Risk Preference Inconsistencies across Low and High Stakes: Evidence from the Field

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Risk Preference Inconsistencies across Low and High Stakes:
Evidence from the Field

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Abstract

We examine whether households' risk preferences differ for small and large stakes losses. We develop a structural model and estimate household loss distributions to analyze decisions for a continuum of risk using flood insurance data comprising 16 million policies. Each household makes two contract decisions: the deductible amount (ranging from $500 to $5,000), which indicates its attitudes toward small losses; the coverage limit (the maximum the insurance would pay in a claim), which indicates its attitudes toward the risk of large losses. Testing several value functions and allowing for the possibility that households distort probabilities, we find that households' risk preferences are inconsistent for decisions involving small versus large stakes. For example, households' deductible and coverage limit decisions imply different coefficients of relative risk aversion. Both decisions are marked by overweighting of small probabilities and diminishing sensitivity to losses. However, households exhibit greater diminishing sensitivity to losses and overweight small probabilities more when selecting a deductible than when selecting a coverage limit. We conclude that despite making these low and high stakes decisions concurrently, households treat them as separable choices toward which they have different risk attitudes.

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1 Introduction

The predominant models of decision making under risk posit that individuals' preferences are stable over a continuum of potential losses ranging from small to large. For example, in expected utility theory, an individual's coefficient of relative risk aversion explains the precautions that she will take when driving a car to avoid both minor dents and loss of life from an accident. This assumption of consistent behavior across a spectrum of outcomes appears in Bernoulli (1738), underlies von Neumann and Morgenstern (1944), and guides the work of Kahneman and Tversky (1979). It is pervasive in research on risk in all fields of economics. But is this assumption valid?

We analyze risk preferences across a large continuum of potential losses using data on insurance decisions by households in flood-prone areas of the United States who purchased flood coverage to protect their homes. Homeowners' insurance does not cover flood risk in the U.S.; flood insurance is provided by the federally-run National Flood Insurance Program (NFIP), one of the largest property insurance programs in the world, with a total insured value of $1.3 trillion annually. About 96 percent of residential flood insurance policies are purchased through this program (Dixon et al., 2006, p.19). Our data span 16 million insurance policies and 30 years.

These data allow for comparisons of two insurance contract decisions that households make concurrently regarding different aspects of the same risk: (1) the size of the deductible (i.e., the amount that they will pay out of pocket before insurance begins covering a loss) and (2) the coverage limit (i.e., the maximum agreed amount that the insurer will pay in the event of an insured loss). Deductible selection reflects concerns about more frequent small losses, while the coverage limit selection indicates concern about less frequent but much larger losses. We estimate households' preferences from their deductible and coverage limit decisions during a seven year period in which a consistent menu of contract options were available to households, with deductibles ranging from $500

to \$5,000 and coverage limits available up to \$250,000.[1] Households most commonly select a \$1,000 deductible and a coverage limit that equals the cost to fully replace the vulnerable home (for which the median value is \$96,300); however, almost a fourth of households select a coverage limit that is less than this cost.

We assess whether households' preferences are *consistent* across these low and high stakes decisions. Specifically, we assess whether households' deductible and coverage limit selections indicate similar parameter values for several of the predominant models of decision making under risk, such as the same coefficient of relative risk aversion.

We estimate household level loss distributions and combine them with a structural model of decision making that assesses households' risk attitudes based on their contract decisions. We begin by examining households' choices using a power value function. This function reflects an overlap with commonly used models of decision making as both constant relative risk aversion (CRRA) utility and cumulative prospect theory (Tversky and Kahneman, 1992) use power functions. We also allow for the possibility that households distort flood probabilities, using a polynomial expansion to estimate these potential distortions.[2]

We conclude that households demonstrate starkly different risk preferences for low and high stakes. Let "low stakes preferences" describe the model parameters derived from households' deductible decisions, and "high stakes preferences" those from their coverage limit decisions. These preferences are so inconsistent that households' low stakes preferences predict that households would select a coverage limit of zero, indicating that effectively no household would purchase flood insurance.

These inconsistent preferences are reflected in households' value functions and probability distortions: each changes depending on whether households are selecting a deductible or

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[1] We consider protection of the home structure only, and do not examine whether households insure their belongings in the home. Only homes worth \$250,000 or less are included in this analysis.

[2] The polynomial expansion allows for more flexibility in assessing the nature of probability distortions than commonly used probability distortion models (e.g., Tversky and Kahneman, 1992; Prelec, 1998).

coverage limit. Regarding value functions, households' low and high stakes preferences both exhibit diminishing sensitivity to losses, a feature of prospect theory that is contrary to the predictions of expected utility theory for a risk averse household: households perceive the difference between a $1,000 loss and $2,000 loss as greater than that between a $2,000 loss and $3,000 loss. However, we find that households' low stakes preferences show much greater diminishing sensitivity to losses than their high stakes preferences.[3] Taken together, these preferences would require a value function that is convex for small stakes losses, concave for some moderate stakes (between the deductible and coverage limit), and then convex again for large stakes losses.

Regarding probability distortions, we also find that households overweight small probabilities when selecting both deductibles and coverage limits, as cumulative prospect theory predicts, but tend to overweight probabilities *more* when selecting deductibles. Indeed, households overweight flood loss probabilities when choosing a deductible at roughly twice the level they do when selecting a coverage limit. When making a deductible decision, households act as if the median annual probability of a flood event is 15 times larger than what it really is.[4]

We additionally test several frequently used value functions and models: CRRA utility, constant absolute risk aversion (CARA) utility, and a model of reference dependent preferences (Kőszegi and Rabin, 2006), and probability distortion models from Tversky and Kahneman (1992), Prelec (1998), and Gonzalez and Wu (1999). Households demonstrate inconsistent preferences across low and high stakes in every model that we have tested. We also consider two theories intended to unify households' preferences across small and large stakes; neither Chetty and Szeidl's (2007) consumption

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[3] For example, consider what change in loss when the stakes are high makes the household indifferent to incurring a $1,000 change in loss when the stakes are low

$$v(\$2,000) - v(\$1,000) = v(x) - v(\$101,000)$$

where v is the households' value function. Preferences derived from coverage limit decisions indicate that $x = \$113,475$. Households perceive a $1,000 difference when the stakes are low as equivalent to a $12,475 difference when the stakes are high. The corresponding value using deductible decision is $80,867 ($x = \$181,867$).

[4] Households treat the median annual claim rate of 1.4 percent as if it occurs with a 22 percent probability.

commitments nor Holt and Laury's (2002) explanation of expo-power utility seem to explain households' preference inconsistencies in our data.

The primary contribution of this study is to show the inconsistencies of these preferences in a context where low and high stakes decisions are directly comparable. Households make these decisions as part of a single contract, choosing them at the same time and for the same risk with both affecting the same premium. These preference estimates reflect the actual purchase decisions of a large number of households from data on an unusually large spectrum of household losses – from a few hundred dollars to the full value of their homes. This study adds to the growing recognition that households' risk attitudes do not follow the curvature of a single value function across all decisions (Barseghyan et al., 2011; Rabin, 2000).

Several constraints typically challenge studying preferences along a large continuum that our data overcome. First, risks are often a function of several hazards, and households' exposures may differ between these hazards, constraining researchers' ability to model the risk, especially for rare, consequential outcomes. For example, a household member may lose employment for a variety of reasons (economic downturns, personal misconduct, etc.). Similarly, homeowners insurance protects a policyholder's property from multiple hazards, including theft, fire, hail, and wind. Our data provides detailed information on flood risk for each insured property (e.g., the approximate likelihood of a claim, the presence of flood obstructing barriers, etc.). The large amount of publicly available information on flood risk allows for more informed decisions by policyholders and direct comparisons across policyholders as we model flood risk. Second, for many risks, households may have difficulty assessing their maximum exposure, such as the healthcare costs associated with unanticipated illnesses. In our context, the potential maximum loss is limited by the value of the home structure, and the flood insurance program provides a specific estimate of that value to households during the application process. Third, compared to other forms of insurance, flood insurance enables one to examine revealed preferences with respect to the

coverage limit across a broader range of choices as it does not maintain a coinsurance clause.[5]

The article is organized as follows. In Section 1.1 we provide a brief literature review. Section 2 describes the data and modeling techniques to estimate households' preferences from their choices. Section 3 provides results. Section 4 considers two explanations for inconsistent preferences. Section 5 provides implications of our results to models of risk attitudes and insurance policy.

1.1   Literature Review

Bernoulli (1738) proposes a means for understanding risky decisions: individuals evaluate the expected utility of outcomes measured in terminal wealth using a concave utility function.[6] Arrow (1965) and Pratt (1964) build on this work, suggesting a method to measure attitudes toward risk, "One might set out to measure concavity [of a utility function] as representing risk aversion" (Pratt, p. 127). This approach marries two potentially distinct concepts: attitudes regarding a range of outcomes (e.g., decreasing marginal utility of wealth) and attitudes toward stochastic outcomes (i.e., risk aversion, Dyer and Sarin, 1982). For example in our data, households' revealed preferences – their purchase of flood insurance – demonstrate a desire to reduce risk, yet whether their preferences regarding a range of outcomes characterize their risky choices is unclear.

Rabin (2000) and Rabin and Thaler (2001) challenge the idea that individuals' aversion to risk are explained well by the decreasing marginal utility of wealth.[7] Their arguments are

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[5] Private property insurance, such as a homeowners' policy normally includes this clause, which requires that policyholders select a coverage limit of at least 80 percent of their property value in order to be fully reimbursed for damage above the deductible.

[6] "If the utility of each possible profit expectation is multiplied by the number of ways in which it can occur, and we then divide the sum of these products by the total number of possible cases, a mean utility will be obtained, and the profit which corresponds to this utility will equal the value of the risk in question" (Bernoulli, 1738, p.24).

[7] Cox and Sadiraj (2006) show that the problems identified by Rabin (2000) and Rabin and Thaler (2001) do not necessarily apply to von Neumann and Morgenstern's (1944) axioms for preference ordering of stochastic outcomes, but do apply to models that evaluate outcomes in terminal wealth.

reinforced by empirical evidence that individuals demonstrate a willingness to pay for protection against small stakes risks such as appliance warranties (Cutler and Zekhauser, 2004) and protection against electrical wiring problems in residential property (Cichetti and Dubin, 1994). For the most common expected utility models, such as CRRA, this behavior implies high levels of risk aversion that predict implausible choices when extended to higher stakes decisions.[8]

Economists have proposed several compelling explanations regarding these preferences: households' decisions may be guided by (1) a simpler conceptualization of complex problems than is found in expected utility theory value functions such as choice bracketing (Rabin and Thaler, 2001), (2) budget constraints such as consumption commitments (i.e., fixed liabilities) that make households sensitive to small value shocks (Chetty and Szeidl, 2007), and/or (3) more mathematically complex utility functions that account for combinations of absolute and relative risk aversion (Holt and Laury, 2002). We return to these explanations for households' preferences later and where possible, examine our data for evidence. For our core analyses, we follow the typical assumptions of models of decision making under risk, that households make decisions following a value function, integrating across potential outcomes by accounting for the (potentially distorted) probability of each.

Several recent studies use households' deductible selections to estimate their risk preferences. Sydnor (2010) assesses homeowners' insurance deductible choices using the expected utility theory models of constant relative risk aversion and constant absolute risk aversion. While typical risk aversion calibrations predict that households would select the highest deductible in his data of $1,000, more than 80 percent of households chose a lower deductible. Using assumptions that households' wealth is approximated by average lifetime earnings or the value of their homes, he finds that their deductible decisions imply extremely high levels of risk aversion (e.g., coefficients of relative risk aversion in the thousands). Only under the assumption that household wealth is around $5,000 does he

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[8] For example, if a CRRA expected utility maximizer rejects a 50/50 bet with outcomes of either losing $100 or gaining $110, even gaining an infinite amount of money would not induce this individual to participate in a 50/50 bet in which she might lose $1,000.

find the type of single digit relative risk aversion coefficients documented in other areas of economics (e.g., Chetty, 2006; Gourinchas and Parker, 2006; Barro and Jin, 2011). He shows that cumulative prospect theory can more plausibly explain households' deductible decisions.

Barseghyan et al. (2011) identify an additional challenge for standard models in explaining low stakes decisions: household preferences are inconsistent across domains of risk. Using households' deductible choices for homeowners, auto liability, and auto comprehensive insurance, they find that households demonstrate greater risk aversion in home than in auto deductible choices. Their findings are robust across models of utility theory and prospect theory.

Substantial evidence indicates that individuals' decisions under risk are marked by probability distortions – misweighting and/or misperceiving the probability of an event (e.g., Preston and Baratta, 1948; Kahneman and Tversky, 1979; Prelec, 1998; Gonzalez and Wu, 1999). Barseghyan et al. (2013) analyze household deductible selections, assessing risk preferences and potential probability distortions. They find that both risk aversion and probability distortions distinctly contribute to households' decisions. Failing to account for probability distortions, which result in an overweighting of small probabilities, leads to much higher estimates of risk aversion.

2 Methods

2.1 Data

Our primary analyses consider homeowners with property coverage against flooding for single-family dwellings. Our data include all policies from 2001 to 2009 insured by the U.S. National Flood Insurance Program (NFIP) and all of its claims from 1982 to 2009, resulting in 16,349,345 policy observations and 635,220 claims observations for the households described above.

We use these data to model flood risk for each policyholder, estimating the probability of a claim and the distribution of losses given a claim. With these flood risk estimates, we

evaluate models of decision making under risk using a subset of the data – policies with claims between 2002 and 2008 ($n = 103{,}084$) – as data from both our policy and claims databases are needed to model preferences.[9] We include only a policyholders' first claim so that each insured household is represented once in the analysis. During this period, households experienced a consistent choice of deductible options ranging from $500, $1,000 up to $5,000, in $1,000 increments, and could purchase property coverage limits up to $250,000. Because of this maximum coverage limit, we examine only homes with values up to $250,000 so that all individuals in the analyses could select a coverage limit to protect the full value of their home.[10] Also, the data during this period include the necessary components to calculate policyholder premiums and so allow for comparisons across all potential policies available to a household.

The U.S. federal government runs the NFIP through the Federal Emergency Management Agency (FEMA) and underwrites all insured risk. Households buy flood insurance from an authorized insurer or insurance agent, frequently the same agent that sells their homeowners coverage. In 2013, the NFIP issued 5.6 million policies for a total insured value about $1.3 trillion.

The households in our primary analyses reside in areas that FEMA designates the "A zone," areas with at least a 1 percent annual flood risk probability but that are not prone to coastal storm surge. This is by far the largest risk category in the program, accounting for 47 percent (or 2.1 million) of all policies for single-dwelling homes in 2012. There is a distinct risk category for homes with at least a 1 percent annual flood probability that are vulnerable not only to inundation but also to wave damage ("V zone"). Under the NFIP all households residing in an area estimated to have at least a 1 percent annual probability of flood damage must purchase flood insurance if they have a federally backed mortgage. A third group of policyholders are those whose properties have an estimated flood risk probabilities of less than 1 percent ("low risk zone"). In Appendix 1, we exploit differences between our

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[9] Each database contains some distinct variables that are important to estimating preferences, primarily related to modeling the flood risk, which we discuss in Section 2.2.3 and the Online Appendix.

[10] Ninety-five percent of all insuring households have homes valued at or below this value.

primary sample in the "A zone," and the "V zone" and low risk zone to conduct robustness checks of some of our key results. We compare policyholders living in zones where flood insurance is required against those in areas where homeowners can purchase it voluntarily, considering the possibility that the requirement to insure may lead households to select different coverage limits than if the decision were voluntary. We conclude that this requirement minimally influences households' selections as the distribution of coverage limits relative to home values is very similar for these two groups.

2.2   Modeling Households' Preferences

Our examination of households' risk attitudes and probability distortions requires a set of inputs to populate a weighted value function. We assume that households' deductible and coverage limit decisions are characterized by

$$\int v(c, d, l, p; \theta)\omega(\pi(l); \boldsymbol{\beta})\ \ dl \quad (1)$$

where v represents households' value function; c coverage limit selected; d deductible selected; l flood losses, which occur with probability π and are potentially distorted following function ω. The focus of our analysis is fitting value function parameter θ and probability distortion parameters $\boldsymbol{\beta}$ using households' deductible and coverage limit decisions.

Our data include households' deductible and coverage limits choices and the pricing schedule that allows us to determine the premium for any combination of deductible and coverage limits. Our data also include an estimate of the home's property value and its replacement cost. Replacement costs provide the amount needed to rebuild the current structure using similar materials and are estimated using insurance industry standards that account for a home's characteristics including its building materials, size, and sales value (NFIP, 2006, p. 4-175). Homeowners are provided an estimate of their replacement cost when they select an insurance policy. A home's property value is estimated onsite when a claim is made. We use this number in modeling loss probabilities; households cannot lose more than the property value. In Equation 1, we apply these probability distributions to a

households' replacement cost (l describes flood losses in terms of a household's cost to address them). The explicit assumption we make is that if a home is damaged by flood, the household will replace what was damaged.[11] Thus, a flood that destroys 50 percent of the home would be expected to cost the household 0.5 times the home's replacement cost.

The remaining material in this section describes our approach for selecting a value function, estimating flood probabilities, and modeling probability distortions.

2.2.1 Household Value Functions

We model households' decisions using the power value function

$$v(x) = -x^\theta \qquad (2)$$

where $\theta > 0$ and $x \geq 0$. In this context, x describes a range of costs: potential flood losses, deductibles, and premium payments. The best possible outcome for households is $x = 0$. For example, a household that purchased insurance for premium p but incurred no loss would derive a value of $v = -p^\theta$.

Using this value function plays to the strengths of our data as it is a direct test of households' attitudes across what we observe, a range of disagreeable outcomes. If $\theta > 1$, households exhibit an increasing sensitivity to losses as losses increase ($v' < 0, v'' < 0$); $\theta < 1$ indicates diminishing sensitivity to losses ($v' < 0, v'' > 0$). We are specifically interested in whether households' decisions regarding deductible and coverage limits imply similar values for θ.

This value function provides overlap with CRRA utility and cumulative prospect theory as both use power functions. For example, it is the cumulative prospect theory value function (Tversky and Kahneman, 1992) under the assumptions that (1) a household uses its wealth before purchasing insurance as its reference point and (2) the coefficient of loss aversion

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[11] Even in cases in which the damage is substantial, we believe this assumption is defensible as households would often benefit from fixing a damaged home before trying to sell the home and property.

is normalized to 1.[12] As our data do not include observations of both gains and losses in this framework, we cannot estimate cumulative prospect theory's loss aversion parameter. In Appendix 2, we show that decreasing marginal utility of wealth is equivalent to increasing sensitivity to losses for CRRA utility. Wakker (2008) reports that CRRA utility is "the most widely used parametric family for fitting utility functions to data" (p.1329).

2.2.2 Insurance Decisions

Households choose a deductible level and coverage limit, affecting the premiums they pay. We allow for households to treat these as separate decisions, but assume that households observe their coverage limit decision when selecting a deductible, and vice versa. This approach allows for risk attitudes to differ across deductible and coverage limit decisions, but in the event that households' attitudes are consistent, it will lead to similar parameter values for each choice. The household deductible selection problem is thus

$$\max_{d \in \{d_1, d_2, .., d_n\}} \int_0^d V(p(d) + l)\omega(l) + \int_d^{c^*} V(p(d) + d)\omega(l) + \int_{c^*}^{\bar{c}} V(p(d) + d + l - c^*)\omega(l) \quad dl \quad (3)$$

where d is the deductible, c^* the coverage limit the household selects, $\bar{c}$ is the total property value, p the premium, l losses with $l \in [0, \bar{c}]$, and $\omega(l)$ the household's transformation of loss probabilities (e.g., overweighting of small probabilities). Equation 3 describes outcomes across the range of potential losses. The first integrand accounts for flood losses less than the deductible, the second accounts for losses above the deductible but less than the coverage limit, and the third accounts for losses greater than the coverage limit selected by the household. Similarly, the households' coverage limit decision is

$$\max_{c \in [\underline{c}, \bar{c}]} \int_0^{d^*} V(p(c) + l)\omega(l) + \int_{d^*}^{c} V(p(c) + d^*)\omega(l) + \int_c^{\bar{c}} V(p(c) + d^* + l - c)\omega(l) \quad dl$$

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[12] Tversky and Kahneman (1992) use the function

$$v(y) = \begin{cases} y^\alpha & \text{if } y \geq 0 \\ -\lambda(-y)^\theta & \text{if } y < 0 \end{cases}$$

where y represents deviations from the households' reference point. Thus, dividing both gains and losses by λ and setting $x = -y$ yields Equation 2.

where d^* is the deductible that the household selects.

2.2.3 Flood Risk

We estimate households' claim rates and loss distributions based on the characteristics of the home that the flood insurance program uses to set premium rates. Here, we provide an overview of our methodology for modeling flood risk; the Online Appendix offers a detailed explanation and modeling results. Flood risk loss probabilities π comprise two elements, the probability of incurring a flood loss $\pi(l > 0)$ and given a flood loss l, the probability of a specific loss $\pi(l|l > 0)$ such that

$$\pi(l) = \pi(l > 0)\pi(l|l > 0).$$

We model the claim rate as an approximation of the probability that a policyholder incurs any flood loss. Unlike many other insurance products, flood insurance premiums in this program are not influenced by previous claims experience. Thus, while other forms of insurance create a disincentive to report small flood losses due to the potential that it will increase future premiums (Braun et al., 2006), this flood insurance motivates those who suffer flood losses to report even minor damage so that a professional adjuster can determine if damages exceed the deductible. For example, 2.5 percent of all flood insurance claims in our dataset are for losses less than the minimum deductible of $500.

We estimate claim rates using a random effects panel logit model with policies and claims data from 2001 to 2009. Only a policyholder's first claim in a given year is included in the analysis. We use detailed information regarding the insured home and its vulnerability as explanatory variables. Examples include the elevation of the home, the number of floors in the home, the presence of obstructions, and an assessment of actions taken by the community to reduce flood risk.[13] To account for the possibility of adverse selection, we also include policyholders' deductible and coverage limit choices.

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[13] Community actions include maintaining and disseminating flood maps of the community, preventing building in floodplains, developing flood warning systems, improving community drainage systems, etc. More information can be found at FEMA (2015).

We also estimate loss distributions for each household in the program. Using all flood claims from 1982 to 2009, we model losses as a percent of the property value and estimate their probability at each percentile. We find that losses are distributed log-normally and model the two parameters of this distribution, μ and σ, based on a households' observable characteristics using an iterative MLE approach following Aitkin (1987) and Western and Bloome (2009).

2.2.4 Probability Distortions

We allow for distortions on the cumulative distribution following Quiggin (1982). While a variety of probability distortion models have been proposed (e.g., Tversky & Kahneman, 1992; Prelec, 1998; Gonzalez & Wu, 1999), the probabilities in our data are small relative to the values tested in those studies. Therefore, we take a more flexible approach, assessing for probability distortions of households' flood loss probabilities with a polynomial expansion. Following Barseghyan et al. (2013), we use Chebyshev polynomials, which are an orthogonal sequence of functions. For example, a third order approximation of distortions would lead to

$$T_0(\Pi) = 1$$
$$T_1(\Pi) = \Pi$$
$$T_2(\Pi) = 2\Pi^2 - 1$$
$$T_3(\Pi) = 4\Pi^3 - 3\Pi$$

$$\Omega = \alpha_0 T_0 + \alpha_1 T_1 + \alpha_2 T_2 + \alpha_3 T_3 \quad (4)$$

where Π is a vector of cumulative probabilities, Ω is the transformed probabilities, T_m is the Chebyshev polynomial of order m, and α_j represent a set of coefficients to be estimated. We impose a penalty in our maximum likelihood estimations that prevents negative probabilities and the sum of distorted flood probabilities from exceeding 1.

For ease of interpretation, we simplify the presentation of our results using the Chebyshev polynomials. Through substitution, we rewrite Equation 4 as

$$\Omega = \alpha_0 - \alpha_2 + (\alpha_1 - 3\alpha_3)\Pi + 2\alpha_2\Pi^2 + 4\alpha_3\Pi^3$$
$$= \beta_0 + \beta_1\Pi + \beta_2\Pi^2 + \beta_3\Pi^3$$

where $\beta_0 = \alpha_0 - \alpha_2$ and $\beta_1 = \alpha_1 - 3\alpha_3$, etc.

2.3 Estimation

Our estimation approach builds on those of Barseghyan et al. (2013), Camerer and Ho (1994), Hey and Orme (1994), and Holt and Laury (2002) who estimate risk preferences using random utility structural models. Barseghyan et al. (2013) provide a set of proofs showing that this framework allows for disentangling risk preferences from insurance purchase decisions and probability distortions (p. 2510). The intuition behind this identification strategy is that household selections across a menu of insurance contract options (e.g., more than two deductible options) allows for differentiation between curvature in the value function and probability distortions through exogenous variation in both the risk of loss and premiums.

We adopt a random utility framework (McFadden, 1974) and fit model parameters using maximum likelihood estimation. For household i, let

$$u_i(k; \theta, \boldsymbol{\alpha}) \equiv w_i(k; \theta, \boldsymbol{\alpha}) + \epsilon_{ik}$$

where w represents the household probability-weighted value function, $k \in K$ a specific lottery among a set of insurance lotteries, θ a value function parameter shown in Equation 2, $\boldsymbol{\alpha}$ a vector of probability distortion parameters shown in Equation 4, and ϵ_{ik} an i.i.d. error component, which is assumed to be distributed type 1 extreme value. The probability that a household chooses lottery k is thus

$$p_{ik} = \frac{\exp u_i(k; \theta, \boldsymbol{\alpha})}{\sum_{k' \in K} \exp u_i(k'; \theta, \boldsymbol{\alpha})}$$

Our estimation strategy solves problem

$$\underset{\theta, \boldsymbol{\alpha}}{\text{argmax}}\, \mathcal{L} = \sum_{i=1}^{N} \sum_{k=1}^{K} y_{ik} \ln p_{ik}$$

where $\mathcal{L}$ is the log-likelihood function and $y_{ik} = 1$ if household i chooses lottery k and 0 otherwise (Cameron and Trivedi, 2005).[14]

We estimate this model for deductible decisions and for coverage limit decisions and compare the parameter values between these estimations. For example, we test the hypothesis that the value function parameter θ differs for deductible and coverage limit decisions ($H_0: \theta_d = \theta_c$). Parameter estimates from these random utility models are normally distributed (Cameron and Trivedi, 2005, p. 497) and can be compared using the Wald test

$$z = \frac{\theta_d - \theta_c}{\sqrt{var(\theta_d) + var(\theta_c) - cov(\theta_d, \theta_c)}}.$$

In our models, we derive and report standard errors using a numerical approximation of the Fisher information matrix for each model; however, the covariance of our parameter estimates is unclear using this approach as we estimate the models for the deductible and coverage limit decisions separately.

We estimate the variance-covariance matrix for model parameters using subsample bootstrapping (Politis and Romano, 1994; Politis et al., 1999). We draw 400 random subsamples of 5,000 households from our data, estimate our models on each subsample, and compare parameter estimates across these subsamples.[15] The statistical values derived from this approach are lower bound estimates as they rely on subsamples of 5,000

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[14] Households select coverage limits between $15,000 and $250,000; options are in $1,000 increments. We impose a minimum coverage limit of $15,000, which ensures that the coverage limit is above household premiums plus the highest deductible option ($5,000) for all households, but still allows for households to partially insure. This condition creates consistency in the deductible and coverage limit menu across households. Over 99 percent of households in the data select coverage limits greater than $15,000.

[15] Bootstrapping our models with our full sample would be prohibitively computationally expensive. Instead, we use 400 random subsamples based on the guidance of Cameron and Trivedi (2005, p.361) that the number of bootstrap samples $B = 96(2 + \gamma)$ where γ is the coefficient of excess kurtosis for the bootstrap estimates of θ. The coefficient of excess kurtosis is larger for the coverage limit decision, $\gamma_c = 1.35$, suggesting that $B \geq 322$. We draw the observations in each subsample without replacement.

households rather than the full sample of 103,084. For the number of random subsamples B, this test uses the t-statistic

$$t = \frac{\overline{\theta_d} - \overline{\theta_c}}{\sqrt{s_{\theta_d}^2 + s_{\theta_c}^2 - s_{\theta_{c,d}}^2}} \quad (5)$$

where $\overline{\theta_d}$ and $\overline{\theta_c}$ are the average coefficient values for the B subsamples and the bootstrapped variance of the parameter estimates for the deductible and coverage limit are respectively $s_{\theta_d}^2 = \frac{1}{B-1}\Sigma_{b=1}^B(\theta_{b,d} - \overline{\theta_d})^2$ and $s_{\theta_c}^2 = \frac{1}{B-1}\Sigma_{b=1}^B(\theta_{b,c} - \overline{\theta_c})^2$ and their covariance is $s_{\theta_{c,d}}^2 = \frac{1}{B-1}\Sigma_{b=1}^B(\theta_{b,d} - \overline{\theta_d})(\theta_{b,c} - \overline{\theta_c})$.

2.4 Households' Flood Probabilities and Contract Selections

Table 1 provides summary statistics on policyholders' risk, premiums, coverage limits, and replacement cost. The estimated average annual flood claim probability is 1.49 percent, and given a claim, the expected damage is 20.3 percent of the home's value. These estimates of risk are quite similar to those of Kousky and Michel-Kerjan (2015) who report on the flood insurance program. Using a longer time series from 1980 to 2012, they find an average annual claim rate of 1.45 percent. Regarding loss distribution estimates, we include our corresponding estimate in brackets in the following excerpt from their paper: "half of claims are for less than 10 percent [9 percent] of the value of the building, roughly 15 percent [12 percent] of claims exceed 50 percent of the building's value, and approximately 7 percent [7 percent] exceed 75 percent of building value" (p.13).

Table 1. Policy Summary Statistics

	Mean	St. Dev.	Percentiles				
			1%	10%	50%	90%	99%
Claim rate	1.49%	0.69%	0.31%	0.68%	1.42%	2.36%	3.67%
Expected loss given a claim	20.3%	26.0%	0.4%	1.5%	9%	59%	100%
Premium ($)	641.90	380.43	165.90	273.99	562.36	1,104.30	1,930.06
Coverage limit ($)	110,700	63,867	10,700	35,000	100,000	210,000	250,000
Replacement Cost ($)	107,177	57,779	13,300	41,000	96,300	195,000	250,000

Note: "Expected loss given a claim" is described as a percent of the insured property's value and reports the median expected loss for each percentile across policyholders. Replacement cost provides the amount needed to rebuild the current structure using similar materials. We derive these claim rate and loss estimates from our flood models described in Section 2.2.3. Core sample of 103,084 households.

Policyholders choose among six deductible options between $500 and $5,000. Table 2 provides households' deductible selections and is consistent with previous studies finding that the majority of households prefer low deductibles, are willing to pay for protection against small stakes risks (e.g., Cutler and Zeckhauser, 2004; Sydnor, 2010). Ninety-four percent of households selected one of the two lowest deductible choices available.

Figure 1 shows the coverage limits selected as a percent of the home's replacement cost across all households and the effective coverage that this provides. That households select a coverage limit that is more than the replacement cost is perhaps surprising as they cannot receive a payment greater than this amount. Households whose property values are higher than their replacement cost are almost twice as likely to over-insure.[16] These households may approach the insurance decision with an estimate of their property value, receive from their insurance agent a lower replacement cost, and buy a coverage limit above the replacement cost to make certain that their coverage is sufficient. Consequently, we treat

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[16] Forty three percent of households who did not over-insure have a property value that is greater than the replacement cost while 72 percent of over-insurers do. Replacement costs can deviate from property values as the costs of building materials change over time.

individuals that insure at or above the replacement cost of their home as intending to fully insure. In Appendix 1, we exclude households that over-insure and retest our models, finding that excluding these households does not alter our main findings.

Table 2. Policyholder Deductible Selection

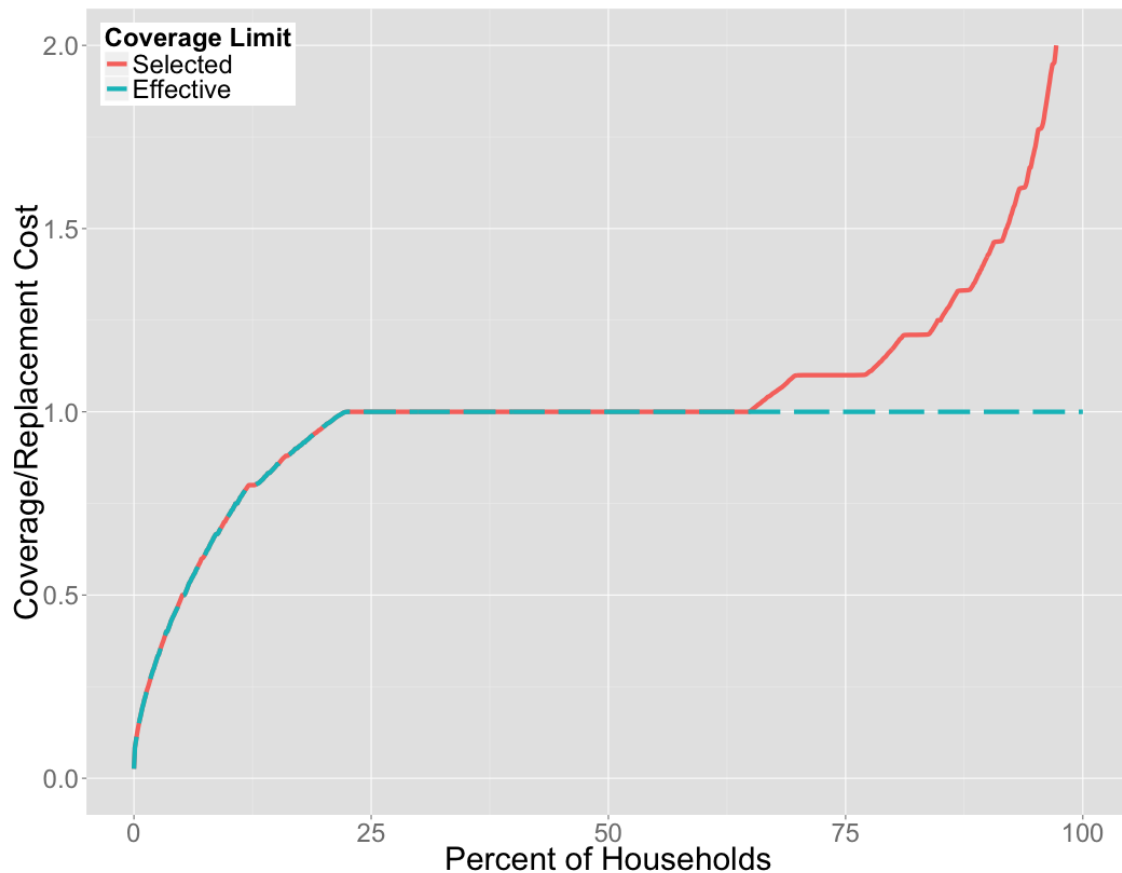| Deductible	Percent of Policyholders
$500	46.6
$1,000	47.4
$2,000	1.4
$3,000	0.5
$4,000	0.2
$5,000	3.8

Note: Core sample of 103,084 households.

Figure 1. Household Coverage Limit Selections

Note: The figure provides household coverage limit selections as a proportion of the replacement costs of their homes. The red line shows the coverage limit selected. The green line shows the maximum the contract would pay, which is the minimum between the coverage limit and replacement cost. Core sample of 103,084 households.

3   Results

This section describes our finding that households' preferences are inconsistent across low and high stakes. We begin with our core model that uses the power value function (Equation 2). Then, we assess expected utility models CRRA and CARA and a model of reference dependent preferences, showing similar behavior across all models. Appendix 2 shows functional forms for the value functions that we test. Table 3 provides an overview of the results to which we refer throughout this section.

3.1   Core Results

We find that households' deductible and coverage limit decisions result in significantly different parameter values for the power value function (Equation 2). Part A of Table 3 shows the model estimates. Parameter θ measures the curvature of households' value functions. Both deductible and coverage limit decisions are characterized by diminishing sensitivity to losses as losses increase ($\theta < 1$). That is, households perceive the difference between a $1,000 loss and $2,000 loss as greater than that between a $2,000 and $3,000 loss. Households' deductible decisions imply much greater diminishing sensitivity with an estimated parameter value of $\theta_d = 0.036$, compared to that from the coverage limit of $\theta_c = 0.413$. Using our bootstrapped variance-covariance matrix, we find that estimates of θ from the deductible and coverage limit decisions are significantly different ($t = -18.72, p < 0.01$) and so reject the null hypothesis that households' preferences are consistent across these low and high stakes decisions.

To illustrate the magnitude of this difference, we consider what change in loss when the stakes are high would make the household indifferent with incurring a $1,000 change in loss when the stakes are low

$$v(\$2,000) - v(\$1,000) = v(x) - v(\$101,000)$$

Preferences derived from coverage limit decisions indicate that $x = \$113,475$; households perceive a \$1,000 difference when the stakes are low as equivalent to a \$12,475 change in loss when the stakes are high. Preferences from the deductible decisions indicate $x = \$181,867$. In this case, households perceive a low stakes change of \$1,000 as equivalent to an \$80,867 change in loss when the stakes are high – over six times the amount found with preferences derived from coverage limit decisions.

Results also show that households overweight small probabilities. Distortions are approximately linear in the range of probabilities that we examine [17]; households' cumulative flood loss probability distribution Π follows $\Omega = \beta_0 + \beta_1 \Pi$.[18] Households overweight all probabilities that we observe by at least eight percentage points when households select a deductible ($\beta_0 = 0.081$). Parameter β_1 shows how transformed probabilities change as objective probabilities change. For example, in selecting a coverage limit households overweight these changes by a factor of four ($\beta_1 = 4.27$).

Households overweight probabilities of a flood when choosing a deductible at roughly twice the level they do when selecting a coverage limit ($t_{\beta_0} = 8.69, p < 0.01; t_{\beta_1} = 7.46, p < 0.01$). For example, we estimate that when making coverage limit decisions, households overweight the median annual claim rate of 1.4 percent by a factor of 8, acting as if it occurs with an 11 percent annual probability.[19] When making deductible decisions, they act as if the median annual claim rate occurs with a 22 percent annual probability. Figure 2 illustrates these probability distortions. The horizontal axis shows objective probabilities; the vertical axis shows distorted probabilities. On the far left, household

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[17] Cumulative flood probabilities across households range from a minimum probability of $2.2e^{-06}$ to a maximum of 0.081.

[18] We examined higher order polynomial expansions of the probability distortions; however, model selection based on the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) motivates using a linear structure for coverage limit selections and a quadratic for deductible selections. The contributions of the quadratic term are small and so for ease of comparisons we use the linear model in Table 3. We provide an example that shows the effects of higher order polynomials on parameter estimates in Section 3.2 (see Table 4).

[19] For example, for the coverage limit and the median claim rate, $\Omega = \beta_0 + \beta_1 \Pi = 0.052 + 4.75 \times 0.0142 = 0.1195$. The ratio of the transformed probability to the objective probability is $\Omega/\Pi = 0.1195/0.0142 = 8.412$.

distortions begin at the median likelihood of a full loss of the home from flood, which occurs with an annual probability of 0.07 percent. On the far right, we show distortions up to the median likelihood of any flood event, which is 1.4 percent.

We use an approximation of the test that we employ to compare parameter estimates across deductible and coverage limit decisions as we extend our analyses to other value functions. In our bootstrap, the Pearson correlation between parameter estimates of θ_d and θ_c is not statistically different than zero $(r = 0.02, p = 0.75)$. If we treat these estimates as uncorrelated, i.e., set $s^2_{\theta_{c.d}} = 0$ in Equation 5, the effect on t is small and results in a more conservative statistic, $t = -18.65$ (compared to $t = -18.72$). Thus, we use

$$z_a = \frac{\theta_d - \theta_c}{\sqrt{se_d^2 + se_c^2}}$$

which relies on standard errors se_d and se_c derived from a numerical estimate of the Fisher information matrix using our full sample.[20]

Appendix 1 discusses robustness tests and sensitivity analyses of our results, examining (1) whether household coverage limit selections are influenced by certain flood insurance program requirements, which might interfere with deriving household preferences from their insurance contracts; (2) household preferences in an area with higher annual flood probabilities than those of our core sample; (3) our probability distortion estimates derived with Chebyshev polynomials to those in which we fit commonly used probability distortion models (e.g., Tversky and Kahneman, 1992); and (4) our estimates when we exclude households that purchased coverage limits greater than their replacement cost. While we find that our parameter estimates somewhat differ across contexts, they remain consistent

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[20] This test is an approximation because it ignores the potential covariance of the parameter estimates. It allows us to compare more models than would be possible using our computationally expensive bootstrapping approach and is facilitated by the type of large effect sizes we reported in our core results. While we caution against relying on this test for inference when z_a is close to critical values, we tend to find values that are several orders of magnitude larger than critical cutoffs when assessing our parameters of interest.

with the pattern of results presented here and our main finding of preference inconsistency across deductible and coverage limit decisions.

Table 3. Parameter Estimates Derived from Deductible and Coverage Limit Selections

	Value Function Parameter(s)		Probability Distortion Parameters		
Part A: Core Results					
	θ		β_0	β_1	Log-likelihood
Deductible	0.036		0.081	10.07	-138,413
	(0.005)		(0.001)	(0.059)	
Coverage limit	0.413		0.052	4.27	-525,600
	(0.006)		(0.001)	(0.282)	

	Part B: Other Value Functions				
	ρ		β_0	β_1	Log-likelihood
CRRA Utility					
Deductible	-24.04		0.031	7.29	-143,191
	(0.289)		(0.001)	(0.068)	
Coverage limit	-3.65		0.019	3.18	-526,909
	(0.07)		(0.0003)	(0.085)	
CARA Utility	η				
Deductible	-4.61E-04		0.059	11.44	-140,523
	(7.18E-06)		(0.002)	(0.167)	
Coverage limit	-1.90E-05		0.013	2.06	-529,056
	(8.05E-06)		(0.0002)	(0.120)	
Reference Dependent Preferences					
	δ	θ			
Deductible	0.60	0.315	0.075	10.05	-138,300
	(0.002)	(0.002)	(0.0005)	(0.005)	
Coverage limit	0.58	0.454	0.078	7.83	-525,763
	(0.009)	(0.004)	(0.001)	(0.245)	

Note: Table compares MLE of model parameters derived from household deductible and coverage limit decisions across behavioral models. Standard errors in parentheses. For the core results (which use a power function, shown in Equation 2) and the reference dependent preferences model, values

for θ of less than 1 indicate diminishing sensitivity to losses. For the utility theory value functions, negative values for the coefficient of relative risk aversion ρ and the coefficient of absolute risk aversion η also indicate diminishing sensitivity to losses (i.e., risk seeking). Parameters $\boldsymbol{\beta}$ show probability distortions $\Omega = \beta_0 + \beta_1\Pi$ where Π is the cumulative objective probability. For CRRA utility, we assume that a household's wealth is its home's replacement cost plus \$1. The reference dependent preferences model treats insurance premiums and flood outcomes as additively separable and weights flood outcomes by δ (Kőszegi and Rabin, 2006, 2007). Appendix 2 provides functional forms for CRRA, CARA, and the reference dependent preferences that we use. Number of observations: 103,084.
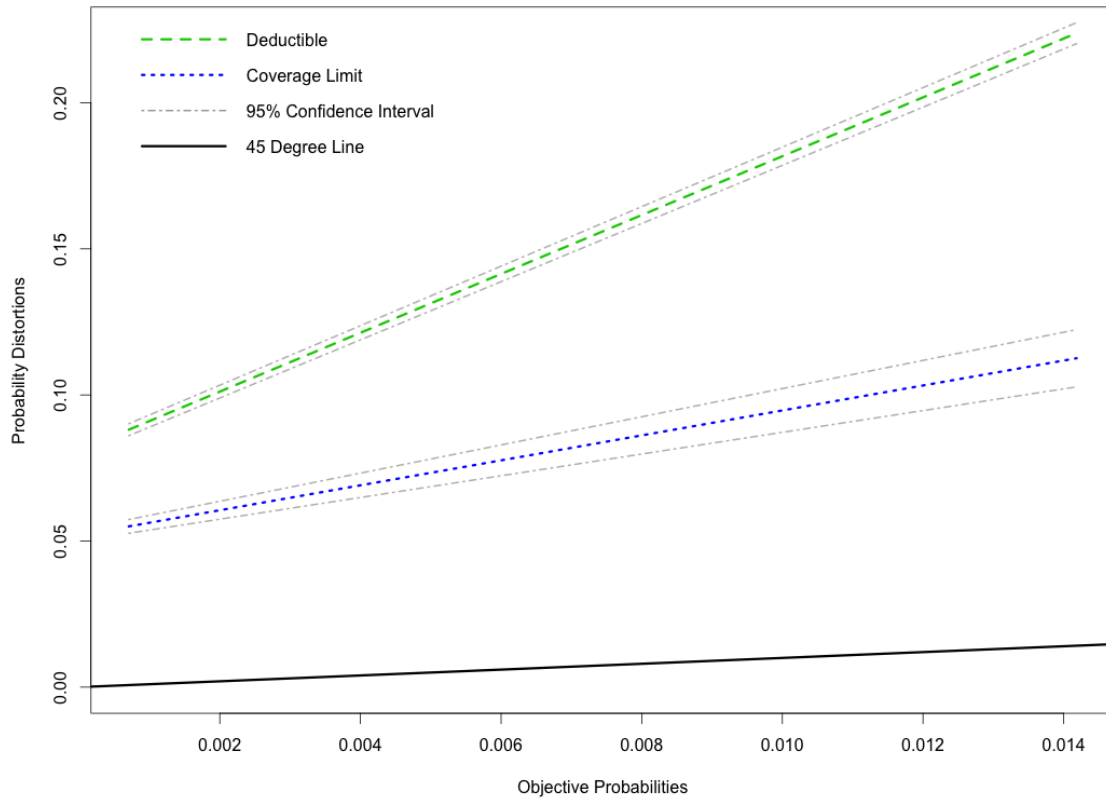

Figure 2 Estimated Probability Distortions

Note: Figure compares households' probability distortions derived from their deductible and coverage limit decisions. The horizontal axis shows objective probabilities; the vertical axis shows distorted probabilities. Lines showing the distortions extend from the median likelihood of a full loss of the home from flood, which occurs with an annual probability of 0.07 percent, up to the median likelihood of any flood event, which is 1.4 percent. The 45 degree line identifies the points at which the transformed probabilities equal the objective probabilities. We model probability distortions using a polynomial expansion with Chebyshev polynomials. The figure shows linear probability distortions $\Omega = \beta_0 + \beta_1\Pi$ where Π is the cumulative objective probability. Model parameters $\boldsymbol{\beta}$ are fit using MLE and the power value function in Equation 2.

3.2   Expected Utility Theory

We estimate utility models assuming first that households do not distort objective probabilities. We assume that household wealth is their home's replacement cost plus \$1 for CRRA utility.[21]

We derive a coefficient of relative risk aversion $\rho = 136$ from household deductible selection. This extremely high level is consistent with the insights of Rabin (2000) and Rabin and Thaler (2001): households' preferences for low deductibles do not conform well to the assumption that the diminishing marginal utility of wealth explains their risk attitudes. Our results are also similar to the unrealistically high levels of risk aversion found by Sydnor (2010) on insurance deductibles. He estimates a lower bound of $\rho = 353$ for households choosing a \$500 deductible (the smallest deductible in our data) using the assumption that wealth equals the value of their home.

Our estimate from coverage limit decisions is much lower, $\rho = 2.07$, and more consistent with estimates found in other domains. For example, Barro and Jin (2011) estimate $\rho = 3$ in their analyses of equity premiums. Chetty (2006) estimates a coefficient of relative risk aversion of about 1 from labor supply, and Gourinchas and Parker (2002) find a similar coefficient based on consumer spending data.

Table 4 shows these results compared to rank dependent utility models (Quiggin, 1982), which allow for probability distortions. Rank dependent utility leads to negative values of ρ, typically described as "risk seeking." Part A provides the results for the deductible, and Part B shows them for the coverage limit. Here, probability distortions $\Omega = \beta_0 + \beta_1 \Pi + \beta_2 \Pi^2 + \beta_3 \Pi^3$ where Π is the objective probability. The table shows distortion models with increasingly higher polynomial expansions. For Row 1, the case in which we assume that households do not distort probabilities, we set $\beta_0, \beta_2, \beta_3 = 0$ and $\beta_1 = 1$ and use MLE to fit ρ. For Row 2, we set $\beta_0, \beta_2, \beta_3 = 0$, and use MLE to fit ρ and β_1, etc.

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[21] Other commonly used assumptions about wealth (e.g., using average lifetime income) do not change our finding of preference inconsistency across deductible and coverage limit decisions.

As we note from the work of Dyer and Sarin (1982) in Section 2.3, the term "risk seeking" is perhaps misleading here as the households we analyze purchased an insurance product that reduces their risk of financial loss by transferring part of their exposure to the flood insurance program, and so we continue to describe the results in terms of diminishing sensitivity to losses. In this context, the behavior of insuring households is explained by their overweighting small probabilities. These probability distortions lead to a greater perceived value of the insurance contract than if it were evaluated using objective probabilities.

Our estimates of ρ for each model are quite stable across higher order polynomial expansions of probability distortions, as shown in Table 4. Most probability distortion models assume that probabilities pass through the origin ($\beta_0 = 0$). We find that this assumption changes our estimates of risk aversion very little relative to the other distortion models (compare Row 2 in Parts A and B to higher number rows), but our model fit is notably improved by allowing for an intercept. The best fitting models, those that minimize the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) values, are shown in bold type.

Part B of Table 3 shows results using the CRRA and CARA values functions from expected utility theory and shows a pattern consistent with our core results. Households demonstrate diminishing sensitivity to losses ($\rho < 0$ and coefficient of absolute risk aversion $\eta < 0$) and overweighting of small probabilities. Each model shows that households demonstrate greater diminishing sensitivity to losses and overweight small probabilities more for deductible than coverage limit decisions. For example, the differences in the coefficients of relative risk aversion for deductible and coverage limit decisions result in $z_{a,\rho} = -68.57, p < 0.01$; for coefficients of absolute risk aversion, $z_{a,\eta} = -40.97; p < 0.01$.

Table 4. Estimates of CRRA Across Probability Distortion Approximations

Part A: Deductible Selection

	ρ	β_0	β_1	β_2	β_3	Log-likelihood	BIC	AIC
(1)	136					-173,414	346,840	346,830
(2)	-23.20		10.40			-143,791	287,605	287,586
(3)	-24.04	0.031	7.29			-143,191	286,417	286,388
(4)	-23.81	0.032	6.65	49.24		-143,184	**286,413**	**286,375**
(5)	-23.81	0.032	6.60	52.68	-1.06	-143,184	286,426	286,378

Part B: Coverage Limit Selection

	ρ	β_0	β_1	β_2	β_3	Log-likelihood	BIC	AIC
(1)	2.07					-544,919	1,089,849	1,089,839
(2)	-3.68		11.00			-537,072	1,074,168	1,074,149
(3)	-3.65	0.019	3.18			-526,909	**1,053,853**	1,053,824
(4)	-3.65	0.020	3.29	-20.98		-526,904	1,053,855	**1,053,817**
(5)	-3.68	0.019	3.33	-20.99	-2.01	-526,904	1,053,867	1,053,819

Note: Table compares MLE of model parameters derived from household deductible and coverage limit decisions using a CRRA utility model where ρ is the coefficient of relative risk aversion. The best fitting models, those that minimize the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) values, are shown in bold type. Parameters **β** show probability distortions $\Omega = \beta_0 + \beta_1\Pi + \beta_2\Pi^2 + \beta_3\Pi^3$ where Π is the objective probability. We assume that a household's wealth is the value of its home plus \$1. Parameters in the table left blank are omitted from the MLE. When β_0, β_2, and β_3 are omitted, they are assumed to equal 0; when β_1 is omitted, it is assumed to equal 1.

3.3 Reference Dependent Preferences: Separating Certain and Uncertain Outcomes

We also test a model of "reference dependent preferences" (Kőszegi and Rabin, 2006, 2007). This model asserts that individuals segregate known and uncertain costs and weight them differently.[22] Barberis (2013) places particular emphasis on this model as an advancement in field research in behavioral economics as it offers a consistent strategy for integrating prospect theory style reference points. Among the utility theory and prospect

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[22] Kőszegi and Rabin (2006) provide the example of shoe shopping in which the consumer expects to pay a certain amount but is surprised by higher prices. The consumer treats the unanticipated additional cost as a loss, weighting it with a loss aversion parameter in the spirit of Kahneman and Tversky (1979).

theory models tested by Sydnor (2010), reference dependent preferences explains homeowners' deductible decisions best.

Following this approach, we segregate premiums p from uncertain flood outcomes y, which are deductible payments and losses in excess of coverage limits, and weight flood outcomes with parameter δ

$$v = -p^\theta - \delta \int y^\theta\, \omega(y)\ dy.$$

Using this model, we also find diminishing sensitivity to losses and overweighting of small probabilities, and that preferences are inconsistent across deductible and coverage limit decisions (see Part B of Table 3). The parameter θ has the same interpretation as in our power function (Equation 2). Compared to our core results, the estimates for θ in this model ($\theta = 0.315$ for deductible choices and $\theta = 0.454$ for coverage limits) are notably closer across low and high stakes decisions, though they are still significantly different ($z_a = -31.1, p < 0.01$).

Both coverage limit and deductible decisions imply $\delta < 1$, that households discount uncertain flood losses relative to paying premiums. While Kőszegi and Rabin (2006, 2007) develop their research in settings where δ assesses aversion to unexpected losses, in our context it may also account for other preferences such as inter-temporal ones since premiums are paid before coverage for flooding begins.[23,24]

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[23] This observation brings up the point that our data are not well equipped to test certain behavioral phenomenon that prospect theory intends to explain; it is therefore perhaps not surprising that our parameters differ from those derived in other settings. For example, Tversky and Kahneman (1992) find diminishing sensitivity to losses, $\theta = 0.88$, in their lab research.

[24] The reference dependent preferences model was in part introduced because prospect theory struggles to explain certain behaviors (e.g., buying insurance) and so we compare it to our core results (Part A of Table 3), which can be understood as the prospect theory value function under the assumptions that (1) a household uses its wealth before purchasing insurance as its reference point and (2) the coefficient of loss aversion is normalized to 1. We conduct a Vuong (1989) test for non-nested models and find that the reference dependent preferences model provides a better fit of deductible decisions at the 1 percent significance level: separating certain and uncertain outcomes helps explain preferences when comparing premiums to small-value deductibles. For coverage limit decisions, the reference dependent preferences estimates of θ are much closer

4   Inconsistent Preferences: Implications and Explanations

For all of the tested models and value functions, we find that not only do households demonstrate inconsistent preferences across low and high stakes for a given type of risk, but that these preferences cannot be universally convex in losses. Because low stakes preferences demonstrate a greater diminishing sensitivity to losses than high stakes preferences, any line connecting the two must be at some point concave. Figure 3 illustrates this point for the median value property (which is $96,300) using the reference dependent preferences model. We use the reference dependent preferences model because its parameter estimates for deductible and coverage limit decisions appear closest among the value functions we test. The solid green line provides the shape of the value function derived from the deductible decision in the range of potential losses related to the deductible (losses up to $5,000). Similarly, the solid blue line provides the shape of the value function derived from the coverage limit decision in the range of potential losses related to selecting a low coverage limit (set at losses greater than 20 percent of the property value for this example). The dotted lines help illustrate the magnitude of this difference. They show how these preferences would extend toward more severe losses for the deductible and less severe ones for the coverage limit.

These differences in preferences are substantial and motivate caution with respect to extrapolating households' preferences from their decisions when the range of outcomes is narrow. For example, we take the MLE parameters for risk preferences and probability distortions derived from household deductible decisions with the reference dependent preferences model and use them to predict what coverage limits households would select. We allow for any coverage limit value between $0 (i.e., the outside option) and $250,000 in $1,000 increments. That is, we consider the possibility that household preferences follow the dotted green line in Figure 3. We find that these low stakes preferences lead to a

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to the traditional prospect theory value function ($\theta = 0.45$ versus 0.41). The traditional function provides a better fit than the reference dependent preferences model when the stakes are high.

prediction that 99.9 percent of households would select a coverage limit of zero: effectively no one in our data would insure.[25]
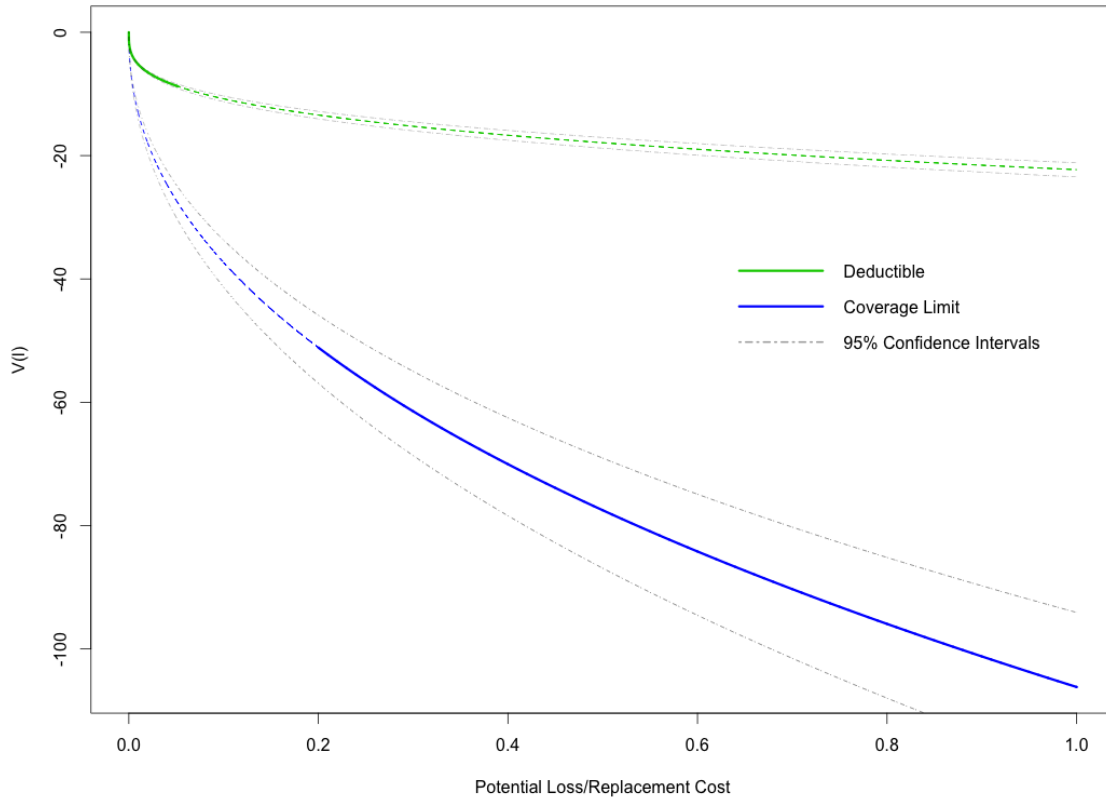

Figure 3 *Risk Preferences from Deductible and Coverage Limit Selections*

Note: Figure shows the reference dependent preferences model with the MLE of model parameters fitted to deductible and coverage limit selections. The solid green line provides the shape of the value function derived from the deductible selection in the range of potential losses related to the deductible (losses up to $5,000). Similarly, the solid blue line provides the shape of the value function derived from the coverage limit selection in the range of potential losses related to selecting a low coverage limit (set at losses greater than 20 percent of the property value for this example). The dotted lines show how these preferences would extend toward more severe losses for the deductible and less severe ones for the coverage limit.

Several compelling explanations to Rabin (2000) and Rabin and Thaler (2001) have emerged regarding why households' preferences differ so substantially across low and high

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[25] Using CRRA, 75 percent would not insure; using CARA 78 percent would not insure; and using our main model with the power function, no one would insure.

stakes. We consider two for which our present study can provide some empirical evidence: Are households' preferences due to consumption commitments (Chetty and Szeidl, 2007)? And do households' preferences follow more mathematically complex value functions such as expo-power utility (Holt and Laury, 2002)?

4.1 Consumption Commitments

Households' preferences may be due to budget or liquidity constraints. For example, Chetty and Szeidl's (2007) theory of consumption commitments posits that households' budgets comprise fixed liabilities (e.g., rent or a mortgage for housing) and discretionary consumption (e.g., food, entertainment) and the two categories are treated as additively separable sources of utility. They find that fixed liabilities account for over 50 percent of the average household's budget. Large shocks lead to adjustments in fixed liabilities; however, such adjustments can be costly so small shocks are fully born by discretionary consumption. These conditions lead to a kinked value function in which households demonstrate higher levels of risk aversion when the stakes are small than when they are large.

We exploit variation in property values in our data to assess for empirical evidence that households' preferences for low deductibles are explained by consumption commitments. While Chetty and Szeidl's (2007) describe consumption commitments as a percent of income, all households in our data face the same deductible menu. As a household's income grows, the utility loss of paying an insurance deductible (of say $500) would be expected to decrease because it represents a smaller proportion of the household's discretionary consumption. This argument predicts that (risk averse) households with higher incomes would select higher deductibles in this program. Using property value as a proxy for income, we find no consistent relationship between households' deductible choices and their property values (shown in Figure 4). Households with high and low property values prefer low deductibles – 94 percent of households choose either the $500 or $1,000 deductible.[26] We conclude that such commitments may influence households'

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[26] We also estimate an ordinal logit model using the deductible choice and property value (in $10,000) for household i: $Deductible_i = \alpha_j + \beta\, PropertyValue_i + \varepsilon_i$ where α_j are $County \times Year$ fixed effects. We find a statistically significant negative (but perhaps not economically meaningful) relationship between

decisions in our data, but our results do not seem to be explained by consumption commitments.
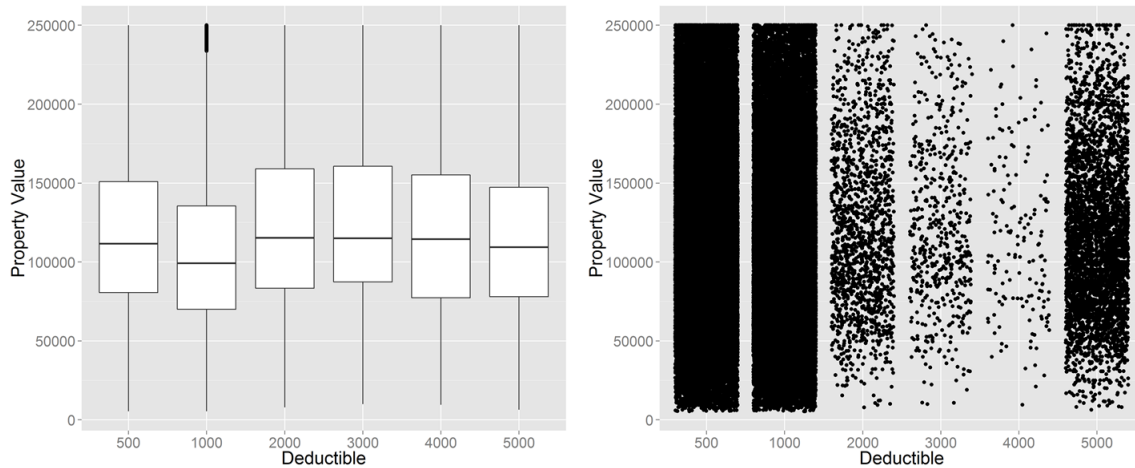

Figure 4 Boxplot and Jitter Plot of Households' Deductible Choices and Property Values

Note: The left figure provides a boxplot of household deductible choices and property values. The solid line in the center of each box shows the median property value, the upper and lower edges of the box provide 25th and 75th percentiles, and the solid lines extend to 1.5 times the interquartile range, the distance between the 25th and 75th percentiles. Dots outside of these lines identify individual outliers. The right figure shows individual observations of deductible choices and property values.

4.2   Expo-Power Utility

Holt and Laury (2002) suggest that households' seemingly inconsistent preferences across low and high stakes might be explained by a value function that accounts for both absolute and relative risk aversion. They examine risk aversion in the lab using payoffs ranging from several dollars to several hundred dollars. They use an "expo-power" utility function (Saha, 1993), which can accommodate a variety of combinations of relative and absolute risk aversion. Participants in their study exhibit a combination of increasing relative risk aversion, which helps explain decisions related to low stakes payoffs, and decreasing absolute risk aversion, which helps explain decisions related to larger lab payoffs.

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property values and deductible choices, an odds ratio of $\beta = 0.986$ ($s.e. = 0.0013$, $z = -10.22$, $p < 0.01$). A \$10,000 increase in property value increases the log odds of selecting a lower deductible by 0.014.

We test Saha's (1993) expo-power utility

$$u(w) = -\exp\left(-\tau w^{\psi}\right) \qquad (6)$$

with parameter restrictions $\tau, \psi \neq 0$ and $\tau\psi > 0$. This model requires an assumption that economic agents are risk averse and that certain combinations of absolute and relative risk aversion are infeasible (e.g., a household cannot demonstrate both constant absolute risk aversion and constant relative risk aversion, Saha, 1993). Parameter $\tau = 1$ describes constant absolute risk aversion, $\tau < 1$ decreasing absolute risk aversion, and $\tau > 1$ increasing relative risk aversion. Parameter $\psi < 0$ indicates decreasing relative risk aversion and $\psi > 0$ increasing relative risk aversion.

We estimate this model without allowing for probability distortions. The only models for which households demonstrate positive CARA and CRRA coefficients in our data are those in which we assume that households make decisions based on objective probabilities. Neither Saha (1993) nor Holt and Laury (2002) allow for probability distortions in their analyses.

This more complex value function does not explain the preference inconsistency we find in our data, either. Similar to Holt and Laury (2002), we find that households demonstrate increasing relative risk aversion and decreasing absolute risk aversion for both deductible and coverage limit decisions (see Table 5); however, while they find that this model leads to consistent preferences across low and high stakes in the lab, we conclude that households' preferences are inconsistent based on the large difference in the parameter related to relative risk aversion ψ, resulting in $z_{a,\psi} = 268.9, p < 0.01$. Households' deductible and coverage limit selections lead to a difference in the parameter capturing absolute risk aversion τ of $z_{a,\tau} = 2.26, p = 0.02$.[27]

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[27] Given the limitations of our test statistic (described in Section 2.3), this value of $z_{a,\tau}$ is sufficiently close to the critical value of 1.96 that we would want to conduct additional analyses before making definitive conclusions about whether τ differs for deductible and coverage limit decisions. The large differences in ψ are sufficient to reject the null hypothesis that households' preferences are consistent under expo-power utility and so we do not pursue these additional tests.

Table 5 Parameters Estimates for Expo-Power Utility Function

	τ	ψ	Log-likelihood
Deductible	1.30E-05	1.32	-166,520
	(2.33E-06)	(0.0005)	
Coverage limit	7.74E-06	1.11	-540,780
	(7.10E-09)	(0.0006)	

Note: Table compares MLE of model parameters derived from household deductible and coverage limit decisions for expo-power utility. Standard errors in parentheses. Saha (1993) proposes an expo-power utility function that allows for a combination of absolute and relative risk aversion, shown in Equation 6. Number of observations: 103,084.

5 Conclusion

We estimate households' risk preferences based on their flood insurance contract selections. Deductible selections provide an indication of households' preferences regarding small stakes losses; coverage limit selections indicate preferences regarding large stakes losses. We find that both value functions and probability distortions help explain households' decisions under risk. Their behavior follows two of the tenants of prospect theory: households demonstrate diminishing sensitivity to losses and overweight small probabilities. However, for all value functions and probability distortion functions that we test, including those from cumulative prospect theory, households' preferences are inconsistent across their deductible and coverage limit decisions. Households' deductible selections demonstrate much greater diminishing sensitivity to losses and overweighting of small probabilities when compared to their coverage limit choices. These findings suggest that estimates of household preferences are a function of the range of outcomes in which they are measured and so motivate caution when extrapolating from research findings on low stakes to high stakes outcomes, or vice versa.

Our results follow both previous findings that households exhibit a strong desire to protect against small stakes risks (Cutler and Zeckhauser, 2004; Kunreuther, Pauly and McMorrow, 2013; Sydnor, 2010) and findings that households' attitudes toward large stakes risks result in single digit coefficients of relative risk aversion in the expected utility of wealth model (Weber, 1970; Friend and Blume, 1975; Szpiro, 1986; Chetty, 2006;

Gourinchas and Parker, 2006; Barro and Jin, 2011). Our context stands out as one that facilitates making low and high stakes choices in concert as they are part of a single contract covering a continuum of losses, yet households seem to treat them as separable decisions toward which they have differing attitudes.

The causes of these preference inconsistencies require clarification through additional research. Households' value functions and probability distortion parameters may be context-specific. Alternatively, other salient factors may differ when households make low and high stakes decisions with decision rules that are not considered in the models that we test. For example, a substantial literature describes the methods by which individuals simplify complex problems such as elimination by aspects (Tversky, 1972), lexicographical models (Fishburn, 1974), and conjunctive screening rules (Payne, 1976) that may be relevant here. In this spirit, Rabin and Thaler (2001) attribute households' decisions, at least in part, to choice bracketing (Read, Loewenstein, and Rabin, 1999) in which households treat decisions in isolation rather than jointly, often overlooking tradeoffs between decisions. Coverage limit and deductible selections represent a tradeoff in premium dollars. About one fifth of the households in our data select a low deductible and partially insure their homes.[28] For the same premium, they could increase both their deductible and their coverage limit, reducing their financial exposure to the most severe events. Whether public policies would be effective that make this tradeoff more explicit during the contract selection process depends on the on the cause of these inconsistencies.

Similarly, the causes of households' probability distortions determine the effectiveness of policies to reduce these distortions such as increasing information on the likelihood of certain types of floods. We are unable to differentiate between distortions caused by *overweighting* versus those from *misperceiving* of small probabilities. Previous research suggests that individuals both overweight and overestimate small probabilities. Individuals

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[28] About one-fourth of households in our data only partially insure their homes but continue to choose low deductibles: 91 percent select either the $500 or $1,000 deductible (compared to 94 percent for the entire sample).

who are given objective probabilities tend to overweight outcomes with small probabilities when making decisions (e.g., Tversky and Kahneman, 1992). Also, recent evidence from surveys of New York City households who are vulnerable to flood shows that households misperceive small probabilities, overestimating the likelihood of a flood event but underestimating the expected damage caused by flood (Botzen, Kunreuther, and Michel-Kerjan, 2015).

Finally, we highlight two limitations of our analyses. First, showing inconsistency requires assuming some household value function and so we cannot rule out the possibility that households may maximize some unconsidered function. We have instead shown inconsistency focusing on the most frequently used value functions. Second, while a notable portion of U.S. households participates in the flood insurance program (which insures more than 5 million policies a year), our sample consists of households residing in areas vulnerable to flood who insure against this hazard. Understanding individuals' risk attitudes when confronted with low-probability, high-consequence events is a relevant area for research but the extent to which the findings from this study generalize to the many decisions households make regarding a variety of risks they face needs to be validated empirically. These points motivate additional research in other contexts regarding the consistency of household preferences across small and large stakes.

6 Appendices

6.1 Appendix 1: Testing modeling assumptions and sensitivity

Recent papers that use insurance data to assess risk preferences such as Sydnor (2010) and Barseghyan et al. (2011, 2013) consider several alternative explanations for their results. For example, Barseghyan et al. (2013) first test a structural model similar to ours and as a robustness test use Markov Chain Monte Carlo simulation, which allows them to assess heterogeneity in preferences across households. They find that both approaches lead to similar conclusions. Sydnor discusses a variety of alternatives to the assumption that insurance contract decisions are guided by households' risk preferences including borrowing constraints, the influence of sales agents, and menu effects. He provides a

rationale or evidence that each alternative does not negate the ability to assess preferences through insurance contract choices.

In this section, we focus on assessing the sensitivity of our results to aspects of our data that have not been discussed in previous literature. First, we consider whether household coverage limit selections are influenced by certain flood insurance program requirements, which might interfere with deriving household preferences from their insurance contracts. Second, we examine household preference consistency in a FEMA-defined flood zone with higher annual flood probabilities than those for our core sample. Third, we compare our probability distortion estimates derived with Chebyshev polynomials to those in which we fit commonly used probability distortion models (e.g., Tversky and Kahneman, 1992). Fourth, we exclude households that purchased coverage limits greater than replacement cost and re-estimate our core results.

6.1.1 Coverage Limit Selection

Households are required to insure against flood if they have a federally backed mortgage and live in a zone in which FEMA estimates of annual flood risk probabilities exceed one percent. While this mortgage requirement is not consistently enforced (Dixon et al., 2006), contracts would not reflect household preferences if, say, lenders determined coverage limits (e.g., required that households fully insure their homes).

We compare coverage limit selections for our core sample, which are subject to the federal requirement to insure, with households that participate in the program but live in a zone not subject to the federal requirement. Figure 5 compares the distribution of coverage limits for our core sample (labeled "Federal Requirement") and the less vulnerable group (labeled "No Requirement"). Their coverage limit selections are remarkably similar, and so would seem to support the assumption that contract coverage limits reflect household preferences.
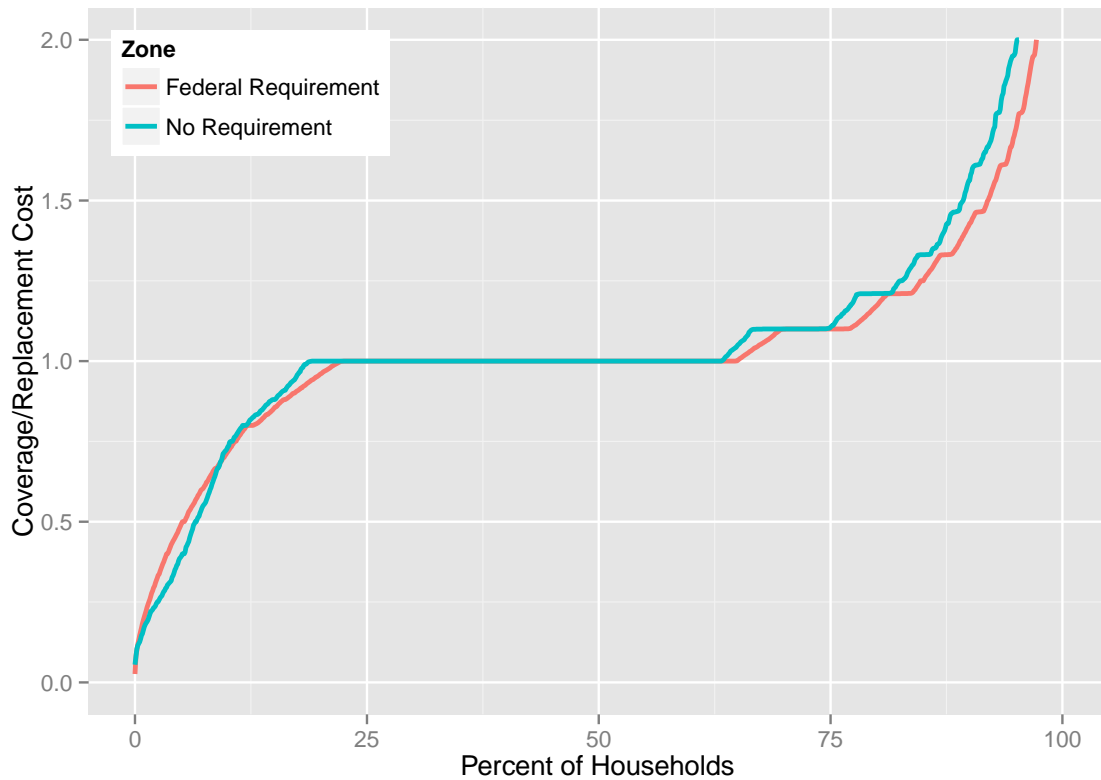
Figure 5 Coverage Limits Selected in Zones Where Insurance is Required vs. Voluntary

Note: The figure compares coverage limit selections for households that live in a zone in which the federal government requires that households with federally backed mortgages insure with a zone in which households are not required to insure.

6.1.2   Assessing Preferences in a Higher Risk Area

We also test our main results in an area with a higher probability of flooding. Since a great deal of research regarding decision making under risk, especially lab research, considers events with likelihoods greater than the average annual claim rate of 1.4 percent in our data, we want to guard against the possibility that our results are a byproduct of examining relatively rare events.

Our data also include a population that is vulnerable to inundation as well as wave damage (dwellings located in FEMA-defined V zones) and their average annual claim rate is 4.7 percent, over three times higher than that of our core sample. This claim rate is similar to

Sydnor (2010) and Barseghyan et al. (2011) who test homeowners insurance purchase decisions.

We find that households in the higher risk zone also demonstrate inconsistent preferences (shown in Table 6, Part A). Using the power function, deductible decisions reveal much greater diminishing sensitivity than those derived from the coverage limit, $\theta = 3.8\text{E-07}$ and $\theta = 0.30$ ($z_a = -32.89, p < 0.01$). Both estimates are smaller compared to households' decision in the lower-risk zone, indicating greater diminishing sensitivity to losses.

While households in this sample also overestimate small probabilities, we observe a different pattern in probability distortions compared to our main results. Compared to our main sample, these models show a larger intercept β_0 and a smaller scalar β_1, which indicate that households more greatly overweight all probabilities in this range of outcomes but are less sensitive to changes in the objective probabilities. For example, for our main sample, the model of household deductible decisions using the power value function yields estimates $\beta_0 = 0.08$ and $\beta_1 = 10.07$ whereas in this sample they are 0.144 and 3.51. Taken together, this pattern is suggestive of the S-shaped probability distortions frequently found in laboratory settings (e.g., Gonzalez and Wu, 1999): at smaller probabilities, we find a steep slope that flattens as probabilities grow. Part B of Table 6 provides the results for the other value functions that we discuss in Section 3 and leads to similar conclusions as the discussed results from Part A.

Table 6. Parameter Estimates Across Models for High Risk Zone

	Value Function Parameter(s)		Probability Distortion Parameters		
Part A: Core Results					
	θ	β_0	β_1	Log-likelihood	
Deductible	5.18E-07	0.145	3.49	-7,982	
	(4.74E-08)	(0.0043)	(0.092)		
Coverage limit	0.296	0.178	2.51	-26,986	
	(0.009)	(0.0045)	(0.349)		

Part B: Other Value Functions					
	ρ	β_0	β_1	Log-likelihood	
CRRA Utility					
Deductible	-23.37	0.102	3.44	-8,149	
	(1.36)	(0.005)	(0.121)		
Coverage limit	-4.12	0.099	2.53	-27,139	
	(0.178)	(0.0036)	(0.227)		
CARA Utility	η				
Deductible	-4.4E-04	0.221	3.76	-8,032	
	(9.47E-06)	(1.54E-05)	(2.63E-04)		
Coverage limit	-1.6E-05	0.059	0.99	-27,276	
	(5.09E-07)	(0.0014)	(0.174)		
Reference Dependent Preferences					
	δ	θ			
Deductible	0.54	0.34	0.151	3.28	-7,933
	(0.007)	(0.011)	(0.003)	(0.0713)	
Coverage limit	0.79	0.41	0.178	2.05	-27,016
	(0.025)	(0.011)	(0.006)	(0.570)	

Note: Table compares MLE of model parameters derived from deductible and coverage limit decisions across value functions for households vulnerable to both inundation and wave damage (the V zone). For core results (which use a power function, shown in Equation 2) and the reference dependent preferences model, values for θ of less than 1 indicate diminishing sensitivity to losses. For the utility theory value functions, negative values for the coefficient of relative risk aversion ρ and the coefficient of absolute risk aversion η also indicate diminishing sensitivity to losses (i.e., risk seeking). Parameters **β** show probability distortions $\Omega = \beta_0 + \beta_1 \Pi$ where π is the objective probability. For CRRA utility, we assume that a household's wealth is the home's replacement cost plus \$1. The reference dependent preferences model treats insurance premiums and flood outcomes as additively separable and weights flood outcomes by δ (Kőszegi and Rabin, 2006,

2007). Section 2.2 provides specific functional forms for the power function. Appendix 2 provides functional forms for CRRA, CARA, and the reference dependent preferences model that we use. Number of observations: 5,397.

6.1.3 Comparisons to Commonly Used Probability Distortion Models

We also test our probability distortion estimates by comparing them to probability distortion models proposed by Tversky and Kahneman (1992), Prelec (1998), and Gonzalez and Wu (1999). We use MLE to fit our power function and these probability distortion models. Appendix 2 provides functional forms for each model. Each model assumes an intercept at the origin and so it is unclear how closely they will align with our results since we consistently find a positive intercept ($\beta_0 > 0$ in Table 3) in the range of outcomes that we observe.

Figure 6 compares the estimated distortions for these models. Probability distortions estimated from coverage limit decisions are shown using solid lines; distortions related to deductible selections are shown in dotted lines. The lines designated "Polynomial" use our estimates from the Chebyshev polynomials (a quadratic model for deductible decisions; and a linear model for coverage limit decisions).

Regarding deductible selection, the MLE parameters for the Prelec and Gonzalez-Wu models closely align with the probability distortions we estimate using the Chebyshev polynomials. For objective probabilities in the range of 0.003 to 0.01, these lines are particularly close. Differences in the distortions that these models estimate are about 0.01 in magnitude. For coverage limits, these models are also similar to our polynomial estimates in the tail of the distribution (the far left in the figure), but diverge somewhat as probabilities increase. This left tail signifies the largest losses, which are most relevant for coverage limit decisions. Tversky-Kahneman probability distortions do not tend to fit the deductible or coverage limit decisions as well as the other distortion models tested. For example, for deductible selection, the Tversky-Kahneman distortions are about half as large as those of the other models for objective probabilities around 0.01. This poorer fit is likely due to degrees of freedom: The Tversky-Kahneman probability distortion model includes a single parameter while Prelec and Gonzalez-Wu models include two parameters.
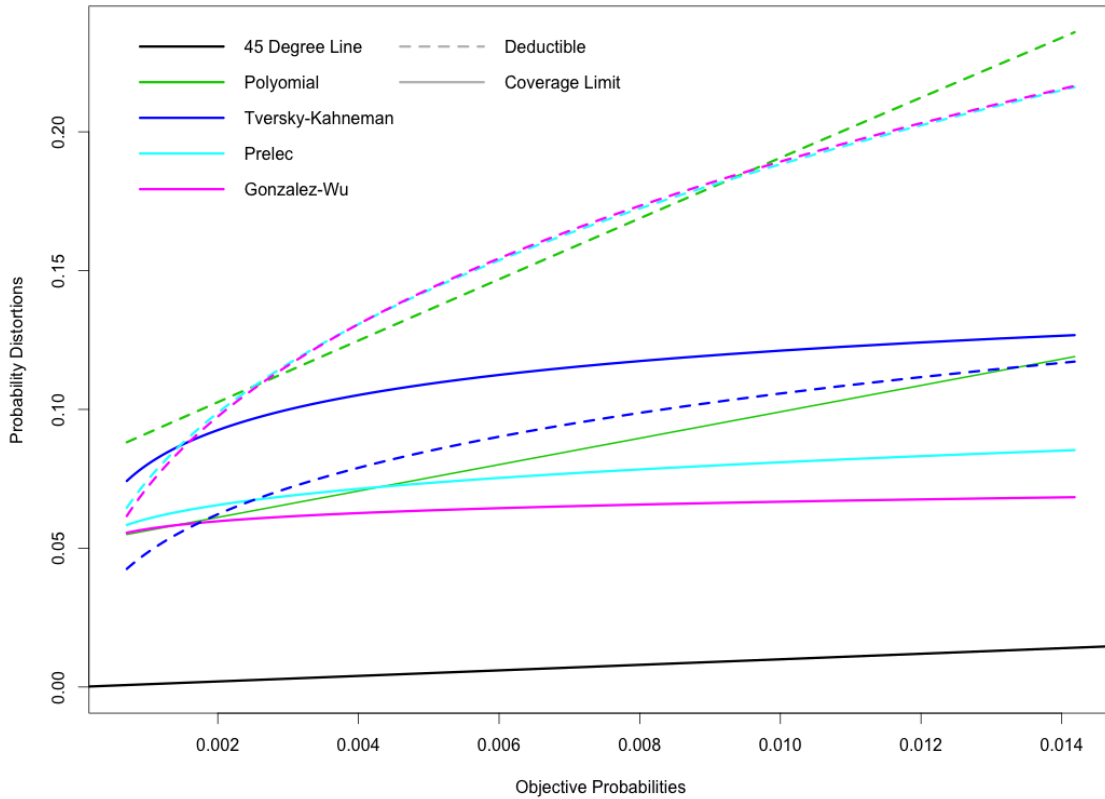
Figure 6 Comparisons of Probability Distortion Models

Note: Figure compares several probability distortion models for household deductible and coverage limit decisions. Model parameters are fit using MLE and the power value function in Equation 2. The lines marked "Polynomial" estimate probability distortions using Chebyshev polynomials. The others use probability distortion models proposed by Tversky and Kahneman (1992), Prelec (1998), and Gonzalez and Wu (1999).

6.1.4   Assessing Preferences of Households Who Do Not Over-Insure

We also test the possibility that our finding of inconsistency is due to the behavior of households who purchase a coverage limit greater than their home's replacement cost. We believe that these households intended to cover their home's replacement cost and purchased higher coverage limit in case their replacement cost estimate was too low.

Perhaps instead they misunderstood the contract and if so, it would not be valid to derive these households' risk preferences from the purchase.

We exclude these over-insurers and re-estimate our core results, shown in Table 7. Our findings are unchanged: in both decisions households demonstrate diminishing sensitivity to losses and overweight small probabilities; their deductible decisions indicate greater diminishing sensitivity to losses and overweighting of small probabilities than those from the coverage limit $\left(z_{a,\theta} = -59.01, p < 0.01; z_{a,\beta_0} = 31.82; p < 0.01; z_{a,\beta_1} = 65.19, p < 0.01\right)$. Excluding over-insurers has very little effect on our parameter estimates for the deductible decision (e.g., $\theta = 0.041$ here versus $\theta = 0.036$ for the full sample).

Differences are greater for our parameter estimates derived from the coverage limit, as might be expected since we are excluding a set of households based on their coverage limits. In these data, households demonstrate less diminishing sensitivity to losses (e.g., $\theta = 0.585$ here versus $\theta = 0.413$ for the full sample). Returning to our example of change in a high stakes loss makes the household indifferent with incurring a $1,000 change in loss when the stakes are low

$$v(\$2,000) - v(\$1,000) = v(x) - v(\$101,000),$$

here, we find $x = \$106,782$ (compared to $\$113,475$ for the full sample).

Our estimates of probability distortions derived from the coverage limit decision using these data also differ from those using the full sample. Our distortion model of households' cumulative flood loss probability distribution Π follows $\Omega = \beta_0 + \beta_1 \Pi$. In the full sample we find that households overweight these changes in objective probabilities by a factor of four ($\beta_1 = 4.27$); however, in this subsample our estimates suggest that households are less sensitive to these change: transformed probabilities change at the same rate as objective ones ($\beta_1 = 0.978$ which is not statistically different from 1). The positive intercept of $\beta_0 = 0.031$ in this sample results in households overweighting the small probabilities studied here. These probability distortions applied to the median annual claim rate of 1.4 percent indicate a transformed probability of 4.47 percent, over three times the actual rate.

Table 7 Parameter Estimates for Households Who Do Not Over-Insure

	Value Function Parameter(s)	Probability Distortion Parameters		
	θ	β_0	β_1	Log-likelihood
Deductible	0.041	0.076	10.63	-90,707
	(0.006)	(0.001)	(0.063)	
Coverage limit	0.585	0.031	0.98	-342,242
	(0.007)	(0.001)	(0.134)	

Note: Table compares MLE of model parameters derived from household deductible and coverage limit decisions across behavioral models. Standard errors in parentheses. The value function is a power function shown in Equation 2. Parameters **β** show probability distortions $\Omega = \beta_0 + \beta_1 \Pi$ where Π is the cumulative objective probability. Number of observations: 66,732.

6.2 Appendix 2: Value Functions and Probability Distortion Models

This appendix provides the functional forms for the value functions and probability distortion models used in the analyses.

6.2.1 Value Functions

Constant Relative Risk Aversion. CRRA utility takes the form

$$u(w) = \begin{cases} \dfrac{1}{1-\rho} w^{1-\rho} & \rho \neq 1 \\ \ln(w) & \rho = 1 \end{cases}$$
$$s.t., w > 0$$

where ρ is the Arrow-Pratt coefficient of relative risk aversion. This model subtracts losses, insurance premiums, etc., from wealth for insurance problems (Mas-Colell et al., 1995). Individuals are said to be "risk averse" if $\rho > 0$ and "risk seeking" if $\rho < 0$.

Here, we show that risk aversion is synonymous with an increasing sensitivity to losses and risk seeking with a diminishing sensitivity to losses. Let the value w represent some

initial wealth w_0 minus losses, $w = w_0 - l$, The first and second derivative with respect to l are

$$\frac{\partial u}{\partial l} = -(w_0 - l)^{-\rho}$$

$$\frac{\partial^2 u}{\partial l^2} = -\rho(w_0 - l)^{-(1+\rho)}$$

The first derivative is negative: individuals dislike larger losses. The second derivative is positive if $\rho < 0$ and negative if $\rho > 0$.

Constant Absolute Risk Aversion. CARA takes the form

$$u(w) = -e^{-\eta w}$$

where η is the constant absolute coefficient of risk aversion and $\eta > 0$ is called "risk aversion" and $\eta < 0$ is called "risk seeking."

Reference-Dependent Preferences. Kőszegi and Rabin (2006, 2007) distinguish between the cost of a purchase that households expect to make and an uncertain cost, treating them as additively separable with only the latter subject to loss aversion. That is, let p represent insurance premiums and y represent probabilistic costs such as flood losses and deductibles. These lead to the value function

$$v = -p^\theta - \int \delta y^\theta \, \omega(y) \, dy$$

$$= -p^\theta - \delta \left(\int_0^d l^\theta \, \omega(l) + \int_d^c d^\theta \, \omega(l) + \int_c^{\bar{c}} (d + l - c)^\theta \, \omega(l) \right) \, dl$$

where δ represents the differential weighting of uncertain outcomes relative to certain ones, θ describes the curvature of the value function, ω is a probability weighting function, d the deductible, c the coverage limit, and l flood losses. The first row in this equation shows this value function generally with the second row applying it to the specific outcomes of our insurance problem.

Expo-power Utility. Saha (1993) proposes a mode of expo-power utility

$$u(w) = -\exp(-\tau w^{\psi})$$

where $\tau, \psi \neq 0$ and $\tau\psi > 0$. Saha notes that this model requires an assumption of risk averse households, and that certain combinations of absolute and relative risk aversion are infeasible (e.g., a household cannot demonstrate both constant absolute risk aversion and constant relative risk aversion). Parameter $\tau = 1$ describes constant absolute risk aversion, $\tau < 1$ indicates decreasing absolute risk aversion, and $\tau > 1$ increasing relative risk aversion. Parameter $\psi < 0$ indicates decreasing relative risk aversion, $\psi > 0$ increasing relative risk aversion.

6.2.2 Probability Distortion Models

We provide the specific functional forms for commonly used probability distortion models tested in Section 4.3. Each of these models transforms cumulative probabilities in the manner described by Quiggin (1982).

Tversky-Kahneman Probability Distortions. Tversky and Kahenman (1992) propose a single parameter probability distortion model. Rather than transforming individual probabilities as proposed in Kahneman and Tversky (1979), it transforms the cumulative distribution, which addresses problems related to indirect violations of stochastic dominance as described by (Quiggin, 1982). Their proposed probability distortion function is

$$\omega(\pi) = \frac{\pi^{\gamma}}{(\pi^{\gamma} + (1 - \pi)^{\gamma})^{1/\gamma}}$$

where γ is a model parameter, and π objective probabilities.

Prelec Probability Distortions. Prelec (1998) proposes a two parameter model to explain individuals' behavior related to the common-ratio effect (Allais, 1953). The common-ratio effect notes that when comparing two gambles, one with a lower probability but higher payout than the other, individuals perceive the attractiveness of the riskier gamble to increase as the odds decrease in equal proportion. Expected utility theory using objective

probabilities cannot explain this behavior. Prelec proposes a model of probability distortions as an explanation

$$\omega(\pi) = e^{-\nu(-\ln(\pi))^\gamma}$$

where γ and δ are model parameters.

Gonzalez-Wu Probability Distortions. Gonzalez and Wu (1999) propose a model that accounts for two potential features of probability distortions: one is how individuals discriminate probabilities γ, a second the attractiveness of gambling ν. They test their model in lab settings in the domain of gains. Their proposed probability distortion function is

$$\omega(\pi) = \frac{\nu\pi^\gamma}{\nu\pi^\gamma + (1-\pi)^\gamma}.$$

Karmakar's (1978) probability distortion model represents a special case in which $\nu = 1$.

6.3 Online Appendix: Estimating Policyholder Risk

This appendix describes our approach to modeling the claim rates and loss distributions of policyholders.

6.3.1 Claim Rates

We assume that policyholders rely on the same information as the flood insurance program in estimating their flood risk. The included observables are those used in determining flood insurance premiums, which Table 8 lists and defines.

The flood insurance program considers whether a home was built before its flood insurance rate maps (FIRM) were developed. Zoning regulations and building codes intend to reduce vulnerability in designated flood hazard areas and so flood claims and losses may substantially differ depending on whether a home was built pre- or post-FIRM. We model flood risk separately for pre- and post-FIRM dwellings.

Table 9 provides the results of the panel logit model of household claim rates. These results are consistent with previous research. For example, Kousky and Michel-Kerjan (2015) find in their assessment of NFIP claims that a community's Community Rating System score, the number of floors in a home, its elevation, and whether it has a basement all statistically significantly influence flood claims and in qualitatively similar ways to our findings.

Table 8. Explanatory Variables Used in Regressions

Explanatory variables	*Description*
Deductible	Menu options include $500, $1,000, $2,000, $3,000, $4,000, and $5,000.
Coverage	Value of the property coverage limit in $100s. Maximum coverage limit: $250,000
CRS class	The community's score on the Community Rating System (CRS). The CRS is a voluntary program that rewards communities for taking actions to mitigate flood risk beyond minimum NFIP requirements. Community actions reduce policyholder premiums by up to 45%. CRS class is the associated premium reduction, ranging from 0 to 45.
Basement	Binary, based on whether the property has a basement
Obstruction binary	Binary, indicates whether an elevated building has an enclosed area and/or machinery attached to the building below the lowest floor.
Obstruction information	The type of obstruction. Values range from 0 to 100. Low values indicate no obstruction; high values indicate a permanent obstruction. For example, a high value would be earned for an obstruction with non-breakaway walls and machinery attached to the building.
Elevation binary	Binary, indicates that elevation data are available and provided by the NFIP. If an elevation estimate is unavailable or if the policyholder has an elevation certificate from a contracted engineer, this variable takes a value of zero.
Elevation certificate binary	Binary, indicates that elevation estimates were collected by a contracted engineer.
Elevation information	An estimate of the elevation in feet of a policyholder's home relative to the 100 year floodplain. In its premium, calculations the NFIP caps the low and high elevation at -2 and 5 feet, respectively, and we do so here.
Permanent	Binary, takes a value of 0 if the structure is a manufactured or mobile home, 1 otherwise.
Floors	Number of floors in the home, taking three possible values: 1, 2, or 3+

Note: More information can be found on these variables from NFIP (2006).

Table 9. Claim Rate Regressions

	Zone A, Pre-FIRM	Zone A, Post-FIRM
Constant	-3.978***	-5.121***
	(0.022)	(0.045)
Deductible (reference group: $500)		
$1,000	-0.261***	-0.315***
	(0.007)	(0.011)
$2,000	-0.582***	-0.321***
	(0.017)	(0.037)
$3,000	-0.602***	-0.350***
	(0.031)	(0.067)
$4,000	-0.797***	-0.657***
	(0.053)	(0.145)
$5,000	-1.148***	-0.954***
	(0.013)	(0.029)
Coverage	-2.06E-04***	-3.42E-04***
	(3.88E-06)	(5.99E-06)
CRS Class	-0.026***	-0.056***
	(3.88E-04)	(0.001)
Basement	-0.020**	-0.371***
	(0.009)	(0.018)
Obstruction binary	0.245***	0.396***
	(0.006)	(0.009)
Obstruction information: Obstruction binary	0.235***	0.169***
	(0.010)	(0.015)
Elevation binary	0.303***	1.373***
	(0.009)	(0.036)
Elevation information: Elevation binary	-0.302***	-0.201***
	(0.004)	(0.003)
Elevation certificate binary	0.293***	0.100*
	(0.009)	(0.052)
Elevation information: Elevation certificate binary	-0.804***	-0.644***
	(0.014)	(0.052)
Permanent	0.039*	0.216***
	(0.022)	(0.029)
Permanent: Floors	0.164***	0.079***
	(0.006)	(0.008)
Log likelihood	- 888,194	- 380,030
Observations	9,108,133	6,171,368

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Logit panel regression model with random effects. Standard errors in parentheses.

6.3.2 Loss Distributions

We model household losses beginning with an examination of the loss distribution, examining losses for all households in the same flood risk category concurrently. From this approach, we find that our flood loss distributions are approximately log-normal. Finally, we fit the parameters of the log-normal distribution for each household based on its observables.

6.3.2.1 Parametric distributions

This section compares parametric specifications for modeling flood losses. Throughout, we use A zone, pre-FIRM as an example.

Given a claim event, the distribution of potential property losses is influenced by the type of event that occurs: events that affect many policyholders result in larger expected losses for each policyholder. We model observations as a mixture of two loss generating processes: (1) isolated loss events, floods affecting an individual or small group of policyholders (e.g., due to unusually heavy, localized rain), or (2) correlated loss events, losses due to a storm, hurricane, etc., affecting many policyholders. We define a correlated loss event as an observation of at least 30 claims with a date of loss on the same day in the same state. That event continues for each consecutive day with at least 30 claims in the same state. The 30 claims threshold is located at the 95th percentile of the distribution of claims by date of loss by state. In other words, for any date on which a flood loss occurs, 95 percent of the time the number of claims is less than 30. These criteria create 1,319 correlated loss events out of a total of 635,220 flood insurance claims occurring between 1982 and 2009. All observations that are not associated with a correlated loss event are considered an isolated loss event.

Observations from isolated loss events are weighted by

$$\phi_h = \frac{\overline{\pi_h}}{n_h}$$

where $\overline{\pi_h}$ describes the average across years of the percent of claims generated by isolated loss events and n_h indicates the total number of claims generated by isolated loss events ($n_h = 85{,}075$). On average, 22 percent of claims are generated by correlated loss events. Observations for correlated loss events are weighted by

$$\phi_{m,j} = \frac{(1 - \overline{\pi_h})}{n_m * n_{m,j}}$$

where n_m indicates the total number of correlated loss events and $n_{m,j}$ indicates the total number of claims generated by correlated loss event j.

These weights provide empirical loss distributions for the isolated and correlated loss events. No time trends are present in the means and variances of the empirical loss distributions across years: regressing respectively the mean and variance of losses as a percent of the property value by year on time results in non-significant F-statistics of 0.89 and 0.60.

Using the weighted empirical loss distribution, we compare parametric models. We fit parametric distributions using maximum likelihood estimation (MLE) and compare models using the Anderson-Darling test, Kolmogorov-Smirnov test, and the Akaike Information Criterion (AIC). Comparisons consistently indicate that the log-normal is the best fitting parametric model; this result is consistent across flood zones. Table 10 provides the results for the A zone, Pre-FIRM, correlated loss events distribution for a subset of the tested parametric distributions.

Table 10. Fit Comparisons Across Parametric Distributions

	A-D	K-S	AIC
Log-normal	53.41	0.060	-14949.5
Pareto III	65.61	0.064	-14286.2
Pareto IV	68.79	0.066	-14364.4
Pareto II	72.06	0.071	-14322.7
Generalized Extreme Value	85.10	0.063	-14175.4
Gamma	143.86	0.100	-13966.1

Note: The results are for the A zone, Pre-FIRM, correlated loss event data. The Anderson-Darling (A-D) and Kolmogorov-Smirnov (K-S) tests and the Akaike Information Criterion suggest that the log-normal is the parametric distribution that best fit the loss data.

As a sensitivity test, we generate several alternative distributions: (1) defining correlated loss events using a minimum of 10 claims (rather than 30) with the same date of loss in a state, (2) using a minimum of 100 claims, (3) treating all claims as independent and equally weighted. Deciles from the cumulatives for these distributions are provided in Table 11, Columns 1 through 5. Excluding the case in which all losses are equally weighted, the distributions are quite similar across approaches. The log-normal results in a slightly thicker right tail than the empirical. The equally weighted approach results in the greatest probability of large losses due to severe events.

Table 11. Cumulative Distributions for A Zone, pre-FIRM

Loss (%)	Homogeneous					Hetero-geneous
	(1) Log-normal	(2) Empirical (30 claims)	(3) Empirical (10 claims)	(4) Empirical (100 claims)	(5) Equally weighted	(6) Log-normal
10	53.1	55.3	58.0	51.9	40.6	50.6
20	73.8	71.7	73.9	68.5	55.4	69.0
30	83.3	80.3	82.1	77.6	64.5	78.0
40	88.4	86.5	87.9	84.3	71.8	83.5
50	91.6	90.8	91.6	89.0	77.6	87.1
60	93.6	93.5	94.0	92.2	81.9	89.6
70	95.0	95.4	95.7	94.3	85.3	91.5
80	96.0	96.7	97.0	96.0	88.2	92.8
90	96.8	97.9	98.0	97.4	91.2	93.9

Note: Alternative specifications of the cumulative distribution for losses. Losses are measured as a percent of the structure's value. These distributions use the correlated loss event definition of 30 claims. Columns 1 through 5 report deciles assuming a homogeneous loss distribution across all policyholders in the A zone, pre-FIRM. Column 1 reports deciles for the log-normal distribution. Columns 2 through 4 report for the weighted non-parametric distribution for which weights are based on definitions of the correlated loss events. Columns 2, 3, and 4 respectively use definitions of a correlated loss event as a minimum of 30, 10, and 100 claims in the same state on the same day. Column 5 reports deciles for the non-parametric distribution using equal weights for all observations. Column 6 reports deciles for the median across the log-normal distributions fit for each household based on observables.

6.3.2.2 Household-level loss distributions

We develop loss distribution estimates for each policyholder using the log-normal distribution and our assumption that the loss generating process is a mixture of isolated and correlated loss events. Our approach is similar that of Aitkin (1987) and Western and Bloome (2009). Aitkin proposes modeling variance heterogeneity as a means to address heteroscedasticity. Western and Bloome note that the estimations of these variance models may themselves be of interest for research related to within-group differences and so adapt Aitkin's approach as a means to study income inequality. They propose an iterative MLE. We use this approach to fit parameters μ and σ of the log-normal distribution. Consider the two-equation model

$$E[\log l_i] = x_i'\beta$$
$$\log \sigma_i^2 = x_i'\lambda$$

where $l_i \in (0,1]$ is the flood loss as a percent of the home value for policyholder i, x_i is a vector of policyholder observables, and σ_i^2 is the estimated variance in losses for each policyholder. We fit the model using an iterative MLE approach:

1. Estimate $\hat{\beta}$ using a Tobit model, which is right censored at 0, as $\log l_i \in (-\infty, 0]$. Save the residuals, $e_i = \log l_i - x_i'\hat{\beta}$

2. Estimate $\hat{\lambda}$ with a gamma regression of the squared residuals e^2, using a log link function. Save the fitted values, $\widehat{\sigma^2} = \exp(x_i'\hat{\lambda})$.

3. Estimate $\hat{\beta}$ using a Tobit model with weights $1/\hat{\sigma}^2$ and update the residuals.

4. Repeat steps 2 and 3 until the log-likelihood converges.

This iterative approach (1) addresses heteroscedasticity in the mean model by weighting observations based on the fitted variance, and (2) corrects the standard errors in the variance model by increasing the precision of the coefficient estimates from the mean model (Western and Bloome, 2009).

Fixed effects in these regressions account for correlated loss events. We order correlated loss events by the number of claims for each event and bin the events every 5 percentiles, creating twenty fixed effects across the distribution of correlated loss events (i.e., vigintiles). For example, a fixed effect is included for all correlated loss events for which the number of claims is below the fifth percentile, another one for events with claims from the fifth and to tenth percentiles, etc.

Table 12 shows the output of the mean and variance models for our core sample (the A zone). Its results are also qualitatively consistent with the findings of Kousky and Michel-Kerjan (2015) with respect to explanatory variables such as elevation, whether the home has a basement, and whether the home is permanent or a mobile home.

Loss observations are associated with a specific event; however, we are attempting to estimate each policyholder's loss distribution across all possible events. That is, for each household, we would like the expected loss given the explanatory variables and the occurrence of a loss event $E[l_i | l_i > 0 \cap x_i]$ but the fixed effects model provides an

observation given specific event m_j, $\mathrm{E}[l_i | l_i > 0 \cap x_i \cap m_j]$. To address this in our probability estimates, we weight each event by its probability in these data. For example, the model of log losses can be written as

$$\log l_i = \alpha + x_i' \beta + FE' \gamma + \epsilon_i$$

where γ is the vector of coefficients on the fixed effects FE. The probability from this equation can then be written as

$$\mathrm{E}[\log l_i | l_i > 0 \cap x_i] = \overline{\pi_h} \alpha + (1 - \overline{\pi_h})(\alpha + \gamma)' \pi_{FE} + x_i' \beta$$

where $\overline{\pi_h}$ is the probability that an observed loss is generated from an isolated loss event (rather than a correlated loss event), and π_{FE} are the probabilities for each fixed effect event. In this case, each quantile has a 5 percent probability, given that a correlated loss event occurs. The term $\overline{\pi_h} \alpha + (1 - \overline{\pi_h})(\alpha + \gamma)' \pi_{FE}$ is a constant and provides the intercept for the predictive model and so can be used to estimate fitted values for each household. The same approach is taken for the variance model. The mean and variance estimates for each household are then used to fit parameters of the log-normal distribution.

Table 11 provides the cumulative loss distribution for the median policyholder at each decile following this approach in Column 6. The median of these loss distributions results in a slightly higher probability of a total loss than the group-level log-normal (Column 1) and the weighted non-parametric distributions (Columns 2–4) but a lower probability than the distribution in which all observations are equally weighted (Column 5).

Table 12. Models of Flood Loss as a Percent of Home Value

	A Zone, pre-FIRM		A Zone, post-FIRM	
	Mean Model (Tobit)	Variance Model (Gamma, log link)	Mean Model (Tobit)	Variance Model (Gamma, log link)
Constant	-2.102***	0.772***	-2.188***	0.818***
	(0.028)	(0.040)	(0.059)	(0.059)
Deductible (ref. group: $500)				
$1,000	0.361***	0.038***	0.171***	-0.137***
	(0.007)	(0.011)	(0.026)	(0.025)
$2,000	0.252***	0.030	0.124	-0.144*
	(0.025)	(0.038)	(0.085)	(0.083)
$3,0000	0.211***	0.098	0.242*	-0.143
	(0.041)	(0.060)	(0.145)	(0.141)
$4,000	0.293***	0.042	-0.074	-0.254
	(0.068)	(0.104)	(0.288)	(0.299)
$5,0000	0.323***	0.150***	0.032	0.091
	(0.020)	(0.029)	(0.070)	(0.062)
Coverage	-1.72E-04***	1.80E-05**	-2.10E-04***	-7.00E-05***
	(-6.00E-06)	(-8.00E-06)	(-1.40E-05)	(-1.20E-05)
Elevation binary	-0.074***	0.527***	0.792***	-0.104***
	(0.014)	(0.017)	(0.020)	(0.019)
Elevation: Elev. binary	-0.089***	-0.014*	-0.166***	0.069***
	(0.007)	(0.008)	(0.007)	(0.006)
Basement	-0.104***	-0.102***	-0.097***	-0.073***
	(0.010)	(0.016)	(0.029)	(0.027)
Permanent	-0.132***	0.039	-0.555***	0.382***
	(0.028)	(0.041)	(0.059)	(0.059)
Permanent: Floors	-0.288***	-0.079***	-0.356***	-0.022
	(0.006)	(0.009)	(0.017)	(0.015)
Log (scale)	0.386***		0.586***	
	(0.002)		(0.004)	
Quantile Fixed Effects	Yes	Yes	Yes	Yes
Log Likelihood	-357963.4	-606644.5	-84230.3	-235387.2
Deviance	452116.2	1124624.9	138670.4	326626.6
Num. obs.	409179	409179	126014	126014
Uncensored	391467		117060	
Right-censored	17712		8954	
Wald Test	35366.3		11702.2	

Note: *** p < 0.01, ** p < 0.05, * p < 0.1, Standard errors in parentheses. Models predict the mean and variance of flood loss for A zone, pre-FIRM and A zone, post-FIRM. We model flood losses between 1982 and 2009. Losses as a percent of home value are mean and variance stationary. The mean and variance models are fit using an iterative maximum likelihood approach proposed by Aitkin (1987). The mean model is a Tobit with a dependent variable of log(loss) where loss is measured as a percent of the structure's value.

They are right censored at 1. The variance model uses the squared residuals of the mean model as a dependent variable. In turn, the inverse of the predicted value of the variance model is used to weight observations in the mean model. The models provide parameters μ and σ for the log-normal distribution and so allow for fitting a loss distribution for each policyholder based on observables. Quantile fixed effects describe a set of dummies we include to account for major storms. We consider correlated loss events those that affect at least 30 policyholders in the same state in the same day. Ordering correlated loss events by the number of claims that create, we group the correlated loss events in five percentage point intervals (i.e., vigintiles) and include a dummy for each group.

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