γ is the CRRA parameter, δ is the discount factor, and σ_{elicit} is the elicitation scale parameter. Estimates are based solely on data from the risk and time elicitation modules, with only γ and δ estimated. Panel (a) imposes an upper bound of 1 on δ, while panel (b) leaves this parameter unrestricted.

For the insurance choices, we define the scale parameter σ_{insure} as a multiple of the elicitation scale. That is, $\sigma_{\text{insure}} = \chi \cdot \sigma_{\text{elicit}}$. We estimate χ to be 8.8 under the baseline neoclassical specification, and then hold it fixed at this value across all other models. This is because in models with more parameters, χ is not separately identified. This approach allows us to anchor the relative scale of the insurance and elicitation modules while avoiding additional identification problems.

Of course, there is no correct level at which to set the scale parameters, since absolute utility levels are arbitrary. Our approach to scale was aimed at producing stable and interpretable point estimates. However, to ensure that our results are not driven by the choice of scale parameters, Appendices F.8 and F.9 present robustness checks. In the first, we fix $\sigma_{\text{elicit}} = 10$ and set $\sigma_{\text{insure}} = 1$; in the second, both parameters are fixed at 1.

D Hyperparameter Tuning Grids for Machine Learning Models

For each machine learning model, we perform a grid search over a set of hyperparameters using 5-fold stratified cross-validation. The full grids used in the tuning procedure are as follows:

Logistic Regression

We tune the following hyperparameters:

- Inverse regularization strength (C): 50 values logarithmically spaced between 10^{-3} and 10^{2}
- Penalty type: L1, L2
- Class weight: None, Balanced

Random Forest

We tune the following hyperparameters:

- Number of trees: {50, 75, 100, 125, 150, 175, 200, 225, 250}
- Maximum depth: {None, 5, 10, 15, 20}
- Minimum samples per leaf: {1, 3, 5, 7, 10}
- Number of features per split: {sqrt, log2, 0.5, None}
- Class weight: None, Balanced

XGBoost

We tune the following hyperparameters:

- Number of boosting rounds: {50, 75, 100, 125, 150, 175, 200, 225, 250}

- Learning rate: {0.01, 0.02, 0.03, 0.05, 0.1}
- Maximum tree depth: {3, 5, 7, 9}

Neural Network

The neural network architecture is a feedforward network with ReLU activations and dropout. We tune:

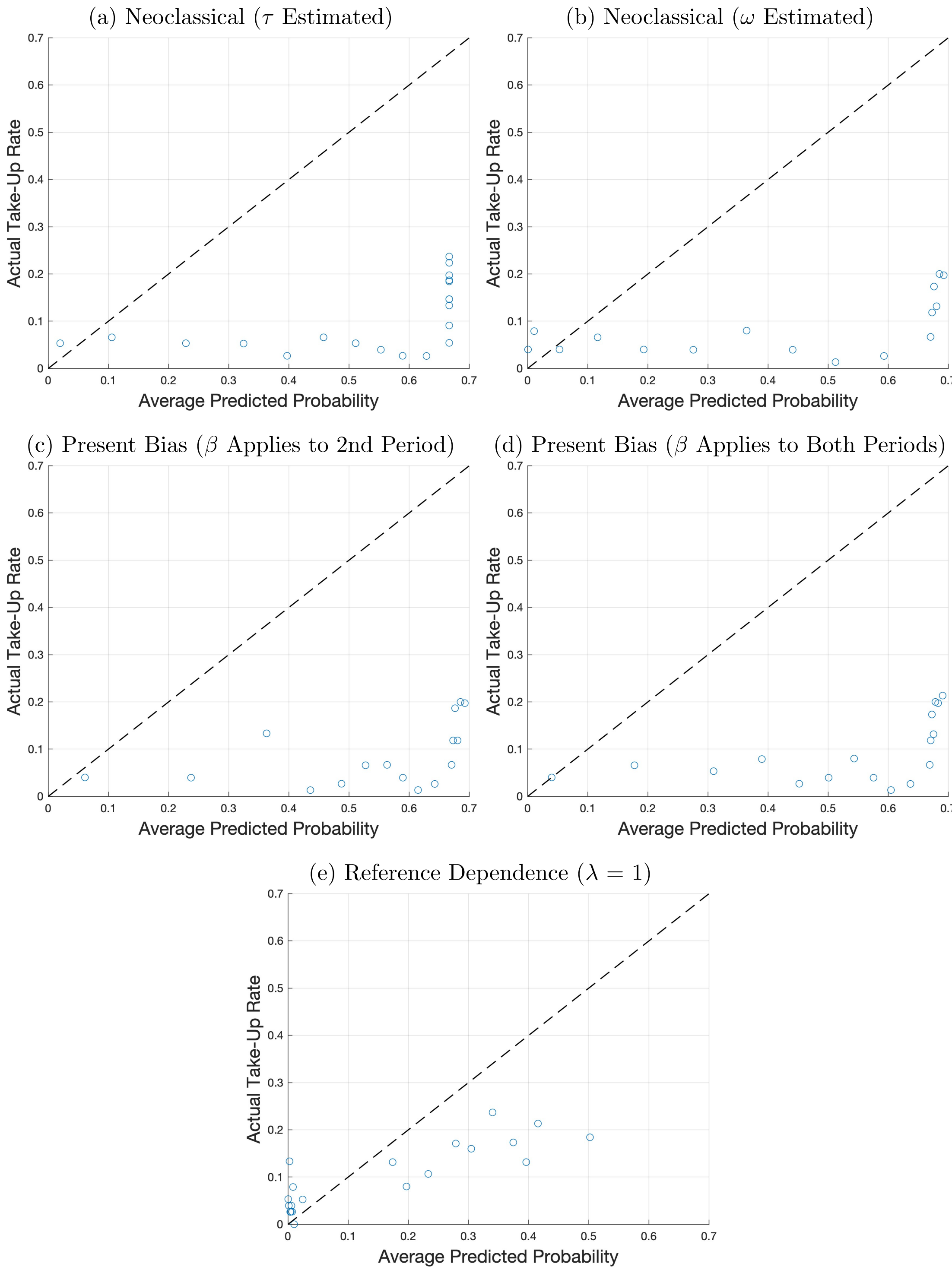
- Hidden units: {16, 32, 64, 96, 128}
- Learning rate: {1e-4, 2e-4, 5e-4, 1e-3, 2e-3}
- Dropout rate: {0.0, 0.1, 0.2, 0.4, 0.5}

E Supplementary Figures of Model Fit

Figure 2 visualized model fit for three specifications without heterogeneity. These were the best-fitting reference-dependent and present-biased models, as well as the baseline neoclassical model. The figure divides predicted choice probabilities into 20 bins, each containing 75 or 76 observations, and plots the average predicted probability against the actual take-up rate within each bin.

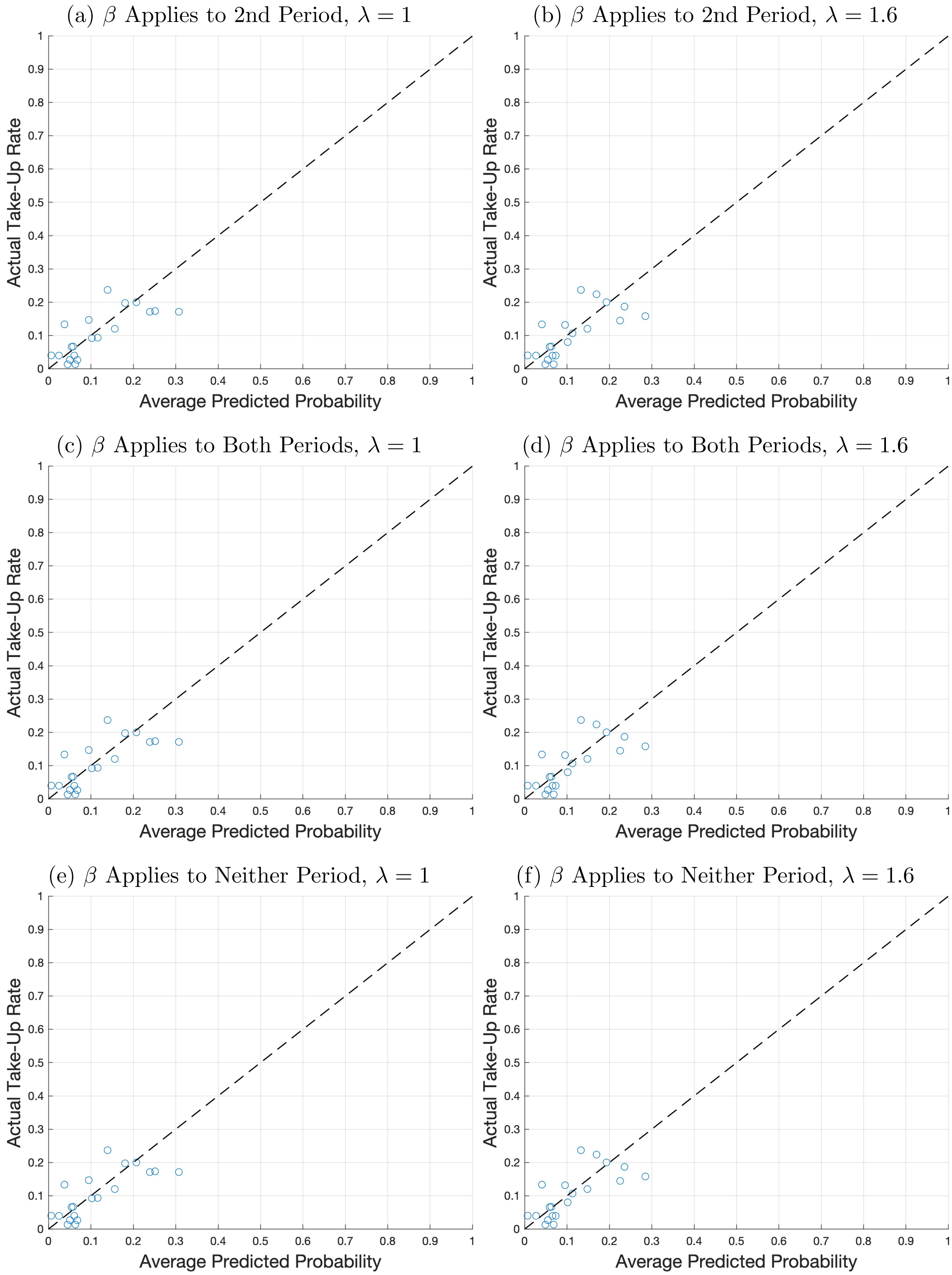
Figure E1 parallels Figure 2 for the remaining specifications without heterogeneity. Figures E2 and E3 do the same for our mixture model specifications. The key takeaways are: 1) models without reference dependence consistently overpredict take-up; 2) while reference-dependent specifications without heterogeneity improve upon the non-reference-dependent models, they tend to underpredict demand at low observed take-up rates and overpredict demand at higher rates; and 3) our mixture models, which estimate around 90% of the population to be reference dependent, avoid systematic over- or underprediction.

Figure E1: Binned Take-Up Predictions vs. Actual Rates – No Heterogeneity



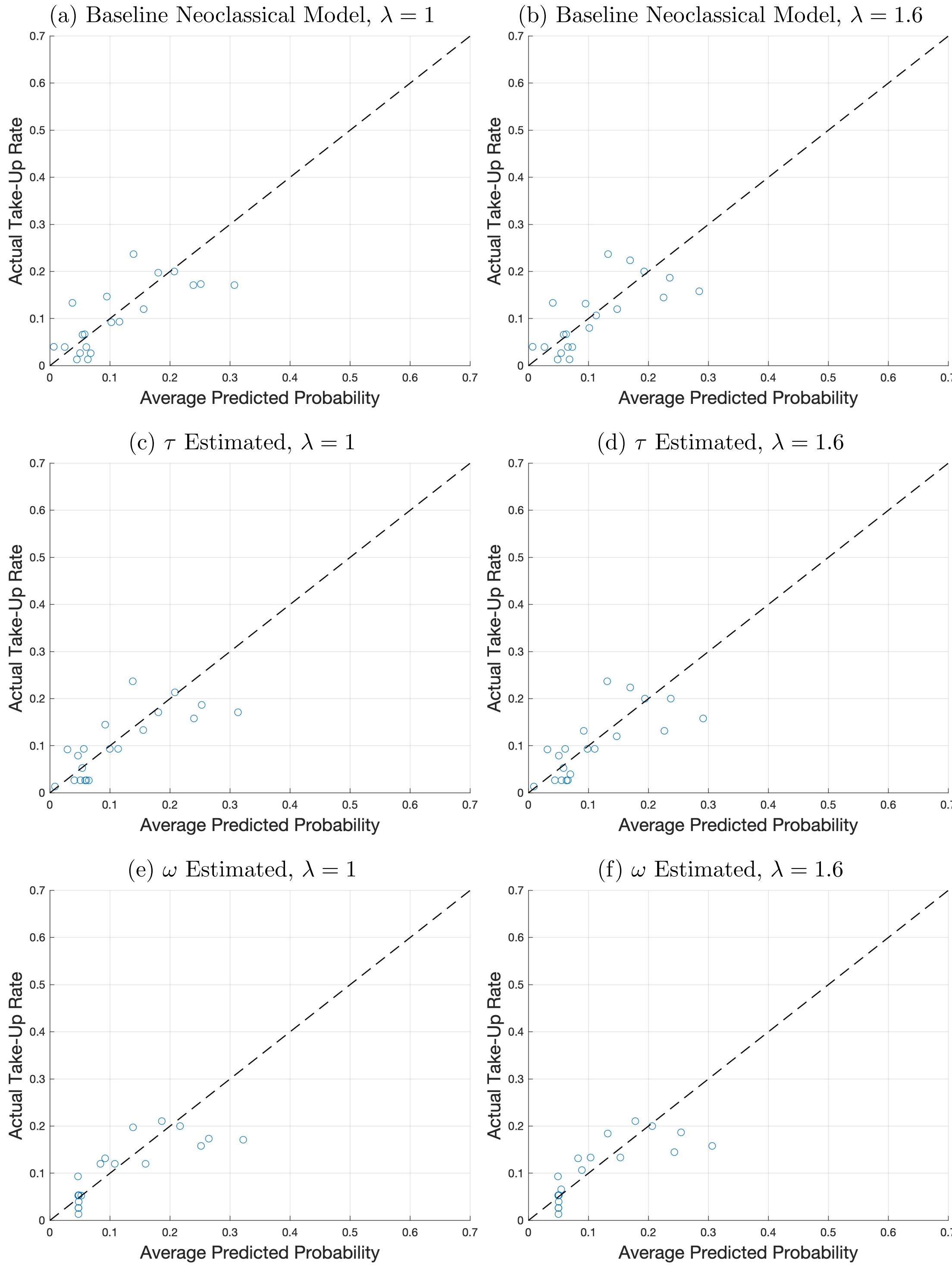
Notes: This figure presents specifications of our main results with no heterogeneity that were not presented in Figure 2. Choice probabilities, computed according to Equation 11, are grouped into 20 bins, each containing 75-76 observations. Panels (a) and (b) present neoclassical models that estimate imperfect trust (captured by τ) and liquidity constraints (captured by ω). Panels (c) and (d) present present-biased models in which β applies to the later payout ("Second") or both payouts ("Both") of the time preference module. Panel (e) presents the reference-dependent model with λ fixed at 1.

Figure E2: Binned Take-Up Predictions vs. Actual Rates – Mixing Between Reference Dependence and Present Bias



Notes: Choice probabilities, computed according to Equation 11, are grouped into 20 bins, each containing 75-76 observations. For the present-biased share of the population, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). For the reference-dependent share of the population, λ is fixed at either 1 or 1.6.

Figure E3: Binned Take-Up Predictions vs. Actual Rates – Mixing Between Reference Dependence and Neoclassical



Notes: Choice probabilities, computed according to Equation 11, are grouped into 20 bins, each containing 75-76 observations. For the neoclassical share of the population, we always estimate baseline parameters, and in alternative specifications add either imperfect trust (captured by τ) or liquidity constraints (captured by ω). For the reference-dependent share of the population, λ is fixed at either 1 or 1.6.

F Robustness Checks

F.1 Alternative Hog Mortality Distribution: $s = 0.5$

Tables F1, F2, and F3 replicate results in Tables 1, 2, and 3 under the assumption that $s = 0.5$, rather than $s = 1$. The scale parameter s, defined in Equation 15, governs the dispersion of hog mortality rates used in the simulation of income and insurance payouts. Appendix A provides further details on the simulation procedure.

Table F1: Estimates with no Heterogeneity ($s = 0.5$)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9273	0.9272	0.9261	0.9253	0.9252	0.9261	0.9252	0.9267
	(0.0011)	(0.0074)	(0.1315)	(0.0012)	(0.1711)	(0.0107)	(0.0420)	(0.0012)
δ	0.9703	0.9702	0.9666	0.9870	0.9685	0.9666	0.9685	0.9679
	(0.0231)	(0.0055)	(1.6726)	(0.0094)	(0.2954)	(0.0076)	(0.3410)	(0.0053)
η	0.0020	0.0012	-	-	-	-	-	-
	(0.0045)	(0.0007)	-	-	-	-	-	-
β	-	-	1.0000	0.5727	0.0000	-	-	-
	-	-	(0.3987)	(0.0591)	(5.8003)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(0.1984)	-
ω	-	-	-	-	-	-	-	0.1031
	-	-	-	-	-	-	-	(0.0037)
Log-Likelihood	-3054.5	-3051.7	-3303.2	-3288.5	-3243.3	-3303.2	-3243.3	-3263.0
Log-Likelihood (Insurance)	-732.4	-729.4	-1492.5	-1408.6	-1312.3	-1492.5	-1312.3	-1371.9
AIC	79422.0	79350.8	85890.3	85505.9	84330.7	85888.3	84330.7	84843.9
BIC	79438.0	79366.8	85906.3	85521.9	84346.6	85899.0	84346.6	84859.8
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F2: Mixture Model Estimates – Reference Dependence & Present Bias ($s = 0.5$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9269	0.9269	0.9269	0.9267	0.9267	0.9267
	(0.0017)	(0.0467)	(0.0016)	(0.0016)	(0.1048)	(0.0020)
δ	0.9695	0.9695	0.9695	0.9694	0.9694	0.9694
	(0.0075)	(0.0180)	(0.0052)	(0.0063)	(1.0086)	(0.0046)
η	0.0038	0.0038	0.0038	0.0024	0.0024	0.0024
	(0.0005)	(0.0049)	(0.0005)	(0.0003)	(0.4590)	(0.0003)
β	0.9999	1.0000	1.0000	0.9999	1.0000	1.0000
	(0.0073)	(0.3353)	(0.0277)	(0.0055)	(1.9334)	(0.0100)
π_η	0.8946	0.8946	0.8946	0.8861	0.8861	0.8861
	(0.0271)	(0.0603)	(0.0264)	(0.0292)	(18.5201)	(0.0288)
Log-Likelihood	-3020.4	-3020.4	-3020.4	-3017.1	-3017.1	-3017.1
Log-Likelihood (Insurance)	-618.5	-618.5	-618.5	-617.7	-617.7	-617.7
AIC	78539.9	78539.9	78539.9	78454.1	78454.1	78454.1
BIC	78566.5	78566.5	78566.5	78480.7	78480.7	78480.7
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F3: Mixture Model Estimates – Reference Dependence & Neoclassical ($s = 0.5$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9269	0.9267	0.9268	0.9267	0.9267	0.9266
	(0.0011)	(0.0002)	(0.0030)	(0.0115)	(0.0307)	(0.0062)
δ	0.9695	0.9694	0.9695	0.9693	0.9693	0.9692
	(0.0045)	(0.0055)	(0.0051)	(0.0110)	(0.0112)	(0.0067)
η	0.0038	0.0024	0.0037	0.0024	0.0034	0.0021
	(0.0005)	(0.0004)	(0.0074)	(0.0004)	(0.0005)	(0.0004)
τ	-	-	1.0000	1.0000	-	-
	-	-	(0.0557)	(0.0375)	-	-
ω	-	-	-	-	8.0140	8.0165
	-	-	-	-	(0.5208)	(2.6319)
π_η	0.8946	0.8861	0.9006	0.8925	0.9271	0.9235
	(0.0253)	(0.0302)	(0.2507)	(0.1096)	(0.0432)	(0.0222)
Log-Likelihood	-3020.4	-3017.1	-3019.8	-3016.5	-3011.4	-3008.5
Log-Likelihood (Insurance)	-618.5	-617.7	-617.0	-616.2	-594.1	-594.1
AIC	78537.9	78452.1	78524.6	78439.6	78306.4	78231.5
BIC	78559.1	78473.3	78551.2	78466.2	78333.0	78258.1
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

F.2 Alternative Hog Mortality Distribution: $s = 2$

Tables F4, F5, and F6 replicate results in Tables 1, 2, and 3 under the assumption that $s = 2$, rather than $s = 1$. The scale parameter s, defined in Equation 15, governs the dispersion of hog mortality rates used in the simulation of income and insurance payouts. Appendix A provides further details on the simulation procedure.

Table F4: Estimates with no Heterogeneity ($s = 2$)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9272	0.9271	0.9258	0.9253	0.9252	0.9258	0.9252	0.9265
	(0.0019)	(0.0006)	(0.0137)	(0.0009)	(0.1023)	(0.0041)	(0.0263)	(0.0116)
δ	0.9704	0.9703	0.9672	0.9801	0.9685	0.9672	0.9685	0.9682
	(0.0056)	(0.0050)	(0.0388)	(0.0642)	(0.1679)	(0.0039)	(0.0734)	(0.0050)
η	0.0020	0.0012	-	-	-	-	-	-
	(0.0002)	(0.0001)	-	-	-	-	-	-
β	-	-	1.0000	0.6592	0.0000	-	-	-
	-	-	(0.0130)	(0.0546)	(0.4706)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(0.4119)	-
ω	-	-	-	-	-	-	-	0.1042
	-	-	-	-	-	-	-	(0.0080)
Log-Likelihood	-3053.7	-3050.3	-3287.5	-3280.0	-3243.3	-3287.5	-3243.3	-3250.8
Log-Likelihood (Insurance)	-729.9	-725.2	-1445.3	-1396.6	-1312.3	-1445.3	-1312.3	-1335.3
AIC	79401.9	79314.3	85480.9	85284.8	84330.7	85478.9	84330.7	84526.1
BIC	79417.9	79330.3	85496.8	85300.8	84346.6	85489.5	84346.6	84542.0
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F5: Mixture Model Estimates – Reference Dependence & Present Bias ($s = 2$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9269	0.9269	0.9269	0.9267	0.9267	0.9267
	(0.0011)	(0.0021)	(0.0665)	(0.0013)	(0.0013)	(0.0132)
δ	0.9696	0.9695	0.9695	0.9695	0.9694	0.9694
	(0.0073)	(0.0056)	(0.0256)	(0.0062)	(0.0054)	(0.0279)
η	0.0038	0.0038	0.0038	0.0024	0.0024	0.0024
	(0.0005)	(0.0012)	(0.0026)	(0.0003)	(0.0003)	(0.0126)
β	0.9998	1.0000	1.0000	0.9999	1.0000	1.0000
	(0.0064)	(0.0159)	(0.3020)	(0.0055)	(0.0101)	(0.0436)
π_η	0.9004	0.9005	0.9005	0.8916	0.8916	0.8916
	(0.0284)	(0.0492)	(0.0949)	(0.0265)	(0.0245)	(1.4594)
Log-Likelihood	-3020.4	-3020.4	-3020.4	-3017.2	-3017.2	-3017.2
Log-Likelihood (Insurance)	-618.2	-618.2	-618.2	-618.3	-618.3	-618.3
AIC	78540.9	78540.9	78540.9	78458.2	78458.2	78458.2
BIC	78567.5	78567.5	78567.5	78484.8	78484.8	78484.8
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F6: Mixture Model Estimates – Reference Dependence & Neoclassical ($s = 2$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9269	0.9267	0.9268	0.9267	0.9266	0.9265
	(0.0015)	(0.0010)	(0.0064)	(0.0025)	(0.0083)	(0.0018)
δ	0.9695	0.9694	0.9695	0.9694	0.9693	0.9692
	(0.0051)	(0.0056)	(0.0318)	(0.0069)	(0.0230)	(0.0011)
η	0.0038	0.0024	0.0038	0.0024	0.0036	0.0022
	(0.0004)	(0.0004)	(0.0014)	(0.0003)	(0.0009)	(0.0003)
τ	-	-	1.0000	1.0000	-	-
	-	-	(0.0625)	(0.0437)	-	-
ω	-	-	-	-	8.0148	8.0190
	-	-	-	-	(0.2499)	(0.0351)
π_η	0.9005	0.8916	0.9053	0.8968	0.9307	0.9268
	(0.0265)	(0.0318)	(0.0393)	(0.0294)	(0.0648)	(0.0177)
Log-Likelihood	-3020.4	-3017.2	-3019.8	-3016.6	-3010.0	-3007.3
Log-Likelihood (Insurance)	-618.2	-618.3	-616.5	-616.6	-589.1	-590.1
AIC	78538.9	78456.2	78524.7	78442.8	78270.7	78198.7
BIC	78560.2	78477.5	78551.3	78469.4	78297.3	78225.3
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

F.3 Alternative Liquidity Assumption: $\omega = 0.1$

Tables F7, F8, and F9 replicate results in Tables 1, 2, and 3 under the assumption that $\omega = 0.1$, rather than $\omega = 0.25$. As defined in Section 3.1, ω captures the proportion of annual income available as liquid wealth at the start of the fattening period.

Table F7: Estimates with no Heterogeneity ($\omega = 0.1$)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9278	0.9277	0.9267	0.9263	0.9262	0.9267	0.9262	0.9266
	(0.0034)	(0.0008)	(0.0058)	(0.0029)	(0.0293)	(0.0097)	(0.3621)	(0.0024)
δ	0.9707	0.9706	0.9681	0.9758	0.9689	0.9681	0.9689	0.9680
	(0.0021)	(0.0064)	(0.0036)	(0.0063)	(0.0272)	(0.0047)	(0.1547)	(0.0283)
η	0.0020	0.0012	-	-	-	-	-	-
	(0.0002)	(0.0001)	-	-	-	-	-	-
β	-	-	1.0000	0.7488	0.0000	-	-	-
	-	-	(0.0039)	(0.0161)	(0.0454)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(2.3419)	-
ω	-	-	-	-	-	-	-	0.1036
	-	-	-	-	-	-	-	(0.0242)
Log-Likelihood	-3095.3	-3092.4	-3256.7	-3253.4	-3224.8	-3256.7	-3224.8	-3256.6
Log-Likelihood (Insurance)	-854.6	-851.0	-1353.1	-1327.4	-1257.4	-1353.1	-1257.4	-1352.8
AIC	80484.6	80407.6	84680.3	84593.2	83850.2	84678.3	83850.2	84677.9
BIC	80500.6	80423.6	84696.3	84609.2	83866.2	84688.9	83866.2	84693.8
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F8: Mixture Model Estimates – Reference Dependence & Present Bias ($\omega = 0.1$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9274	0.9274	0.9274	0.9273	0.9273	0.9273
	(0.0020)	(0.0014)	(0.0871)	(0.0014)	(29.9243)	(0.0635)
δ	0.9701	0.9699	0.9699	0.9699	0.9698	0.9698
	(0.0061)	(0.0044)	(0.6663)	(0.0065)	(3.6627)	(0.0690)
η	0.0042	0.0042	0.0042	0.0028	0.0028	0.0028
	(0.0006)	(0.0006)	(0.1094)	(0.0004)	(0.2532)	(0.0011)
β	0.9998	1.0000	1.0000	0.9999	1.0000	1.0000
	(0.0049)	(0.0291)	(0.2204)	(0.0044)	(131.5339)	(0.0280)
π_η	0.8477	0.8477	0.8477	0.8341	0.8341	0.8341
	(0.0312)	(0.0310)	(0.4498)	(0.0244)	(38.4345)	(0.2029)
Log-Likelihood	-3052.6	-3052.6	-3052.6	-3048.8	-3048.8	-3048.8
Log-Likelihood (Insurance)	-711.6	-711.6	-711.6	-710.0	-710.0	-710.0
AIC	79377.2	79377.2	79377.2	79278.7	79278.7	79278.7
BIC	79403.8	79403.8	79403.8	79305.3	79305.3	79305.3
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F9: Mixture Model Estimates – Reference Dependence & Neoclassical ($\omega = 0.1$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9274	0.9273	0.9274	0.9272	0.9267	0.9265
	(0.0063)	(0.0011)	(0.0019)	(0.0110)	(0.0537)	(0.0017)
δ	0.9699	0.9698	0.9699	0.9698	0.9693	0.9692
	(0.0091)	(0.0025)	(0.0054)	(0.2135)	(0.1719)	(0.0047)
η	0.0042	0.0028	0.0042	0.0028	0.0034	0.0021
	(0.0006)	(0.0004)	(0.0007)	(0.0164)	(0.0042)	(0.0002)
τ	-	-	1.0000	1.0000	-	-
	-	-	(0.0098)	(0.2537)	-	-
ω	-	-	-	-	7.9840	7.9795
	-	-	-	-	(1.9038)	(0.1354)
π_η	0.8477	0.8341	0.8520	0.8383	0.9291	0.9254
	(0.0228)	(0.0311)	(0.0392)	(1.0185)	(0.1129)	(0.0167)
Log-Likelihood	-3052.6	-3048.8	-3051.1	-3047.3	-3010.7	-3007.9
Log-Likelihood (Insurance)	-711.6	-710.0	-707.1	-705.4	-591.8	-592.2
AIC	79375.2	79276.7	79337.4	79238.6	78287.7	78214.8
BIC	79396.5	79297.9	79364.0	79265.2	78314.3	78241.4
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

F.4 Alternative Liquidity Assumption: $\omega = 0.5$

Tables F10, F11, and F12 replicate results in Tables 1, 2, and 3 under the assumption that $\omega = 0.5$, rather than $\omega = 0.25$. As defined in Section 3.1, ω captures the proportion of annual income available as liquid wealth at the start of the fattening period.

Table F10: Estimates with no Heterogeneity ($\omega = 0.5$)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9270	0.9269	0.9263	0.9253	0.9251	0.9263	0.9251	0.9266
	(0.0007)	(0.0087)	(1.7375)	(0.0655)	(0.1264)	(0.0011)	(0.7932)	(0.0024)
δ	0.9702	0.9702	0.9663	0.9930	0.9684	0.9663	0.9684	0.9680
	(0.0055)	(0.0048)	(5.6313)	(0.0070)	(0.1127)	(0.0044)	(0.1412)	(0.0283)
η	0.0021	0.0013	-	-	-	-	-	-
	(0.0002)	(0.0007)	-	-	-	-	-	-
β	-	-	1.0000	0.5187	0.0000	-	-	-
	-	-	(0.5957)	(0.1115)	(0.4990)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(3.5509)	-
ω	-	-	-	-	-	-	-	0.1036
	-	-	-	-	-	-	-	(0.0242)
Log-Likelihood	-3041.1	-3038.2	-3348.6	-3327.8	-3275.8	-3348.6	-3275.8	-3256.6
Log-Likelihood (Insurance)	-692.2	-688.8	-1628.6	-1516.0	-1409.8	-1628.6	-1409.8	-1352.8
AIC	79074.7	78998.0	87070.0	86528.6	85177.1	87068.0	85177.2	84677.9
BIC	79090.7	79013.9	87085.9	86544.5	85193.1	87078.6	85193.2	84693.8
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F11: Mixture Model Estimates – Reference Dependence & Present Bias ($\omega = 0.5$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9267	0.9267	0.9267	0.9266	0.9266	0.9266
	(0.0041)	(0.0017)	(0.0058)	(0.0043)	(0.0163)	(0.0025)
δ	0.9695	0.9694	0.9694	0.9693	0.9693	0.9693
	(0.0059)	(0.0053)	(0.0055)	(0.0316)	(0.1528)	(0.0098)
η	0.0036	0.0036	0.0036	0.0023	0.0023	0.0023
	(0.0005)	(0.0004)	(0.0007)	(0.0038)	(0.0015)	(0.0008)
β	0.9999	1.0000	1.0000	0.9999	1.0000	1.0000
	(0.0068)	(0.0216)	(0.0911)	(0.0085)	(0.5848)	(0.0617)
π_η	0.9187	0.9187	0.9187	0.9131	0.9131	0.9131
	(0.0181)	(0.0214)	(0.0226)	(0.1526)	(0.3946)	(0.0296)
Log-Likelihood	-3014.0	-3014.0	-3014.0	-3011.0	-3011.0	-3011.0
Log-Likelihood (Insurance)	-600.8	-600.8	-600.8	-600.8	-600.8	-600.8
AIC	78373.9	78373.9	78373.9	78296.4	78296.4	78296.4
BIC	78400.5	78400.5	78400.5	78323.0	78323.0	78323.0
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F12: Mixture Model Estimates – Reference Dependence & Neoclassical ($\omega = 0.5$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9267	0.9266	0.9267	0.9266	0.9267	0.9265
	(0.0087)	(0.0014)	(0.0681)	(0.0014)	(0.0018)	(0.0080)
δ	0.9694	0.9693	0.9694	0.9693	0.9693	0.9692
	(0.0119)	(0.0046)	(0.0060)	(0.0144)	(0.0036)	(0.0075)
η	0.0036	0.0023	0.0036	0.0022	0.0034	0.0021
	(0.0004)	(0.0002)	(0.0029)	(0.0003)	(0.0003)	(0.0003)
τ	-	-	1.0000	1.0000	-	-
	-	-	(0.1858)	(0.0267)	-	-
ω	-	-	-	-	7.9840	7.9795
	-	-	-	-	(0.0572)	(0.1537)
π_η	0.9187	0.9131	0.9233	0.9182	0.9293	0.9255
	(0.0227)	(0.0209)	(0.0801)	(0.0228)	(0.0187)	(0.0296)
Log-Likelihood	-3014.0	-3011.0	-3013.9	-3011.0	-3010.7	-3007.9
Log-Likelihood (Insurance)	-600.8	-600.8	-600.8	-600.9	-591.8	-592.2
AIC	78371.9	78294.4	78372.7	78296.0	78287.7	78214.8
BIC	78393.2	78315.7	78399.3	78322.6	78314.3	78241.4
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

F.5 Alternative Interest Rate: $R^s = 1.05$

Tables F13, F14, and F15 replicate results in Tables 1, 2, and 3 under the assumption of an interest rate of 5% rather than no interest on savings carried into the second period of the insurance problem described in Section 3.1.

Table F13: Estimates with no Heterogeneity ($R^s = 1.05$)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9272	0.9271	0.9259	0.9253	0.9252	0.9259	0.9252	0.9266
	(0.0015)	(0.0069)	(0.5492)	(0.0022)	(0.0495)	(0.0012)	(0.2989)	(0.0012)
δ	0.9704	0.9703	0.9669	0.9833	0.9685	0.9669	0.9685	0.9680
	(0.0038)	(0.0059)	(0.6462)	(0.0070)	(0.0100)	(0.0027)	(0.4593)	(0.0103)
η	0.0020	0.0012	-	-	-	-	-	-
	(0.0002)	(0.0003)	-	-	-	-	-	-
β	-	-	1.0000	0.6146	0.0000	-	-	-
	-	-	(0.3220)	(0.0162)	(0.0938)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(0.3447)	-
ω	-	-	-	-	-	-	-	0.1036
	-	-	-	-	-	-	-	(0.0154)
Log-Likelihood	-3053.6	-3050.7	-3295.0	-3284.3	-3243.3	-3295.0	-3243.3	-3256.6
Log-Likelihood (Insurance)	-729.9	-726.3	-1467.9	-1403.0	-1312.3	-1467.9	-1312.3	-1352.8
AIC	79400.4	79323.4	85676.3	85397.0	84330.7	85674.3	84330.7	84677.9
BIC	79416.4	79339.4	85692.3	85412.9	84346.6	85685.0	84346.6	84693.8
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F14: Mixture Model Estimates – Reference Dependence & Present Bias ($R^s = 1.05$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9269	0.9269	0.9269	0.9267	0.9267	0.9267
	(0.0008)	(0.4670)	(0.0022)	(0.0022)	(48298.0985)	(0.0046)
δ	0.9696	0.9695	0.9695	0.9694	0.9694	0.9694
	(0.0073)	(0.0389)	(0.0050)	(0.0063)	(88931.5497)	(0.0133)
η	0.0038	0.0038	0.0038	0.0024	0.0024	0.0024
	(0.0004)	(0.0315)	(0.0004)	(0.0003)	(9521.6689)	(0.0003)
β	0.9999	1.0000	1.0000	0.9999	1.0000	1.0000
	(0.0055)	(0.1088)	(0.0135)	(0.0053)	(112379.8518)	(0.0568)
π_η	0.8976	0.8976	0.8976	0.8889	0.8889	0.8889
	(0.0230)	(0.1812)	(0.0248)	(0.0260)	(155190.0422)	(0.0315)
Log-Likelihood	-3020.4	-3020.4	-3020.4	-3017.2	-3017.2	-3017.2
Log-Likelihood (Insurance)	-618.7	-618.7	-618.7	-618.2	-618.2	-618.2
AIC	78540.3	78540.3	78540.3	78456.6	78456.6	78456.6
BIC	78566.9	78566.9	78566.9	78483.2	78483.2	78483.2
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F15: Mixture Model Estimates – Reference Dependence & Neoclassical ($R^s = 1.05$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9269	0.9267	0.9268	0.9267	0.9267	0.9265
	(0.0101)	(0.0079)	(0.0047)	(0.0034)	(0.0146)	(0.0015)
δ	0.9695	0.9694	0.9695	0.9694	0.9693	0.9692
	(0.0085)	(0.0051)	(0.0186)	(0.0061)	(0.0214)	(0.0281)
η	0.0038	0.0024	0.0037	0.0024	0.0034	0.0021
	(0.0010)	(0.0003)	(0.0005)	(0.0012)	(0.0004)	(0.0006)
τ	-	-	1.0000	1.0000	-	-
	-	-	(0.0348)	(0.0161)	-	-
ω	-	-	-	-	7.5183	7.5217
	-	-	-	-	(0.5467)	(0.1174)
π_η	0.8976	0.8889	0.9030	0.8948	0.9291	0.9253
	(0.1236)	(0.0293)	(0.0420)	(0.1191)	(0.0201)	(0.0219)
Log-Likelihood	-3020.4	-3017.2	-3019.8	-3016.6	-3010.7	-3007.9
Log-Likelihood (Insurance)	-618.7	-618.2	-617.0	-616.6	-591.8	-592.2
AIC	78538.3	78454.6	78524.2	78441.3	78287.7	78214.8
BIC	78559.6	78475.9	78550.8	78467.9	78314.3	78241.4
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

F.6 Full Trust in the Insurance Provider: $\tau = 1$

Tables F16, F17, and F18 replicate results in Tables 1, 2, and 3 with τ fixed at 1 for all individuals. As described in Section 3.1, τ is the perceived probability of receiving an insurance payout when one is due. In all of our other results, individuals are assigned their surveyed τ values (unless τ itself is estimated).

Table F16: Estimates with no Heterogeneity ($\tau = 1$)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9271	0.9271	0.9263	0.9253	0.9252	0.9263	0.9252	0.9269
	(0.0016)	(0.0079)	(2.9737)	(0.0463)	(0.0020)	(0.0010)	(0.0085)	(0.0125)
δ	0.9701	0.9700	0.9662	0.9942	0.9685	0.9662	0.9685	0.9677
	(0.0049)	(0.0053)	(17.8776)	(0.6054)	(0.0069)	(0.0014)	(0.0059)	(0.0055)
η	0.0018	0.0011	-	-	-	-	-	-
	(0.0001)	(0.0002)	-	-	-	-	-	-
β	-	-	1.0000	0.5096	0.0000	-	-	-
	-	-	(0.8669)	(0.2537)	(0.2273)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(0.1478)	-
ω	-	-	-	-	-	-	-	0.0997
	-	-	-	-	-	-	-	(0.0074)
Log-Likelihood	-3032.8	-3030.6	-3318.7	-3296.1	-3243.3	-3318.7	-3243.3	-3271.6
Log-Likelihood (Insurance)	-668.7	-667.2	-1538.6	-1419.0	-1312.3	-1538.6	-1312.3	-1397.7
AIC	78858.3	78802.8	86290.9	85704.8	84330.7	86288.9	84330.7	85068.7
BIC	78874.3	78818.8	86306.9	85720.8	84346.6	86299.6	84346.6	85084.7
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F17: Mixture Model Estimates – Reference Dependence & Present Bias ($\tau = 1$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9268	0.9268	0.9268	0.9267	0.9267	0.9267
	(0.0007)	(0.5242)	(0.0020)	(0.0435)	(0.0054)	(0.0013)
δ	0.9694	0.9694	0.9694	0.9693	0.9693	0.9693
	(0.0068)	(0.2566)	(0.0086)	(0.0153)	(0.0051)	(0.0182)
η	0.0027	0.0027	0.0027	0.0017	0.0017	0.0017
	(0.0002)	(0.0079)	(0.0004)	(0.0011)	(0.0002)	(0.0006)
β	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(0.0058)	(1.6669)	(0.0552)	(0.0075)	(0.0313)	(0.1725)
π_η	0.9095	0.9095	0.9095	0.9046	0.9046	0.9046
	(0.0074)	(0.4072)	(0.0273)	(0.2168)	(0.0294)	(0.0866)
Log-Likelihood	-3015.8	-3015.8	-3015.8	-3013.7	-3013.7	-3013.7
Log-Likelihood (Insurance)	-612.4	-612.4	-612.4	-613.0	-613.0	-613.0
AIC	78421.9	78421.9	78421.9	78366.7	78366.7	78366.7
BIC	78448.5	78448.5	78448.5	78393.3	78393.3	78393.3
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F18: Mixture Model Estimates – Reference Dependence & Neoclassical ($\tau = 1$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9268	0.9267	0.9268	0.9267	0.9266	0.9265
	(0.0004)	(0.0036)	(0.0013)	(0.0017)	(0.0014)	(0.0013)
δ	0.9694	0.9693	0.9695	0.9694	0.9692	0.9691
	(0.0037)	(0.0116)	(0.0052)	(0.0037)	(0.0018)	(0.0138)
η	0.0027	0.0017	0.0037	0.0024	0.0025	0.0015
	(0.0003)	(0.0005)	(0.0011)	(0.0003)	(0.0002)	(0.0001)
τ	-	-	1.0000	1.0000	-	-
	-	-	(0.0090)	(0.0522)	-	-
ω	-	-	-	-	8.0184	8.0214
	-	-	-	-	(0.0151)	(0.1938)
π_η	0.9095	0.9046	0.9030	0.8948	0.9352	0.9333
	(0.0204)	(0.1264)	(0.0437)	(0.0464)	(0.0192)	(0.0198)
Log-Likelihood	-3015.8	-3013.7	-3019.8	-3016.6	-3006.4	-3004.5
Log-Likelihood (Insurance)	-612.4	-613.0	-617.0	-616.6	-585.2	-586.1
AIC	78419.9	78364.7	78524.2	78441.3	78177.0	78127.0
BIC	78441.1	78386.0	78550.8	78467.9	78203.6	78153.6
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

F.7 Alternative Reference Points for Risk and Time Elicitation

Tables F19, F20, and F21 replicate results in Tables 1, 2, and 3 with alternative reference points for the risk and time preference modules. For reference-dependent estimation, our main results made the standard assumption that the reference point for these tasks is zero. However, an alternative assumption is that participants anchor on the certain payout of 1000 RMB for the risk preference module, and on the constant, early payout of 100 RMB for the time preference module. See Appendix B for details of the risk and time preference tasks.

Table F19: Estimates with no Heterogeneity (Alternative Reference)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9275	0.9270	0.9259	0.9253	0.9252	0.9259	0.9252	0.9266
	(0.0029)	(0.0015)	(11.4513)	(0.0017)	(2.5099)	(0.0024)	(0.0985)	(0.0024)
δ	0.9634	0.9648	0.9669	0.9833	0.9685	0.9669	0.9685	0.9680
	(0.0243)	(0.0054)	(7.8741)	(0.0097)	(2.9862)	(0.0086)	(0.4624)	(0.0283)
η	0.0020	0.0014	-	-	-	-	-	-
	(0.0011)	(0.0001)	-	-	-	-	-	-
β	-	-	1.0000	0.6146	0.0000	-	-	-
	-	-	(2.5846)	(0.0164)	(2.2727)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(0.7344)	-
ω	-	-	-	-	-	-	-	0.1036
	-	-	-	-	-	-	-	(0.0242)
Log-Likelihood	-3053.1	-3026.4	-3295.0	-3284.3	-3243.3	-3295.0	-3243.3	-3256.6
Log-Likelihood (Insurance)	-730.0	-730.1	-1467.9	-1403.0	-1312.3	-1467.9	-1312.3	-1352.8
AIC	79387.2	78693.6	85676.3	85397.0	84330.7	85674.3	84330.7	84677.9
BIC	79403.2	78709.5	85692.3	85412.9	84346.6	85685.0	84346.6	84693.8
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F20: Mixture Model Estimates – Reference Dependence & Present Bias (Alternative Reference)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9274	0.9274	0.9274	0.8728	0.8724	0.8784
	(0.0016)	(0.0190)	(0.0294)	(0.0038)	(0.3325)	(0.0067)
δ	0.9564	0.9563	0.9563	0.7893	0.3748	0.3795
	(0.0074)	(0.0064)	(0.0056)	(0.0809)	(0.0612)	(0.0330)
η	0.0037	0.0037	0.0037	0.2407	0.2420	0.2211
	(0.0004)	(0.0011)	(0.0005)	(0.0142)	(0.5354)	(0.0066)
β	0.9998	1.0000	1.0000	0.8329	0.2003	1.0000
	(0.0069)	(0.0552)	(0.0490)	(0.0182)	(0.2501)	(0.8670)
π_η	0.8987	0.8987	0.8987	0.8264	0.7847	0.8010
	(0.0264)	(0.0267)	(0.0354)	(0.0213)	(0.0492)	(0.0349)
Log-Likelihood	-3019.9	-3019.9	-3019.9	-1790.6	-1789.9	-1819.8
Log-Likelihood (Insurance)	-618.9	-618.9	-618.9	-638.2	-649.7	-640.5
AIC	78528.0	78528.0	78528.0	46564.5	46547.8	47324.4
BIC	78554.6	78554.6	78554.6	46591.1	46574.4	47351.0
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F21: Mixture Model Estimates – Reference Dependence & Neoclassical (Alternative Reference)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9274	0.8784	0.9274	0.8783	0.9272	0.8768
	(0.0011)	(0.0249)	(0.0048)	(0.0280)	(0.0026)	(0.0025)
δ	0.9563	0.3795	0.9564	0.3793	0.9572	0.3728
	(0.0038)	(0.0116)	(0.0059)	(2.2370)	(0.0080)	(0.0003)
η	0.0037	0.2211	0.0037	0.2212	0.0034	0.2261
	(0.0003)	(0.0114)	(0.0005)	(0.8297)	(0.0003)	(0.0104)
τ	-	-	1.0000	1.0000	-	-
	-	-	(0.0206)	(0.6781)	-	-
ω	-	-	-	-	7.9502	1.6893
	-	-	-	-	(0.3005)	(0.0960)
π_η	0.8987	0.8010	0.9039	0.8047	0.9296	0.8436
	(0.0239)	(0.0264)	(0.0260)	(0.1780)	(0.0196)	(0.0214)
Log-Likelihood	-3019.9	-1819.8	-3019.3	-1819.0	-3010.2	-1809.2
Log-Likelihood (Insurance)	-618.9	-640.5	-617.2	-638.2	-591.8	-609.2
AIC	78526.0	47322.4	78511.9	47304.6	78274.1	47050.3
BIC	78547.3	47343.7	78538.5	47331.2	78300.7	47076.9
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

F.8 Alternative Scale Assumption: $\sigma_{\textbf{insure}} = \sigma_{\textbf{elicit}} = 1$

Tables F22, F23, and F24 replicate results in Tables 1, 2, and 3 with $\sigma_{\text{insure}} = \sigma_{\text{elicit}} = 1$. We define scale for the insurance choice as a multiple of the elicitation scale: $\sigma_{\text{insure}} = \chi \cdot \sigma_{\text{elicit}}$. In our main results, we fix $\sigma_{\text{elicit}} = 10$ and $\chi = 8.8$ (the latter is estimated under the baseline neoclassical model). See Appendix C for full details of our assumptions about scale.

Table F22: Estimates with no Heterogeneity ($\sigma_{\text{insure}} = \sigma_{\text{elicit}} = 1$)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9055	0.9017	0.8887	0.8887	0.8876	0.8884	0.8876	0.8917
	(0.0444)	(0.0353)	(1.1114)	(0.0566)	(0.3062)	(0.0247)	(0.0553)	(72532.5283)
δ	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(0.5157)	(0.0972)	(1.8119)	(0.2070)	(0.7132)	(0.0407)	(0.3721)	(101458.1426)
η	0.1877	0.1219	-	-	-	-	-	-
	(0.0950)	(0.0797)	-	-	-	-	-	-
β	-	-	1.0000	1.0000	0.0000	-	-	-
	-	-	(0.1893)	(1.0701)	(2.4509)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(2.5280)	-
ω	-	-	-	-	-	-	-	0.0000
	-	-	-	-	-	-	-	(0.8281)
Log-Likelihood	-1329.1	-1321.0	-1641.4	-1641.4	-1639.3	-1640.8	-1639.3	-1426.5
Log-Likelihood (Insurance)	-660.1	-657.2	-1654.5	-1654.5	-1648.1	-1652.8	-1648.1	-1009.7
AIC	34561.8	34353.1	42681.5	42681.5	42626.9	42664.9	42626.9	37094.4
BIC	34577.8	34369.1	42697.4	42697.4	42642.9	42675.5	42642.9	37110.3
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F23: Mixture Model Estimates – Reference Dependence & Present Bias ($\sigma_{\text{insure}} = \sigma_{\text{elicit}} = 1$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9076	0.9076	0.9076	0.9028	0.9028	0.9028
	(0.8729)	(0.1266)	(0.1578)	(0.1943)	(0.0136)	(0.0297)
δ	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(1.2164)	(1.2819)	(1.1403)	(1.0343)	(0.2117)	(0.4303)
η	0.2629	0.2629	0.2629	0.1822	0.1822	0.1822
	(1.9717)	(0.4451)	(0.4135)	(0.1905)	(0.0289)	(0.0334)
β	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(0.9274)	(1.6380)	(8.6505)	(1.0669)	(1.1298)	(30.2291)
π_η	0.9437	0.9437	0.9437	0.9359	0.9359	0.9359
	(0.7008)	(0.1364)	(0.1030)	(0.2386)	(0.0356)	(0.0417)
Log-Likelihood	-1319.4	-1319.4	-1319.4	-1308.6	-1308.6	-1308.6
Log-Likelihood (Insurance)	-607.2	-607.2	-607.2	-601.9	-601.9	-601.9
AIC	34315.3	34315.3	34315.3	34033.4	34033.4	34033.4
BIC	34341.9	34341.9	34341.9	34060.0	34060.0	34060.0
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F24: Mixture Model Estimates – Reference Dependence & Neoclassical ($\sigma_{\text{insure}} = \sigma_{\text{elicit}} = 1$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9076	0.9028	0.9076	0.9028	0.9076	0.9028
	(0.1056)	(0.1339)	(0.1686)	(13.3157)	(8.1076)	(0.1144)
δ	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(1.1751)	(1.4491)	(1.3128)	(1.0668)	(1.1007)	(0.6310)
η	0.2629	0.1822	0.2629	0.1822	0.2628	0.1821
	(0.0796)	(0.5192)	(1.3392)	(30.6686)	(28.7312)	(0.8117)
τ	-	-	1.0000	1.0000	-	-
	-	-	(58.4353)	(72.5803)	-	-
ω	-	-	-	-	7.5778	7.5799
	-	-	-	-	(2.2031)	(3.3120)
π_η	0.9437	0.9359	0.9437	0.9359	0.9439	0.9362
	(0.1209)	(0.2060)	(0.0981)	(0.8451)	(2.7601)	(0.0745)
Log-Likelihood	-1319.4	-1308.6	-1319.4	-1308.6	-1319.4	-1308.5
Log-Likelihood (Insurance)	-607.2	-601.9	-607.2	-601.9	-607.0	-601.8
AIC	34313.3	34031.4	34315.2	34033.3	34314.1	34032.3
BIC	34334.6	34052.6	34341.8	34059.9	34340.7	34058.9
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.

F.9 Alternative Scale Assumption: $\chi = 1$

Tables F25, F26, and F27 replicate results in Tables 1, 2, and 3 with $\chi = 1$, rather than $\chi = 8.8$. We define scale for the insurance choice as a multiple of the elicitation scale: $\sigma_{\text{insure}} = \chi \cdot \sigma_{\text{elicit}}$. Under the current specification, as well as in our main results, we fix $\sigma_{\text{elicit}} = 10$. See Appendix C for full details of our assumptions about scale.

Table F25: Estimates with no Heterogeneity ($\chi = 1$)

	Reference Dependence		Present Bias			Neoclassical		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	0.9277	0.9273	0.9260	0.9260	0.9258	0.9260	0.9258	0.9245
	(0.0012)	(0.0021)	(0.0041)	(0.0146)	(0.0932)	(0.0013)	(0.0405)	(0.0007)
δ	0.9708	0.9705	0.9685	0.9685	0.9688	0.9685	0.9688	0.9680
	(0.0056)	(0.0054)	(0.2080)	(0.0056)	(0.0065)	(0.0051)	(0.0087)	(0.0053)
η	0.0143	0.0093	-	-	-	-	-	-
	(0.0006)	(0.0006)	-	-	-	-	-	-
β	-	-	1.0000	0.9999	0.0000	-	-	-
	-	-	(0.0384)	(0.0352)	(0.5382)	-	-	-
τ	-	-	-	-	-	-	0.0000	-
	-	-	-	-	-	-	(0.7083)	-
ω	-	-	-	-	-	-	-	0.0095
	-	-	-	-	-	-	-	(0.0007)
Log-Likelihood	-3061.3	-3047.6	-3343.7	-3343.7	-3333.6	-3343.7	-3333.6	-3256.0
Log-Likelihood (Insurance)	-669.3	-662.2	-1614.0	-1614.0	-1583.6	-1614.0	-1583.6	-1349.3
AIC	79600.2	79242.7	86941.1	86941.1	86678.3	86939.1	86678.3	84661.3
BIC	79616.2	79258.6	86957.1	86957.1	86694.3	86949.8	86694.3	84677.3
Observations	1510	1510	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	-	-	-	-	-	-
Elicitation periods for β	-	-	Second	Both	Neither	-	-	-

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. In the present-biased model, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into specifications in which τ itself is not estimated.

Table F26: Mixture Model Estimates – Reference Dependence & Present Bias ($\chi = 1$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9277	0.9278	0.9279	0.9275	0.9273	0.9275
	(0.0014)	(0.0076)	(0.0082)	(0.0015)	(0.0071)	(0.0121)
δ	0.9762	0.9734	0.9707	0.9704	0.9730	0.9702
	(0.0049)	(0.0060)	(0.0420)	(0.0066)	(0.0053)	(0.0055)
η	0.0180	0.0184	0.0185	0.0131	0.0130	0.0131
	(0.0015)	(0.0111)	(0.0254)	(0.0010)	(0.0014)	(0.0020)
β	0.9742	0.2921	0.9998	0.9993	0.3327	1.0000
	(0.0080)	(0.2667)	(0.5894)	(0.0187)	(0.1078)	(0.1576)
π_η	0.9649	0.9564	0.9538	0.9440	0.9468	0.9440
	(0.0159)	(0.0185)	(0.1252)	(0.0211)	(0.0152)	(0.0165)
Log-Likelihood	-3056.0	-3055.5	-3056.5	-3038.8	-3038.0	-3038.8
Log-Likelihood (Insurance)	-629.9	-627.0	-625.8	-610.3	-611.2	-610.3
AIC	79465.8	79453.1	79478.8	79018.5	78997.8	79018.5
BIC	79492.4	79479.7	79505.4	79045.1	79024.4	79045.1
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1.6$	$\lambda = 1.6$
Elicitation periods for β	Second period	Both periods	Neither	Second period	Both periods	Neither

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. β is the present-bias parameter. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Under reference dependence λ fixed at either 1 or 1.6. Under present bias, β applies either to the later payout in the time preference module ("Second"), to both payouts ("Both"), or only to the insurance decision ("Neither"). The surveyed, individual-specific τ values are incorporated into all specifications presented in this table.

Table F27: Mixture Model Estimates – Reference Dependence & Neoclassical ($\chi = 1$)

	(1)	(2)	(3)	(4)	(5)	(6)
γ	0.9279	0.9275	0.9279	0.9275	0.9279	0.9274
	(0.0013)	(0.0009)	(0.0027)	(0.0035)	(0.0007)	(0.0012)
δ	0.9707	0.9702	0.9707	0.9702	0.9707	0.9702
	(0.0053)	(0.0058)	(0.0049)	(0.0054)	(0.0184)	(0.0044)
η	0.0185	0.0131	0.0185	0.0131	0.0185	0.0130
	(0.0024)	(0.0010)	(0.0015)	(0.0017)	(0.0025)	(0.0009)
τ	-	-	1.0000	0.9998	-	-
	-	-	(0.2305)	(0.1052)	-	-
ω	-	-	-	-	7.8190	7.8236
	-	-	-	-	(0.2171)	(0.0358)
π_η	0.9538	0.9440	0.9541	0.9444	0.9552	0.9461
	(0.0179)	(0.0181)	(0.0173)	(0.0178)	(0.0576)	(0.0164)
Log-Likelihood	-3056.5	-3038.8	-3056.5	-3038.8	-3055.7	-3038.1
Log-Likelihood (Insurance)	-625.8	-610.3	-625.8	-610.3	-623.6	-608.4
AIC	79476.8	79016.5	79478.4	79018.2	79458.7	78999.5
BIC	79498.1	79037.8	79505.0	79044.8	79485.3	79026.1
Observations	1510	1510	1510	1510	1510	1510
Fixed λ value	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$	$\lambda = 1$	$\lambda = 1.6$

Notes: Standard errors, in parentheses, are calculated as the square roots of the diagonal elements of the inverse Hessian matrix obtained from the numerical optimization. γ is the CRRA parameter. δ is the discount factor. η is the weight on gain-loss utility. τ reflects the perceived probability of receiving an insurance payout when one is owed. ω is the proportion of annual income that is available as liquid wealth at the start of the fattening period. π_η is the reference-dependent population share. We report log-likelihoods for all decisions, for the insurance decision only, along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The reference-dependent model is estimated with λ fixed at either 1 or 1.6. The surveyed, individual-specific τ values are incorporated for population shares in which τ itself is not estimated.