Effects of Risk Attitudes and Information Friction on Willingness to Pay for Precautionary Building Standards

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Abstract

Take-up rates for windstorm-resistant buildings remain relatively low even in areas with high exposure to hurricanes and tropical storms. To further investigate this issue, we extend the theory on WTP for prevention to include risk attitudes up to the fourth order, deriving total effects and testable predictions for mixed risk averters and mixed risk lovers' WTP relative to higher order risk-neutral benchmarks. We then employ field experiments to elicit and test the effects of higher order risk attitudes (HORAs) and information friction on coastal homeowners' WTP for precautionary building standards with insurance discounts. To elicit risk attitudes and WTP, we employ 50-50 model-free risk apportionment lotteries and payment card WTP experiments. Empirical analyses reveal insightful heterogeneity in the correlation between homeowners' HORA subgroups and WTP for precautions that is partially consistent with theory. We demonstrate strong causal effects of information friction on WTP for precaution in the absence of a truncated WTP range; however, the effects appear to be positive among risk lovers. Predicted WTP estimates reveal the need for subsidies to promote the mitigation of windstorm losses.

Keywords: Risk attitudes, Information friction, Homeowners insurance, Willingness to pay, Field experiment, Natural disasters

JEL Classifications: D81, G22, Q51, Q54

1 Introduction

Advances in architectural and construction engineering over the last decades have led to the development of cost-effective windstorm-resistant building standards, which reduce property damage by up to 72% (Simmons et al., 2018). Nevertheless, take-up rates for these precautionary buildings remain relatively low even in areas with high exposure to hurricanes.[1] To shed light on this issue, we use theoretical and empirical analyses to investigate the effects of higher order risk attitudes (HORAs) on coastal homeowners' demand for precautionary building standards with corresponding insurance discounts.

First, we revisit and extend the theory on WTP for prevention and examine comparative statics up to the fourth order risk attitude, focusing on both risk averters and risk lovers.[2] Second, we derive total effects of HORA on the marginal WTP to reduce the probability of loss, p, and develop critical (and testable) conditions under which mixed risk averters or mixed risk lovers will choose higher (lower) WTP than second, third, and fourth degree risk-neutral agents.[3] To empirically test for the relationships predicted in our model, we employ field experiments with homeowners in coastal counties in Alabama who are highly vulnerable to hurricane risk. The first experiment employs a series of 50-50 model-free risk apportionment lotteries (Eeckhoudt and Schlesinger, 2006) to elicit homeowners' first through fourth order risk attitudes. The second is a repeated WTP payment cards experiment (Cameron and Huppert, 1989; Cameron et al., 2002) designed with actual levels of protection and insurance discounts available to the subjects in our sample, mimicking the decisions homeowners face in managing hurricane risk.

Specifically, we consider precautionary building standards that are characterized by two levels (Bronze and Silver) in the FORTIFIED Home™ program (henceforth *Fortified*) that are potentially both self-insuring and self-protecting.[4] *Fortified* is a set of engineering and building standards based on research by the Insurance Institute for Business & Home Safety.[5] The standards are designed to strengthen new and existing homes through system-specific upgrades to minimum building code requirements that will reduce damage from specific natural hazards. The *Fortified* hurricane program enables existing single-family homes to be retrofitted to mitigate high winds and wind-driven water damage.

There are three incremental *Fortified* levels (Bronze, Silver, and Gold) designed to improve roofs, reduce water intrusion through attic ventilation systems, strengthen gable end construction (Bronze), protect openings (Silver), and strengthen critical elements of the continuous load path from the roof to the foundation

[1] About 33 million single-family residential properties, along U.S coast from Texas to Maine, are at moderate or greater hurricane wind risk in the 2022 hurricane season with about $10.5 Trillion USD in reconstruction value cost (CoreLogic, 2022).

[2] Analysis of the joint effects of HORA, up to the fourth order, with attention to risk-seeking behavior are lacking, although significant correlation exists among HORA. For example see Dachraoui et al. (2004), Eeckhoudt and Gollier (2005), Dionne and Li (2011), Meyer and Meyer (2011), and Jindapon (2013).

[3] We use the terms order and degree interchangeably.

[4] For actions taken to reduce the severity of loss, self-insurance theory generally predicts that a more risk-averse agent will demand more self-insurance than a less risk-averse agent; however, in the case of actions that reduce the probability and severity of expected losses, self-insurance-cum-protection, a more risk-averse agent does not necessarily choose more protection.

[5] See www.ibhs.org for additional information on FORTIFIED Home™ program.

(Gold). A trained and certified inspector must inspect the house at several specific points in the building process for a house to receive a *Fortified* designation. Because it is not practical to retrofit an existing house to the *Fortified* Gold standard, we only consider Bronze and Silver designations.

The WTP experiment is designed with two attribute levels of precaution (*Fortified* Bronze and *Fortified* Silver), three attribute levels of homeowners insurance discounts (20%, 35%, and 45%), and two attribute levels of payment card range (low and high). The insurance premium discounts are calculated using commercial catastrophe models and represent loss-reduction estimates associated with the uptake of corresponding levels of *Fortified* (i.e., the discounts are actuarially fair). The payment card attributes allow us to test for and accommodate endpoint bias in payment card methods.

During face-to-face meetings to pre-test our instruments, some homeowners indicated that lack of information regarding the relative efficacy of *Fortified* was one of the main reason for non-adoption. This motivated us to test for causality between WTP for *Fortified* and information friction about the efficacy of *Fortified* using randomized information treatment. To achieve this final design attribute, we randomly assigned half of our sample to watch a credible video[6] demonstrating the performance of *Fortified* and conventional building standards side-by-side under hurricane-like winds prior to their participation in the WTP experiment. The video was not presented to the other half of the sample. This treatment allows us to isolate and separately identify the causal effects of information friction regarding the performance of *Fortified* on WTP (from HORA) experimentally.[7]

Alabama's coastal region is an ideal setting for our experiment because it includes more than 75% of all *Fortified* houses.[8] In addition, Alabama regulators enforce a benchmark insurance discount for each level of *Fortified* designation as a percentage of the wind portion of homeowners' insurance premiums.

Although *Fortified* houses sell for a premium that exceeds the cost of retrofitting to the standard, and several public information campaigns were launched to educate homeowners and contractors in the region about *Fortified* construction and wind insurance discounts, current take-up of *Fortified* relative to conventional standards is disappointingly low.[9] Such low take-up could be explained by other salient factors that affect WTP, such as homeowners' lack of complete information regarding the attributes and performance of *Fortified* to clearly delineate its distinction from conventional building standards.

Our research design and data allow us to test theoretical predictions on the relationship between WTP for precautionary actions and HORA, thus extending the literature on several fronts. Specifically, we (1) develop

[6]The video can be accessed at https://tinyurl.com/fortified-video or https://vimeo.com/17764719.

[7]To keep the theoretical model relating HORA on WTP tractable and maintain our research focus, we do not introduce information friction.

[8]At the time of our survey (2016), there were about 4,000 *Fortified* houses in Alabama. The *Fortified* program is available in several other states, but has gained the most traction in Alabama. In 2020, there were more than 16,000 *Fortified* houses in Alabama out-of over 2 million single family residential houses.

[9]It costs 3% - 5% of a house's value to retrofit a conventional house to the *Fortified* standard and *Fortified* houses sell at a 7% premium on average (Awondo et al., 2019); thus, the *Fortified* designation is a sound economic investment, even without accounting for other direct and indirect benefits.

the total effects for second, third, and fourth degree risk attitudes and critical conditions under which mixed risk averters and mixed risk lovers will choose more or less WTP for precautions than second, third, or fourth degree risk-neutral agents; (2) establish and empirically test hypotheses relating mixed risk averters' and mixed risk lovers' WTP for precaution based on theorized higher order risk-neutral benchmarks and our experimental design; (3) measure the causal effects of *Fortified* performance information friction on homeowners' WTP for precautionary building standards; and (4) test for ending-point bias in WTP payment card experimental design.[10] In addition, our study paves the way for the comparison and generalization of findings across settings.

To properly estimate heterogeneous treatment effects while minimizing the potential for type I error, we employ both multiple hypothesis testing (MHT) and multivariate regression methods in our analysis.[11] In the former, we use the multiplicity adjustment methods proposed by List et al. (2016), comparing the results with adjustments proposed by Bonferroni (1935) and Holm (1979). In the latter, we estimate a series of panel-level random-effects Tobit regression models that also control for socio-demographic variables (including income), housing characteristics, and HORA. Finally, we compare predicted marginal WTP for mixed risk lovers and risk averters over salient experimental design attributes and low ($\leq 25^{\text{th}}$ percentile) to high ($\geq 75^{\text{th}}$ percentile) household income levels.

We contribute to existing literature both theoretically and empirically. Theoretically, we uncover new critical bounds of p that allow for both risk-averters and risk-lovers to be prudent, and we develop testable propositions comparing mixed risk averters and mixed risk lovers' WTP for *Fortified* to higher order risk-neutral benchmarks. Our empirical analyses generally demonstrate strong correlations among HORAs and WTP for precautionary building standards, which are partially consistent with our theoretical predictions. More specifically, we find that homeowners exhibiting risk-averse, prudent, and temperate preferences choose significantly higher WTP ($4,461) than those who are risk averse and third degree risk-neutral, and risk-loving, imprudent, and intemperate homeowners choose significantly lower WTP ($3,195) than risk loving and third degree risk-neutral agents, consistent with theory. However, comparing second and fourth degree risk-neutral agents, we find no statistical difference in WTP. Additionally, we find that homeowners exhibiting risk-loving, prudent, and intemperate preferences consistently choose a significantly higher WTP ($2,738 and $4,451) than second and fourth degree risk-neutral agents, respectively.

Surprisingly, we find that prudent risk lovers are generally willing to pay significantly more than prudent risk-averse homeowners relative to their corresponding risk-neutral benchmarks. Overall, the effects of HORAs on WTP for precautionary building standards are highly heterogeneous across HORA subgroups

[10]The payment card method is the most popular approach used in non-market valuation including valuing risk reduction(Carlsson et al., 2004; Covey et al., 2007) due to its low cognitive burden on respondents and its ability to reveal preference information (Covey et al., 1989) unlike other competing methods. Nevertheless, empirical evidence show that it is vulnerable to range (and centering) bias when its range does not cover respondents' desired distribution(Rowe et al., 1996).

[11]Recent literature (Maniadis et al., 2014; List et al., 2016) highlights the increased likelihood of false positives in experimental studies involving multiple treatments and subgroups.

and household income levels.

Our analysis also reveals heterogeneous causal effects of information friction on WTP for precautionary building standards among homeowners treated with a higher bound WTP payment card range but not those treated with a lower bound payment range; however, the effects are weakly positive among mixed risk lovers. Specifically, we find that information friction appears to increase WTP among risk-loving, prudent, and intemperate homeowners and the effect doubles for fourth degree risk-neutral agents. These results reveal strong evidence of endpoint bias in the lower bound WTP payment card and that the absence of a truncated payment card upper bound is necessary to properly value the effects of information friction on WTP for *Fortified*, in support of existing literature on range bias (Covey et al., 1989; Whitehead, 2002; Rowe et al., 1996).

Besides marginally closing a gap between theory and practice, our results also have significant policy implications on the promotion of precautionary building standards in particular, and the disaster risk management and economic resilience agenda in general. The Congressional Budget Office (CBO, 2019) estimates the annual expected economic value of hurricane losses in the U.S. to be $54 billion, indicating the importance of research on this topic. There is a broad consensus among researchers, insurers, and some policymakers that adoption and enforcement of stronger building codes is critical to disaster risk management, and building resilient communities. Five states, including Alabama, now have policies mandating that insurers offer wind insurance discounts for *Fortified* houses. In addition, the Alabama Department of Insurance recently launched the Strengthen Alabama Homes program, which offers subsidies to help homeowners retrofit existing homes to meet *Fortified* standards. The results of our study can be used to calibrate the appropriate mix of loss-mitigation discounts and subsidies to achieve desired results based on the observed prevalence of HORAs, WTP, and expected losses.

The remainder of our study is organized as follows. In Section 2, we provide a brief review of previous literature. In Section 3, we revisit and extend the theory on WTP for loss-prevention up to the fourth order (kurtosis) risk and develop critical and testable conditions under which mixed risk averters/lovers will choose a higher/lower WTP than risk-neutral agents. Section 4 examines the payment card WTP experimental design and the 50-50 model-free risk apportionment lotteries used to elicit homeowners WTP and HORA, respectively. This section also presents survey sampling and administration strategy details. We then present a summary of the data collected and conduct multiple hypothesis tests in Section 5. Section 6 presents and discusses our regression results. Section 7 concludes.

2 Prior literature

Extensive economic theory links agents' propensity for precautionary actions with risk attitudes. However, most findings are model-specific and focus on risk aversion, a second order risk attitude, even though HORA also play a key role in individuals' decision making under risk. Kimball (1990) provides early evidence. He finds that individuals who are third degree risk averse, whom he terms "prudent," save more when faced with an uncertain stream of future income. In a subsequent study, Kimball (1993) finds that when faced with an unavoidable risk, fourth degree risk-averse agents, whom he calls "temperate," seek to reduce the exposure to another risk even if both risks are statistically independent.[12] Equivalently, a prudent agent prefers a loss distribution with less positive skewness, and a temperate agent prefers a loss distribution with less positive kurtosis. Subsequent studies reveal salient effects of prudence and temperance on the propensity to take actions that reduce probabilities of hazards (Eeckhoudt and Gollier, 2005), insurance demand (Fei and Schlesinger, 2008), precautionary bidding in auctions (Eso and White, 2004), and other behaviors under risk (White, 2008; Treich, 2010; Gomes and Michaelides, 2005; Snow and Warren, 2005).

Although there is a growing body of literature relating HORA to demand for precautions, attention is largely focused on risk averters, despite the appearance of risk-seeking behavior in empirical results, and ambiguous perceptions of the role of risk seekers in society (Crainich et al., 2013; Jindapon, 2013; Noussair et al., 2014). A few recent studies reveal distinct patterns of prudence and temperance among risk lovers and risk averters with potential implications on the demand for precautionary actions. Leaning on expected utility theory (EUT) and Eeckhoudt et al.'s (2009) characterization of HORAs, while assuming that risk lovers prefer to combine "good with good" and "bad with bad," Crainich et al. (2013) theoretically show that risk lovers are both prudent and intemperate. Deck and Schlesinger (2014) generalize and test theoretical findings up to the sixth order using experiments on students finding similar results. Generally, they also find risk averters and risk lovers behave similarly with odd-order risk attitudes (e.g., prudence) and differently with even-order risk attitudes (e.g., temperance). Similarly, using a price list experiment defined on risk compensation, Ebert and Wiesen (2014) find that both risk averters and risk lovers are prudent. They also find that risk averters are more temperate than risk lovers.

These studies and others (Maier and Rüger, 2011; Deck and Schlesinger, 2010; Ebert and Wiesen, 2014) rely on lab experiments using students to investigate the prevalence and (to a limited extent) effects of HORAs on decision making.[13] None of these studies examines the effects of HORAs beyond the setting of precautionary savings.

In addition, recent and growing empirical evidence suggests that demand frictions such as cognitive ability (Fang et al., 2008), inertia (Handel, 2013), risk perception bias (Cutler and Zeckhauser, 2004; Abaluck and Gruber, 2011), and information friction (Handel and Kolstad, 2015; Spinnewijn, 2017) also explain considerable variation in demand for insurance. Using unique survey and claims data on health insurance plans for a large employer in the U.S, Handel and Kolstad (2015) show that ignoring information friction leads to upward bias in risk aversion estimates. Whether or not information friction on the attributes of precau-

[12] We use the terms prudent (temperate) and third order risk averse (fourth order risk averse) interchangeably.

[13] Only Noussair et al. (2014) studies the impact of HORAs on precautionary savings using both student and non-student samples with mixed results.

tionary building standards exists, and the extent to which it affects WTP remain open questions, especially given existing ambiguous relations between risk attitudes and the demand for prevention and insurance. The scarcity of empirical applications jointly linking explicit measures of HORAs and information friction to decisions made by economic agents in the field, and the lack of literature that studies these relationships within the framework of precautionary building standards, motivate our efforts.

3 Theoretical framework

3.1 Willingness to pay for self-protection

We develop and examine the total effects of second, third, and fourth order risk attitudes on risk lovers' and risk averters' marginal WTP for prevention under expected utility theory. We build on model frameworks proposed by Dionne and Li (2011), Eeckhoudt and Gollier (2005), Meyer and Meyer (2011), and more closely Jindapon (2013) and Crainich et al. (2015). To keep the analysis tractable, we do not introduce information friction to the model. Instead, we opt to identify its causal effects on WTP experimentally.

Consider an agent with initial wealth w_0 facing potential future loss Ł $\leq w_0$ with probability p, and no loss with probability $1-p$, $p \in [0,1]$. The agent has the option to spend c to reduce the probability and severity of a loss. Consider a binary lottery with outcomes $x_1 = w_0 - c$ and $x_0 = w_0 - c - L_x$ and probabilities $1-p$ and p, respectively. In the absence of market insurance, the agent's expected utility can be represented as

$$EU = pu(x_0) + (1-p)u(x_1), \tag{1}$$

where the utility function, u, is continuous and at least four-times differentiable with a positive first order derivative ($u^{'} > 0$). The first order condition derived from equation (1) is

$$WTP = \frac{dx}{dp} = \frac{u(x_1) - u(x_0)}{pu^{'}(x_0) + (1-p)u^{'}(x_1)} > 0, \tag{2}$$

Where $\frac{dx}{dp}$, the marginal rate of substitution between x and p, represents the WTP to reduce the probability of the low-wealth state. Let $\bar{x} = px_0 + (1-p)x_1 = E(\tilde{x})$, then $x_1 - \bar{x} = pL_x$ and $x_0 - \bar{x} = -(1-p)L_x$. Then, using a fourth order Taylor series expansion around $\bar{x}$ we can approximate

$$u(x_1) \approx u(\bar{x}) + pL_x u^{'}(\bar{x}) + \frac{(pL_x)^2}{2}u^{''}(\bar{x}) + \frac{(pL_x)^3}{6}u^{'''}(\bar{x}) + \frac{(pL_x)^4}{24}u^{''''}(\bar{x}) \tag{3}$$

and

$$u(x_0) \approx u(\bar{x}) - (1-p)L_x u^{'}(\bar{x}) + \frac{((1-p)L_x)^2}{2}u^{''}(\bar{x}) - \frac{((1-p)L_x)^3}{6}u^{'''}(\bar{x}) + \frac{((1-p)L_x)^4}{24}u^{''''}(\bar{x}). \tag{4}$$

From equation (3) and (4), we can derive the numerator of equation (2) as

$$u(x_1)-u(x_0)=u^{'}(\bar{x})L_x-(\frac{1}{2}-p)L_x^2u^{''}(\bar{x})+(\frac{1}{6}-\frac{p}{2}+\frac{p^2}{2})L_x^3u^{'''}(\bar{x})-(\frac{1}{24}-\frac{p}{6}+\frac{p^2}{4}-\frac{p^3}{6})L_x^4u^{''''}(\bar{x}). \quad (5)$$

Similarly, we approximate $u^{'}(x_1)$ and $u^{'}(x_0)$ using a Taylor series to obtain

$$u^{'}(x_1)\approx u^{'}(\bar{x})+pL_xu^{''}(\bar{x})+\frac{(pL_x)^2}{2}u^{'''}(\bar{x})+\frac{(pL_x)^3}{6}u^{''''}(\bar{x}) \quad (6)$$

and

$$u^{'}(x_0)\approx u^{'}(\bar{x})-(1-p)L_xu^{''}(\bar{x})+\frac{((1-p)L_x)^2}{2}u^{'''}(\bar{x})-\frac{((1-p)L_x)^3}{6}u^{''''}(\bar{x}). \quad (7)$$

From equation (6) and (7), we can approximate and simplify the denominator of equation (2) as

$$pu^{'}(x_0)+(1-p)u^{'}(x_1)\approx u^{'}(\bar{x})+p(1-p)\frac{L_x^2}{2}u^{'''}(\bar{x})+p(1-p)(2p-1)\frac{L_x^3}{6}u^{''''}(\bar{x}). \quad (8)$$

Using equations (5) and (8), we can rewrite equation (2) as

$$WTP=\frac{dx}{dp}=\frac{1+(\frac{1}{2}-p)L_xR(\bar{x})+(\frac{1}{6}-\frac{p}{2}+\frac{p^2}{2})L_x^2D(\bar{x})+(\frac{1}{24}-\frac{p}{6}+\frac{p^2}{4}-\frac{p^3}{6})L_x^3K(\bar{x})}{1+\sigma_{\tilde{x}}^2D(\bar{x})+\mu_{3\tilde{x}}K(\bar{x})}L_x, \quad (9)$$

where $R(\bar{x})=-\frac{u^{''}(\bar{x})}{u^{'}(\bar{x})}$ is the Arrow-Pratt measure of absolute risk aversion, $D(\bar{x})=\frac{u^{'''}(\bar{x})}{u^{'}(\bar{x})}$ is the measure of local downside risk aversion introduced by Modica and Scarsini (2005) and Crainich and Eeckhoudt (2008), $K(\bar{x})=-\frac{u^{''''}(\bar{x})}{u^{'}(\bar{x})}$ is a measure of local kurtosis risk aversion, $\sigma_{\tilde{x}}^2=\frac{p(1-p)L_x^2}{2}=var(\tilde{x})$, $\mu_{3\tilde{x}}=p(1-p)(2p-1)\frac{L_x^3}{6}=skewness(\tilde{x})$. Equation (9) reveals that the WTP to reduce the probability of low-wealth is a product of a risk-neutral (linear utility) individual's marginal rate of substitution between x and p, L_x, and an adjustment term, $\frac{1+(\frac{1}{2}-p)L_xR(\bar{x})+(\frac{1}{6}-\frac{p}{2}+\frac{p^2}{2})L_x^2D(\bar{x})+(\frac{1}{24}-\frac{p}{6}+\frac{p^2}{4}-\frac{p^3}{6})L_x^3K(\bar{x})}{1+\sigma_{\tilde{x}}^2D(\bar{x})+\mu_{3\tilde{x}}K(\bar{x})}$. Therefore, we can use the WTP of risk-neutral agents as our benchmark for comparing homeowners' WTP with HORA. Using equation (9), we derive the partial effects of $R(\bar{x})$, $D(\bar{x})$, and $K(\bar{x})$ on WTP as follows:

$$\frac{\partial WTP}{\partial R(\bar{x})}=\frac{(\frac{1}{2}-p)L_x}{1+\sigma_{\tilde{x}}^2D(\bar{x})+\mu_{3\tilde{x}}K(\bar{x})}L_x \quad (10)$$

$$\frac{\partial WTP}{\partial D(\bar{x})}=\frac{(\frac{1}{6}-\frac{p}{2}+\frac{p^2}{2})(1+\mu_{3\tilde{x}}K(\bar{x}))L_x^2}{(1+\sigma_{\tilde{x}}^2D(\bar{x})+\mu_{3\tilde{x}}K(\bar{x}))^2}L_x \quad (11)$$

$$\frac{\partial WTP}{\partial K(\bar{x})}=\frac{(\frac{1}{24}-\frac{p}{6}+\frac{p^2}{4}-\frac{p^3}{6})(1+\sigma_{\tilde{x}}^2D(\bar{x}))L_x^3}{(1+\sigma_{\tilde{x}}^2D(\bar{x})+\mu_{3\tilde{x}}K(\bar{x}))^2}L_x. \quad (12)$$

Each of the partial effect (in equations (10), (11), and (12)) is the product of a risk-neutral agent's WTP and an adjustment term for which the sign and magnitude depends on the values of p, L_x, $D(\bar{x})$, and $K(\bar{x})$. The denominators of equations (9), (10), (11), and (12) increase in both the variance of wealth and downside risk aversion, but can either increase or decrease in kurtosis risk aversion depending on the sign of the skewness. Equation (10) reveals that when $p = \frac{1}{2}$ the numerator is zero and so is the partial effect. When $p < \frac{1}{2}$, the numerator is positive and increases in L_x and the denominator increases in $\sigma^2_{\tilde{x}}$ and $D(\bar{x})$ but decreases in $K(\bar{x})$ because $\mu_{3\tilde{x}}$ is negative. The intuition in the former case is that, when $p < \frac{1}{2}$, a decrease in p decreases the variance of wealth ($\sigma^2_{\tilde{x}}$), which is appealing to risk-averse agents. Hence, risk-averse agents are willing to pay more for the decrease in p. In the latter case, when $p < \frac{1}{2}$, a decrease in p increases the skewness of wealth ($\mu_{3\tilde{x}}$), making it less appealing to downside risk-averse agents, hence they are willing to pay less for the decrease in p. When $1 + \sigma^2_{\tilde{x}} D(\bar{x}) > |\mu_{3\tilde{x}} K(\bar{x})|$, the denominator is positive and so is the partial effect of $R(\bar{x})$ on WTP. Because the skewness ($\mu_{3\tilde{x}} K(\bar{x})$) is negative, when $1 + \sigma^2_{\tilde{x}} D(\bar{x}) < |\mu_{3\tilde{x}} K(\bar{x})|$, the denominator is negative and so is the partial effect of $R(\bar{x})$ on WTP. The opposing effects in the denominator imply an increase (decrease) in downside risk aversion and a decrease (increase) in kurtosis risk aversion will jointly increase (decrease) the denominator leading to a decrease (increase) in WTP. A decrease in the denominator, when $p < \frac{1}{2}$, increases WTP. On the contrary, when $p > \frac{1}{2}$, the numerator is negative and the denominator is positive and increases in both $D(\bar{x})$ and $K(\bar{x})$ because $\mu_{3\tilde{x}}$ is positive. This implies an increase (decrease) in only risk aversion will decrease (increase) WTP to reduce p. Intuitively, when $p > \frac{1}{2}$, a decrease in p increases $\sigma^2_{\tilde{x}}$ which is appealing to risk-loving agents, thus they put a positive value on it and are willing to pay more for the decrease in p. However, when $p > \frac{1}{2}$, a decrease in p decreases the skewness of wealth ($\mu_{3\tilde{x}}$), hence downside risk-averse agents are willing to pay more for a decrease in p.

Similarly, equation (11) reveals that when $p > \frac{2}{5}$ and $K(\bar{x}) > \frac{1}{\mu_{3\tilde{x}}}$, the numerator is negative and so is the partial effect, implying an increase (decrease) in downside risk aversion decreases (increases) WTP to reduce p. When $p < \frac{2}{5}$ and $K(\bar{x}) < \frac{1}{\mu_{3\tilde{x}}}$, the numerator is positive and so does the partial effect.

Equally, equation (12) reveals that the partial effects of kurtosis risk aversion (temperance) depend on a critical initial probability of loss. When $p = \frac{1}{2}$ the numerator is zero and so is the partial effect. When $p < \frac{1}{2}$, the numerator is positive and increases in L_x, indicating that an increase (decrease) in kurtosis risk aversion will increase (decrease) WTP to reduce p. On the contrary, when $p > \frac{1}{2}$, the numerator is negative and an increase (decrease) in kurtosis risk aversion will decrease (increase) WTP to reduce p.

Given that higher order risk attitudes are correlated, we need to simultaneously evaluate all three partial effects when examining the effects of one measure of risk attitude on the marginal WTP to reduce the probability of loss. This yields the total effect. Proposition 1 summarizes the total effect for specific scenarios under which the joint effects of second, third, and fourth order risk attitudes on marginal WTP is unambiguous. These are scenarios in which a change in risk attitude generally leads to either (i) an increase in the numerator and a decrease in the denominator of the adjustment term in all three partial effects or (ii) a decrease in the numerator and an increases in the denominator of the adjustment term in all three partial effects. This allows us to predict WTP of mixed risk averters/lovers relative to risk-neutral benchmarks.

Proposition 1.1
When $p = \frac{1}{2}$, all risk averse/loving, prudent, and (in)temperate agents will choose a lower WTP for precaution than a second or third degree risk-neutral agent.

Proposition 1.2
When $\frac{2}{5} < p < \frac{1}{2}$, $K(\bar{x}) > \frac{1}{\mu_{3\tilde{x}}}$, and $R(\bar{x})$ and $K(\bar{x})$ are positively correlated with $D(\bar{x})$, all risk averse, prudent, and temperate agents will choose a higher WTP for precaution than a second or third degree risk-neutral agent.

Proposition 1.3
When $p < \frac{2}{5}$, $K(\bar{x}) < \frac{1}{\mu_{3\tilde{x}}}$, and $R(\bar{x})$ and $K(\bar{x})$ are positively correlated with $D(\bar{x})$, all risk averse, prudent, and temperate agents will choose a higher WTP for precaution than a second or third degree risk-neutral agent.

Proposition 1.4
When $\frac{2}{5} < p < \frac{1}{2}$, $K(\bar{x}) > \frac{1}{\mu_{3\tilde{x}}}$, and $R(\bar{x})$ and $K(\bar{x})$ are positively correlated with $D(\bar{x})$, all risk loving, imprudent, and intemperate agents will choose a lower WTP for precaution than a second or third degree risk-neutral agent.

Proposition 1.5
When $p < \frac{2}{5}$, $K(\bar{x}) < \frac{1}{\mu_{3\tilde{x}}}$, and $R(\bar{x})$ and $K(\bar{x})$ are positively correlated with $D(\bar{x})$, all risk loving, imprudent, and intemperate agents will choose a lower WTP for precaution than a second or third degree risk-neutral agent.

Proposition 1.6
When $p > \frac{1}{2}$ and $R(\bar{x})$ and $K(\bar{x})$ are positively correlated with $D(\bar{x})$, all risk loving, imprudent, and intemperate agents will choose a higher WTP for precaution than a second or third degree risk-neutral agent.

Proposition 1.7
When $p > \frac{1}{2}$ and $R(\bar{x})$ and $K(\bar{x})$ are positively correlated with $D(\bar{x})$, all risk averse, prudent, and temperate agents will choose a lower WTP for precaution than a second or third degree risk-neutral agent.

One interesting and novel prediction of this analysis is that an increase in downside risk aversion, relative to a risk-neutral benchmark, will reduce the marginal WTP for precautionary building codes. Mathematically, this stems from the fact that an increase in downside risk aversion increases the denominator of equations (9), (10), (11), and (12). Intuitively, if one invests in precautionary building standards and a loss still occurs, say due to a category 5 hurricane, one will be worse off because their final wealth will be much lower compared to a scenario with no investment in precaution. Therefore, a prudent agent may invest less in precaution to increase their final wealth in the loss state, especially if the likelihood of a loss occurring is sufficiently high. In other words, an increase in downside risk aversion causes a greater increase in marginal utility in a low-wealth state, resulting in a higher utility cost of sacrificing wealth when a loss occurs. This subdues agents' willingness to sacrifice wealth to reduce the probability of loss.

Our theoretical results complement and extend those developed by Eeckhoudt and Gollier (2005), Jindapon (2013) and Crainich et al. (2015). Additionally, Peter (2021) finds similar results using risk-neutral benchmarks to examine optimal prevention of agents with the same second and third order risk preference comparative static predictions. By examining the total effects of risk attitudes up to the fourth order for both risk averse and risk-loving agents, we estimate a tighter range of critical initial probabilities of loss and constraints on which an individual's WTP to reduce the probability of loss hinges. This allows us to develop more precise and reliable conditions under which WTP can unambiguously be increased or decreased for individuals exhibiting higher order risk attitudes. Our results also demonstrate that the critical initial probability required to interpret the effects of second and fourth order risk attitudes on WTP are identical.

Although we can confidently assume that the initial probability of windstorm related loss $p < \frac{1}{2}$, it is clear that the degrees to which higher order risk attitudes effect WTP for precautionary building standards are best addressed as empirical questions. If we assume that $p < \frac{2}{5}$ and that $WTP \geq 0$, in line with our WTP experimental design, two clear testable hypotheses emerge as follows.

Hypothesis 1: When $p < \frac{2}{5}$, and $R(\bar{x})$ and $K(\bar{x})$ are positively correlated with $D(\bar{x})$, all risk averse, prudent, and temperate agents will choose a higher WTP for precaution than a second or third degree risk-neutral agent.

Hypothesis 2: When $p < \frac{2}{5}$, and $R(\bar{x})$ and $K(\bar{x})$ are positively correlated with $D(\bar{x})$, all risk loving, imprudent, and intemperate agents will choose a lower WTP for precaution than a second or third degree risk-neutral agent.

We test these relationships and seek to unbundle others in a field experiment that elicits risk attitudes and WTP for precautionary building standards, using levels of precautions (Fortified home designations) and premium discounts that are available to participants in our sample. As outlined in section 4.2 below, our experimental design also tests for causal effects of information friction and ending-point bias in a payment card WTP experiment.

3.2 Risk apportionment

Eeckhoudt and Schlesinger (2006) and Eeckhoudt et al. (2009) describe risk attitudes based on principles of risk apportionment. Let $M > 0$, $z_1 > 0$, and $z_2 > 0$ be strictly positive monetary outcomes. Consider two lotteries $A = [M, M - z_1 - z_2]$ and $B = [M - z_1, M - z_2]$, each with equally likely outcomes. A risk-averse individual will prefer B over A for all possible values of M.

Eeckhoudt and Schlesinger (2006) relate the preference for B over A as a preference for "disaggregating the harms" and term it risk apportionment of order two. In this case z_1 and z_2 represent the "harms." Prudence is characterized as a preference for disaggregating a zero-mean risk v and a sure loss of wealth z_2, across two equally likely states of nature. To elicit prudence with lotteries A and B, the authors replace one of the harms of a sure loss with v resulting in $A = [M, M + v - z_2]$ and $B = [M + v, M - z_2]$. A preference for lottery B over A for all values of M, $z_2 > 0$, and v defines prudence and satisfies a convex marginal utility under EUT. Intuitively, this means prudent individuals prefer adding a zero-mean risk to a higher wealth level than to a lower wealth level. Similarly, they characterize temperance as a preference for disaggregating two independent zero-mean risks (v and e). A temperate individual will prefer $B = [M + v, M + e]$ over $A = [M, M + v + e]$. These choices will be consistent with any model of preference with an increasing, concave, and continuously differentiable utility function (u) with alternating pattern of signs of successive derivations such that the sign of $u^n(.) = (-1)^{(n+1)}$ for $n = 1, ..., N$. These restrictions produce results consistent under EUT and $non - EUT$ models.

Using a similar theorem, Deck and Schlesinger (2014) posit that mixed risk individuals – with preferences for combining "good with good," and "bad with bad" – satisfy risk apportionment of order n when n is odd, but dislike risk apportionment when n is even. As such, risk averters and risk lovers are predicted to demonstrate similar preferences when n is odd and dissimilar preferences when n is even. Based on this theorem, mixed-risk lovers are expected to be prudent but intemperate. Whether or not risk averters are indeed mixed-risk averters and risk lovers are mixed-risk lovers in practice is an empirical question our study also seeks to answer. Because the uptake of precautionary building standards for hurricane-related losses reveals aversion to downside risk, or prudence, we expect both risk lovers and risk averters to have a positive association between prudence and level of precaution.

Willingness to pay estimates are commonly used to guide public policy. Promoting stronger building standards is key to disaster risk management and economic resilience. Determining specific codes to promote in specific risk environments needs to also account for homeowners' WTP. The latter could vary significantly depending on exposure, information, and risk attitudes. Gaining insight on the prevalence of

HORA and their relationship with homeowners' WTP could help guide the selection and promotion of an optimal portfolio of loss mitigation features and subsidies for targeted segments of the population.

4 Experimental design

4.1 Higher Order Risk Attitude experiment

We employ a series of 50-50 model-free risk apportionment lotteries (Eeckhoudt and Schlesinger, 2006) to measure the first four orders of homeowners' risk preferences in two coastal counties in the U.S.[14] Subjects were presented with 14 lottery pairs (Table 1) and were asked to choose the preferred option.[15] Two tasks seek to measure monotonicity, or the principle that "more money is preferred to less." Four tasks each measure second, third, and fourth order risk preferences. In each case, if option B is chosen over A, it implies the individual prefers more money to less (first order), is risk averse (second order), prudent (third order), and temperate (fourth order). This design sufficiently varies in the lottery pairs within each category, enabling us to elicit second, third, and fourth order risk attitudes with reasonable confidence. [16]

Following Deck and Schlesinger (2014), we presented each choice task as a lottery with equally likely payoffs depicted as cash amounts in association with other lotteries to ease understanding and to enable respondents to see it as combining "good with bad" or combining "good with good." In addition to written descriptions and instructions (see Online Appendix 2) made available to respondents, we created and uploaded short video clips describing the risk preference choice tasks in detail using a visual example. We required participants to watch the clips and confirm their understanding before engaging in the choice tasks. The tasks appeared to survey participants in random order.

We paid each participant $40 for taking part in the survey. In addition, each earned a bonus of $0 to $60 depending on the outcomes of two randomly selected lotteries. Details on the bonus calculation including examples were made available to all respondents. Total potential compensation earned by each survey participant ranged from $40 to $100, which is substantial compared to compensation offered in other studies, as well as the median hourly wage in the counties where we implemented the survey. Online Appendix 2 provides more detail examples of the lottery choice tasks and bonus calculation.

[14] We also elicited homeowners risk attitudes using a price-list experiment à la Tanaka et al. (2010), except that we do not enforce monotonicity. The lotteries are also specified in the gain domain in terms of loss reductions from retrofitting a house. We analyze and compare results from the two experiments in a separate paper that addresses issues beyond the scope of this study, and also for brevity.

[15] These lotteries are adapted from those used in the experiment by Deck and Schlesinger (2014). The full lottery design used by the authors was intended to broadly investigate consistency in risk attitudes, an objective we do not pursue in this study.

[16] Note that the 50-50 model free generic lotteries used are not framed in the windstorm loss domain and generally imply that the probability of loss or low-wealth state is $\frac{1}{2}$ in second order lotteries, $\frac{1}{4}$ in third order lotteries, and $\frac{1}{8}$ in fourth order lotteries.

Table 1: Choice tasks

Task	Order	Option A	Option B
1	1	$20	$20 + $10
2	1	[$2+[$10,$20],$20]	[$25,$27+[$-1,$1]]
3	2	[$5, $10+$5]	[$5+$5, $10]
4	2	[$2, $4+$8]	[$2+$8, $4]
5	2	[$2, $4+$3]	[$2+$3, $4]
6	2	[$20, $40+$30]	[$20+$30, $40]
7	3	[$5+[$-2,$2],$10]	[$5,$10+[$-2,$2]]
8	3	[$10+[$-4,$4],$20]	[$10,$20+[$-4,$4]]
9	3	[$8+[$2,$-2],$10]	[$8,$10+[$2,$-2]]
10	3	[$12+[$1,$-1],$14]	[$12,$14+[$1,$-1]]
11	4	[[$14,$20]+[$14,$20],[$10,$24]+[$10,$24]]	[[$10,$24]+[$14,$20],[$14,$20]+[$10,$24]]
12	4	[[$7,$10]+[$7,$10],[$5,$12]+[$5,$12]]	[[$5,$12]+[$7,$10],[$7,$10]+[$5,$12]]
13	4	[$14+8A, $24+8B]	[$14+8B,$24+8A]
14	4	[$7+7A,$12+7B]	[$7+7B,$12+7A]

Source: Adapted from Deck and Schlesinger (2014)

4.2 Willingness to Pay (WTP) Experiment

We elicited homeowners' WTP for *Fortified* using a payment card experiment. We did not incentivize the payment card responses. We acknowledge a segment of the literature that is critical of hypothetical WTP elicitation (Cummings et al., 1995, 1997). Following our experiment, we observed a series of contractor bids for *Fortified* retrofits. Our WTP estimates are reasonably similar to the accepted bids. Moreover, professionals who perform and evaluate *Fortified* retrofits agree that our average estimates are similar to their experience. Although our confidence is bolstered by these observations, we cannot fully dismiss the possibility of hypothetical bias.

Our experimental design involves four attributes, each with two or three levels. The main attributes, *Fortified* designation and premium discount, have two (*Fortified* Bronze and *Fortified* Silver) and three (20%, 35% and 45%) attribute levels, respectively. The premium discounts capture the reduction in expected windstorm loss due to *Fortified* home standards, and are based on estimates from commercial catastrophe models. Note that Alabama law mandates insurance premium discounts on the wind portion of premium[17] by 20% and 35% for *Fortified* Bronze and 35% and 45% for *Fortified* Silver, depending on the age of the roof.[18]

The payment card method is the most widely used in contingent valuation studies. However, empirical evidence shows that it is also vulnerable to range bias when the range of payment values offered to survey participants does not cover their desired distribution(Rowe et al., 1996; Whitehead, 2002). Starting point

[17]The wind portion of homeowners insurance premiums ranges from 60% to 80% of total premium in our sample region.

[18]The smaller discount applies if a roof is more than five years old.

bias, in which WTP estimates are sensitive to the amount of the lower range bound, has been widely investigated(Covey et al., 1989; Cameron and Huppert, 1991; Boyle et al., 1985) whereas ending-point bias (sensitivity of WTP estimates to the upper range bound) has received less attention. To test for this potential drawback in our research design, we introduce payment card WTP range as an attribute and consider two payment card ranges. The first has a low upper bound, ranging from $0 to $25,000 ($0, $2,500, $5,000, $7,500, $10,000, $12,500, $15,000, $17,500, $20,000, ≥ $25,000), henceforth "$WTP_{LUB}$." The second has a high upper bound, ranging from $0 to $35,000 ($0, $2,500, $5,000, $7,500, $10,000, $12,500, $15,000, $17,500, $20,000, $25,000, $30,000, ≥ $35,000) henceforth "$WTP_{HUB}$." In addition to testing for bias, using multiple endpoints partially mitigates the effects of endpoint bias in our estimates.

As a final attribute of our survey design, we randomly assign half of the survey respondents to watch a video from the IBHS lab demonstrating the performance of *Fortified* and conventional homes side-by-side in the face of hurricane-speed winds.[19] In this video, the conventional home quickly collapses; while the *Fortified* home remains undamaged. This treatment allows us to gauge the effect of information friction on the performance of *Fortified* versus conventional home construction on homeowners' WTP. We hypothesize that seeing the video will reduce information friction and increase confidence in the attributes and performance of *Fortified*, resulting in higher WTP for precautionary standards. Table 2 summarizes the attributes and attribute levels in our design and Appendix 1 illustrates a WTP question.

Table 2: Attributes and attribute levels of WTP experiment

Attributes	Attribute levels
Fortified designation	Bronze, Silver
Insurance premium discount	20%, 35%, 45%
Payment card WTP range	WTP_{LUB} ($0 ≥ $25,000), WTP_{HUB} ($0 ≥ $35,000)
Information on performance of *Fortified*	watched video, no video

The full factorial experimental design based on the four attributes and attribute levels includes 24 unique combinations. By implementation, we indirectly block the full factorial into four treatment blocks based on whether or not the participant watched the video and the payment card range. These blocks include (i) no video, WTP_{LUB} (ii) watched video, WTP_{LUB} (iii) no video, WTP_{HUB} and (iv) watched video, WTP_{HUB}. Each block has all possible combinations of *Fortified* designation and insurance discount attribute levels, but different combinations of payment card range and information on the performance of *Fortified* versus conventional construction. Each homeowner is randomly assigned to one block and thus responds to six hypothetical WTP questions elicited with all six attribute level combinations of *Fortified* designation and insurance premium discount (Bronze, 20%; Bronze, 35%; Bronze, 45%; Silver, 20%; Silver, 35%; and Silver, 45%). An exemplar question presented to each respondent appears in Online Appendix

[19] Watch the video at https://tinyurl.com/fortified-video or https://vimeo.com/17764719.

1.

Our experimental design and data enable us to empirically test for causal relationships between information friction, payment card range, and WTP for precautions. Formally stated, our experimental hypotheses are as follows.

Hypothesis 3: Information friction decreases homeowners' WTP for *Fortified* houses. Homeowners who watch the video illustrating the performance of *Fortified* and conventional homes side-by-side under hurricane-like winds will choose a higher WTP than those who did not.

Hypothesis 4: Endpoint bias in the payment card approach affects agents' WTP for *Fortified* houses.

Therefore, our study seeks to unbundle and empirically test two hypotheses relating HORA and WTP for precautionary bulding standards, one hypothesis relating information friction and WTP for *Fortified*, and another testing ending-point bias in WTP payment card design.

The WTP experiment was implemented as part of an online survey of homeowners insurance in Mobile and Baldwin counties in Alabama. We elicited homeowners' risk preferences up to the fourth order using 50-50 risk apportionment lotteries (Deck and Schlesinger, 2014). In addition, the survey collected information about precautionary home investments against windstorm risk, risk perception, socio-demographic information, and housing data.

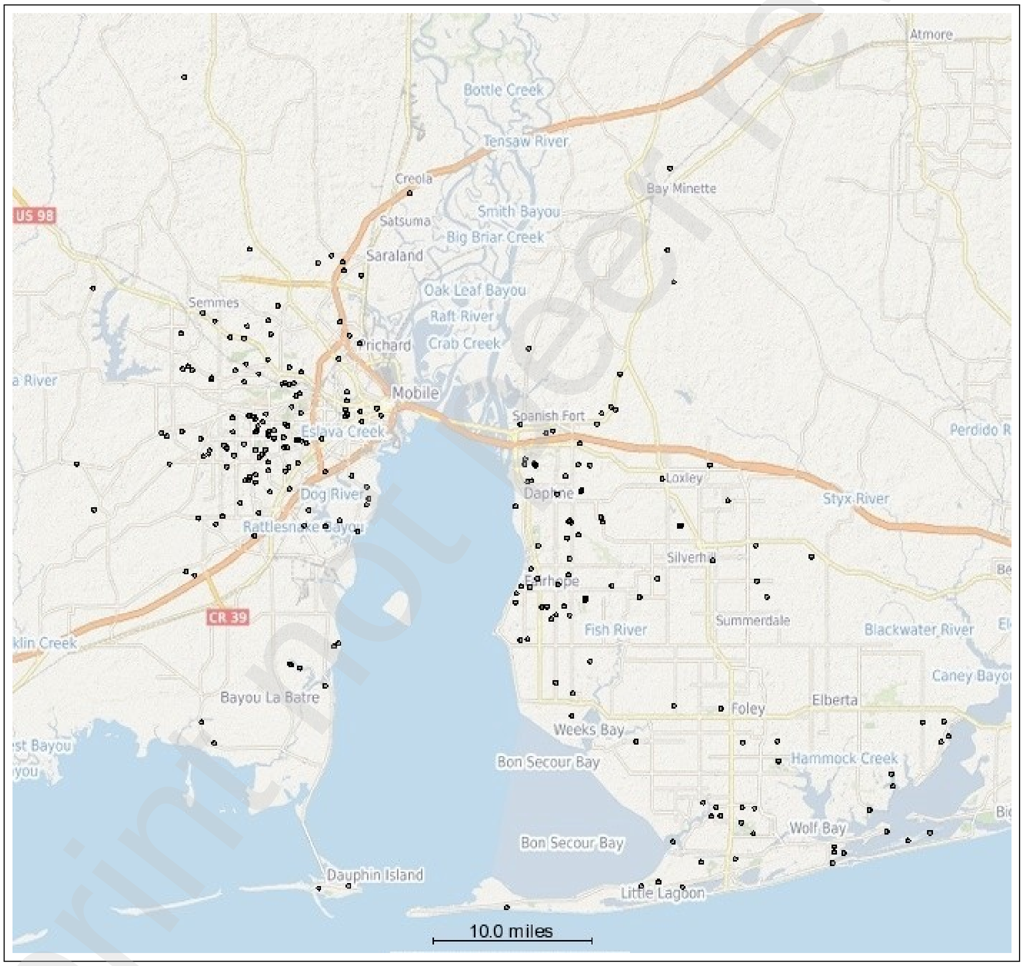
We pretested an initial version of the survey in face-to-face interviews with a total of 16 participants in three successive sessions. We updated the survey after each session to ensure the questions were unambiguous. Results from the final round of pretesting show that participants generally understood the survey content.

Using 2015 property tax data from Mobile and Baldwin counties as the population, we obtained a random sample of 6,500 homeowners. To increase the chances of obtaining a representative sample, we stratified the survey design by county, wind speed zone, flood risk zone, and property value. We conducted random sampling at the block-level, allocating sample size across blocks by population. The survey was administered to the random sample of homeowners during summer of 2016.

We solicited participants by mail using a cover letter including the survey link and password, as well as an RSVP card with five options for indicating a recipient's intention to participate in the survey, and whether or not they needed assistance (via telephone, online, or in-person) in taking the survey. We followed up with the target sample through two waves of reminders mailed out every fourth day following the initial solicitation, in addition to phone calls and emails to those who returned a response card. To access and complete the online survey, an individual must have been at least 18 years old, a resident of either Mobile or Baldwin County, and a homeowner living in an owner-occupied property.

We identified homeowners who had not adopted any level of *Fortified* designation using preliminary questions, and directed them to participate in the WTP section of the survey.[20] Homeowners indicated that lack of information on *Fortified* and initial cost of investment are the top reasons they have not adopted *Fortified* building standards, thus emphasizing the importance of our research questions. In the end, we received 213 WTP survey responses. Figure 1 shows the locations of survey respondents. Our sample includes a diverse group of respondents with respect to neighborhood value and relative windstorm risk (measured by distance from the coast). Each survey participant was paid \$40 participation fees and up to \$60 in bonus based on their responses to randomly selected experimental question.

Figure 1: Location of survey respondents



[20]We address the potential sample selection bias created by this filter in Section 6.

5 Data summary and multiple hypothesis tests

Table 3 reports summary statistics for the variables in our analysis. Monotonic choices is the number of times option B is chosen over option A out of two lottery choice tasks (showing that "more money is preferred to less"). Safe choices is the number of times (out of four) option B is chosen over option A, indicating the homeowner is risk averse. Similarly, Prudent choices and Temperate choices are the number of times (out of four) option B is chosen over option A, indicating the homeowner is downside risk averse or kurtosis risk averse, respectively. Option B is chosen more than half of the times in each category of choices indicating that, on average, homeowners prefer more money to less, and are risk averse, prudent, and temperate.

For the WTP variables, Bronze/Silver and 20%/35%/45% are the WTP for each combination of precaution level and insurance-premium discount percentage. "Watched video" and "no video" indicate homeowners who watched and did not watched the video illustrating the performance of *Fortified* relative to conventional homes prior to responding to the WTP questions. Low upper bound and high upper bound indicate the treatment block assigned based on the payment card range. Hurricane risk perception is the number of category-three hurricanes (wind speed $>$110 mph) a homeowner anticipates affecting their community in the next 50 years. Income is household income, calculated using the midpoints of income ranges selected by survey participants.[21] We use the natural logarithm of income in subsequent tests. Female is a dummy variable equal to one if the survey respondent is female. House size is square feet of living area in the house.

Observed WTP ranges from \$0 to \$17,500 for homeowners who were assigned to the payment card with a low upper bound (WTP_{LUB}) and from \$0 to \$25,000 for homeowners who were assigned to the high upper bound (WTP_{HUB}), indicating that our data are only left-censored.[22] Results reported in Table 3 suggest that homeowners are willing to pay more for stronger building standards and corresponding homeowners insurance premium discounts. The average WTP ranges from \$1,955 for *Fortified* Bronze with 20% premium discount to \$3,509 for *Fortified* Silver with 45% premium discount.

The average WTP for homeowners who watched the video demonstrating the performance of *Fortified* houses before stating their WTP is nominally higher than that of those who did not watch the video; however, the difference (\$178.88) is not statistically significant (p-value=0.35).

The average WTP in the four design treatment blocks ranges from \$2,175 for homeowners who watched the video and were assigned WTP_{LUB} to \$3,526 for those who watched the video and were assigned WTP_{HUB}. On average, homeowners who were assigned WTP_{HUB} have higher WTP than those assigned WTP_{LUB}. However, watching the video, on average, increases the WTP among those assigned WTP_{HUB}

[21] The maximum income category is "greater than \$250,000 per year." We insert the income value \$275,000 for the handful of respondents that selected this range. While this is in part a judgment call, \$275,000 is approximately two standard deviations from the mean income if we exclude the highest category. Results and conclusions are not sensitive to alternative choices for highest income level. We use percentiles of income, rather than the mean, when predicting WTP later in the article.

[22] Figure A1 in Appendix 3 shows the full distribution of WTP responses.

but not among those assigned WTP_{LUB}.

Table 3: Data summary

Variable	Count	Mean	Std. Dev.	Min.	Max
Monotonic choices	191	1.7	0.6	0	2.0
Safe choices	191	2.6	1.4	0	4.0
Prudent choices	191	2.7	1.4	0	4.0
Temperate choices	191	2.3	1.1	0	4.0
WTP: Bronze with 20% discount	211	1,955	2,673	0	15,000
WTP: Bronze with 35% discount	212	2,618	3,432	0	25,000
WTP: Bronze with 45% discount	209	3,313	4,050	0	25,000
WTP: Silver with 20% discount	213	2,078	2,924	0	17,500
WTP: Silver with 35% discount	213	2,664	3,171	0	17,500
WTP: Silver with 45% discount	213	3,509	4,061	0	20,000
WTP: Watched video	107	2,778	3,523	0	25,000
WTP: No video	105	2,599	3,407	0	25,000
WTP: Low upper bound, no video	49	2,262	2,738	0	15,000
WTP: Low upper bound, watched video	59	2,175	3,324	0	17,500
WTP: High upper bound, no video	57	2,892	3,878	0	25,000
WTP: High upper bound, watched video	48	3,526	3,624	0	25,000
Hurricane risk perception	213	2.9	1.8	0	6.0
Income	199	76,533	54,591	10,000	275,000
Female	213	0.5	0.5	0	1.0
House size	213	2,140	803	800	5,600

Note: Monotonic choices is the number of choices (out of 2) indicating the respondent prefers more to less. Safe/Prudent/Temperate choices is the number of choices (out of 4) indicating respondent is risk averse/prudent/temperate. The variables beginning with WTP are willingness-to-pay responses for the six combinations of precaution and premium discount. Hurricane risk perception is the number of category three hurricanes the respondent expects will affect their community in the next 50 years. Income is household income. Female is a dummy variable equal to one if respondent is female. House size is square feet of living space. Count varies when respondents choose not to answer a question or when questions are randomly assigned.

Next, we classify individuals into categories of second, third, and fourth order risk subgroups based on choice counts. We classify homeowners who chose option B zero or one time out of four choice tasks used to elicit second-degree risk attitudes as risk lovers. Those who chose option B two times out of the four choice tasks are risk neutral, and those who chose B three or four times are risk averse.

Similarly, we classify homeowners as imprudent, prudence neutral, and prudent if they have zero or one count, two counts, and three or four counts, respectively. We classify homeowners as intemperate, temperance neutral, and temperate in the same way based on the results of the fourth-degree risk attitudes choice tasks. Table 4 reports the frequency distribution of second, third, and fourth degree risk attitudes by risk categories. Results reveal high prevalence of risk-averse, prudent, and temperate homeowners. A two-sided Wilcoxon sign rank test and t-tests comparing the observed counts to a randomly-generated sample reject the null hypothesis that the counts from both samples are equal at the 1% level.

Figure 2: Frequency distribution of homeowners risk attitudes

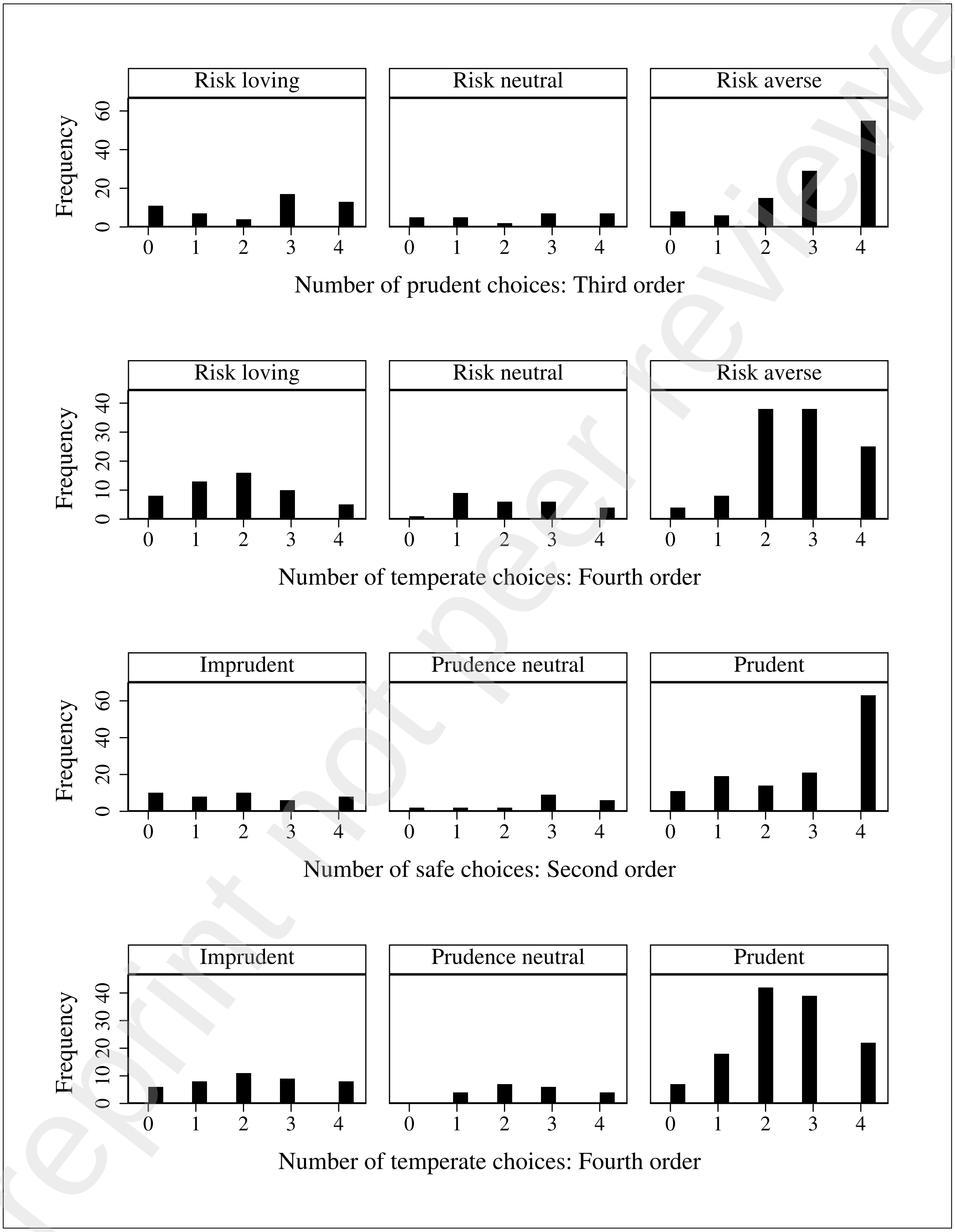


Table 4: Frequency distribution of Higher Order Risk Attitudes (N=191)

	Risk loving	Risk neutral	Risk averse
Second degree	52	26	113
Third degree	42	21	128
Fourth degree	43	60	88

Figure 2 presents frequency distributions of homeowners risk attitudes by second and third order risk classification. The top two rows show the frequency distribution of third and fourth order risk attitudes for risk lovers, risk-neutral agents, and risk averters. The lower two rows depict the distribution of second and fourth order risk attitudes by third-order risk classification. The figures suggest that homeowners are most likely to be risk averse, prudent, and temperate.

5.1 Multiple Hypothesis Testing

We conduct Multiple Hypothesis Testing (MHT) to test for heterogeneous treatment effects among experimental blocks and risk attitude subgroups. In MHT, a cluster of hypotheses is tested simultaneously, while properly adjusting for the likelihood of committing type I errors and reaching false positives. We follow the same process as List et al. (2016), who apply four methods to adjust standard errors for multiplicity. They develop two novel measures and compare them to existing methods proposed by Bonferroni (1935) and Holm (1979).

Table 5 presents results of MHT comparing the four treatment blocks. The difference in mean WTP between the "WTP_{LUB} / no video" and "WTP_{HUB} / no video" and between the "WTP_{LUB} / watched video" and "WTP_{HUB} / watched video" treatment blocks are positive and significantly different from zero at at the 9% level or less, using all four multiplicity adjustment methods. Consistent with ending-point bias in the WTP payment card experiment, this indicates that homeowners exposed to a higher payment card range choose a higher WTP than those exposed to a lower payment card range. Additionally, the difference in mean WTP between the "WTP_{LUB} / no video" and "WTP_{LUB} / watched video" treatment is not significantly different from zero using all four methods while that between the "WTP_{HUB} / no video" and "WTP_{HUB} / watched video" treatments is positive and significantly different from zero at the 9% level, using three of the four methods. These results are consistent with a negative effect of information friction on WTP, because homeowners who watched the *Fortified* demonstration video and were assigned to the higher upper bound payment card chose a significantly higher WTP than those who did not watch the video. Generally, the results depicted in Table 5 also suggest that having a sufficiently high upper bound is necessary to capture the effects of information friction on WTP for precautions.

Next, we measure the video (information friction) treatment effect within risk attitude subgroups. Results of the MHT appear in Table 6. We find statistically significant differences in mean WTP (at the 6%

Table 5: MHT: Comparing average WTP across treatment blocks

Treatment block 1	Treatment block 2	Diff.	Unadj	LXS1	LXS2	Bonf	Holm
WTP_{LUB} / no video	WTP_{LUB} / watched video	-87	0.708	0.708	0.708	1	0.708
WTP_{LUB} / no video	WTP_{HUB} / no video	630	0.014	0.037	0.014	0.084	0.042
WTP_{LUB} / no video	WTP_{HUB} / watched video	1,264	0.000	0.000	0.000	0.002	0.002
WTP_{LUB} / watched video	WTP_{HUB} / no video	717	0.012	0.040	0.032	0.074	0.049
WTP_{LUB} / watched video	WTP_{HUB} / watched video	1,351	0.000	0.000	0.000	0.002	0.002
WTP_{HUB} / no video	WTP_{HUB} / watched video	634	0.037	0.072	0.037	0.222	0.074

MHT abbreviates Multiple Hypothesis Testing. Diff. is the mean WTP for treatment block 2 minus that of treatment block 1. Unadj is the unadjusted p-value. LXS1 and LXS2 are p-values obtained by applying correction procedures proposed by List et al (2015) to Unadj. Bonf and Holm are p-values obtained by applying Bonferroni adjustment and Holm adjustment, respectively to Unadj.

level or less) in three of the four mixed risk-loving subgroups and none within mixed risk-averse subgroups. These results suggest a positive relation between information friction and WTP for mixed risk lovers. The effect of information friction appears highest among risk-loving, prudent, temperate homeowners. To explain this result, we lean on results from our WTP theory and argue that homeowners who are risk-lovers are also ambiguity-lovers (Brunette et al., 2014). Exposing this group to the video information treatment reduces their ambiguity around the effectiveness of *Fortified* and the uncertainty of wealth, thereby negatively affecting their WTP for the precaution. This explanation is analogous to the effect of reducing the initial probability of loss on the variance of wealth revealed in our theoretical findings.

The results in Table 6 also highlight the multiplicity problem in the risk-loving, prudent, intemperate subgroup whose statistical significance at the 5% level disappears after adjusting the p-values for multiplicity.

Table 6: MHT: Comparing information friction treatment effect within risk attitude subgroups

Risk attitude subgroup	Diff.	Unadj	LXS1	LXS2	Bonf	Holm
Risk-loving/imprudent/intemperate	-2,014	0.000	0.002	0.002	0.002	0.002
Risk-loving/imprudent/temperate	-1,250	0.008	0.044	0.044	0.058	0.042
Risk-loving/prudent/intemperate	-2,778	0.045	0.172	0.172	0.317	0.181
Risk-loving/prudent/temperate	-3,103	0.000	0.000	0.000	0.002	0.002
Risk-averse/imprudent/temperate	111	0.879	0.879	0.879	1	0.879
Risk-averse/prudent/intemperate	139	0.869	0.983	0.983	1	1
Risk-averse/prudent/temperate	142	0.698	0.969	0.969	1	1

MHT abbreviates Multiple Hypothesis Testing. Diff. is the difference in means for participants who watched the IBHS video minus that of those who did not watch the video. Unadj is the unadjusted p-value. LXS1 and LXS2 are p-values obtained by applying correction procedures proposed by List et. al (2015) to Unadj. Bonf and Holm are p-values obtained by applying Bonferroni adjustment and Holm adjustment, respectively to Unadj. We omit the risk-averse/imprudent/intemperate category due to small sample size.

6 Regression analysis, results, and discussion

We use regression analysis to assess the heterogeneous treatment effects on WTP for precautionary building standards across risk attitude subgroups. This allows us to test the theoretical predictions and hypotheses while controlling for socio-demographic and housing variables. Multivariate analysis demonstrates the validity of our experimental design, and boosts confidence in our results above what can be gleaned from the multiple hypothesis tests.

Homeowners could place negative values on investments in precaution, but the lowest WTP choice in our experiment is zero. Therefore, we estimate hurdle models with the full-sample and risk attitude subsamples to account for the left-censored data. With several such models available, we perform a series of tests to determine the best specification for our analysis.

The original Tobit model is a natural starting place. It is limited by the requirement to use the same variables in estimating the first (discrete participation) and second stage (continuous amount) equations. However, unlike Cragg's model, which can use different variables for the first and second stages, the Tobit model can accommodate panel data.

First, we estimate pooled and panel-level random-effects Tobit models. A likelihood ratio test between pooled and random-effects models rejects the null hypothesis that the variance of random-effects is zero, indicating that the panel structure of our data has significant effects on our estimates.[23] We then compare the results from the pooled Tobit model to those from Cragg's hurdle model,[24] revealing nearly identical results, which suggests that the limitation of requiring identical variables for both stages of estimation is not binding for our analysis.

Sample selection bias is another potential econometric concern, as we only include responses from homeowners who do not already live in *Fortified* houses. We address this concern by estimating Heckman selection models. Again, the results of the Heckman model are quite similar to those estimated using the pooled Tobit model, indicating that sample selection bias does not affect our results.[25] Given the presence of panel effects and the absence of other potential problems (model constraints and sample selection), we ultimately choose the random-effects Tobit model for our analysis.

Table 7 presents the results of five nested random-effects Tobit regression models with WTP as the dependent variable, left censored at zero. Model 1 is based on the attribute levels in the experimental design. Models 2-5 include additional controls for demographics (house size, income, and gender), hurricane risk perception, and number of choices associated with each HORA (risk aversion, prudence, and temperance), to gauge the robustness of results from Model 1. In all models, indicator variables for *Fortified* Bronze, 20%

[23] Note that the interpretation of WTP in the Tobit model is based on the unobserved or latent variable (WTP^*). For $WTP \leq 0$ (left-censored), it is with respect to WTP^*, for $0 < WTP <= 25,000$, observed $WTP = WTP^*$ and for $WTP > 25,000$, the dependent variable is latent.

[24] These results appear in Online Appendix 3.

[25] These results are presented and discussed in Online Appendix 3.

premium discount and WTP_{LUB} / no video are the baseline categories.

Table 7: Random-effects Tobit regression models, full sample

	Model 1	Model 2	Model 3	Model 4	Model 5
Fortified Silver	190	183	201	200	200
	(126)	(128)	(128)	(128)	(128)
35% ins discount	1,162**	1,119**	1,128**	1,128**	1,128**
	(157)	(160)	(160)	(160)	(160)
45% ins discount	2,375**	2,353**	2,298**	2,298**	2,298**
	(157)	(159)	(159)	(159)	(159)
WTP_{LUB} / watched video	-404	-36	-773	-807	-1,007
	(1,235)	(1,091)	(988)	(965)	(965)
WTP_{HUB} / no video	1,068	1,054	282	197	119
	(1,250)	(1,122)	(974)	(951)	(944)
WTP_{HUB} / watched video	2,566*	2,382*	2,125*	2,155*	1,867^{+}
	(1,283)	(1,140)	(1,004)	(980)	(989)
Hurricane risk perception		393^{+}			
		(230)			
Female		-608			
		(807)			
Income		1,773**	1,498**	1,472**	1,512**
		(504)	(438)	(429)	(426)
House size		1,311^{+}	1,239*	1,153^{+}	1,279^{+}
		(711)	(630)	(676)	(683)
Safe choices			376	216	340
			(242)	(243)	(254)
Prudent choices				695**	711**
				(259)	(257)
Temparate choices					-504
					(324)
Constant	-1,801^{+}	-31,882**	-27,505**	-28,018**	-28,468**
	(937)	(7,126)	(6,175)	(6,345)	(6,333)
Panel-level variance (σ_u)	5,658**	5,089**	4,325**	4,225**	4,191**
	(382)	(349)	(307)	(300)	(298)
Overall variance (σ_e)	1,811**	1,787**	1,741**	1,741**	1,740**
	(52)	(53)	(53)	(53)	(53)
Observations	1,271	1,187	1,065	1,065	1,065
Survey Participants	213	199	178	178	178

Dependent variable is WTP for precautionary building standards. Model 1 is based on the attribute levels in the experimental design. Models 2, 3, 4 and 5 include additional controls and higher order risk attitudes. Hurricane risk perception is the number of category three hurricanes the respondent expects will affect her community in the next 50 years. Income is the natural log of household income. Female is a dummy variable equal to one if respondent is female. House size is the natural log of square feet of living space. Safe/Prudent/Temperate choices is the number of choices indicating respondent is risk averse/prudent/temperate. Number of participants and observations vary when respondents choose not to answer questions. Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

The results for all five models reported in Table 7 show that the coefficients on our experimental design attribute levels (Model 1) are robust to model specification. The signs and, for the most part, the magnitude of coefficient estimates on the experimental design variables remain consistent, even after controlling for demographics, housing characteristics, and HORA. This indicates that our design is nearly orthogonal with respect to the design attributes. Additionally, results reported in models 2-5 show that HORA, demographics, and house size also are correlated with homeowners' WTP for precautionary building standards with insurance discounts. Based on the Bayesian Information Criterion, Model 5 provides the best fit for the full sample.

We can test for information friction and endpoint bias by comparing coefficient estimates between the appropriate treatment block pairs. We use the post estimation chi-square statistic to test whether the estimates significantly differ from zero.

To test for endpoint bias, we compare coefficient estimates between "WTP_{HUB} / watched video" and "WTP_{LUB} / watched video" and/or between "WTP_{HUB} / no video" and "WTP_{LUB} / no video". Results reported for the full sample show that there is no statistical difference in the effect on WTP between "WTP_{HUB} / no video" and "WTP_{LUB} / no video" treatment blocks. However, unlike "WTP_{LUB} / watched video" with no differential effect on WTP compared to the baseline, the effects of "WTP_{HUB} / watched video" on WTP is positive and statistically significant at the 10% level, indicating the presence of endpoint bias in WTP payment card design among homeowners who watched the *Fortified* video demonstration but no endpoint bias among homeowners who did not watch the video.

To test for information friction we compare the coefficient estimates in each payment card range between those who watched the video and those who did not, testing the null hypotheses "WTP_{HUB} / no video" = "WTP_{HUB} / watched video" and "WTP_{LUB} / no video" = "WTP_{LUB} / watched video". Once again, the results are split. Among the subset of those who were dealt the higher payment card range, WTP is significantly higher for those who saw the informational video. For the other half of the sample, the difference is not statistically significant. Akin to MHT, these results reveal that the payment card with lower upper bound (WTP_{LUB}) is truncated and fails to cover the desired (higher) WTP values induced by the reduction of information friction from watching the video, resulting to underestimation of the WTP estimates and therefore endpoint bias. In contrast, the payment card with higher upper bound (WTP_{HUB}) accommodates higher WTP values induced by the informational video, suggesting that the absence of endpoint bias in payment card method is a necessary condition to accurately value the effect of information friction on WTP for *Fortified* in line with earlier findings (Rowe et al., 1996).

In addition, the results reported for the full sample show that homeowners are not willing to pay significantly more for a *Fortified* Silver designation compared to Bronze. The coefficient estimate is nominally positive, but is not statistically significant at the 10% level. The coefficient estimates for 35% and 45% complementary premium discounts are positive and statistically significant at the 1% level, indicating, as expected, that homeowners' WTP increases with the level of premium discount. Specifically, switching from a 20% discount to a 35% (45%) discount, while holding all other variables constant, increases WTP by $1,128 ($2,298).

The coefficients on income and house size for the full sample are also positive and significant, indicating a positive correlation between each variable and WTP for *Fortified* designations. The correlation between income and WTP suggests an opportunity for means-tested subsidies to increase the adoption of *Fortified* construction standards.

The coefficient on prudent choices is positive and statistically significant at the 1% level, whereas, both second and fourth order risk attitudes, appear to have no effect on WTP in the full sample model.

To test the hypotheses relating HORA to WTP, we re-estimate seven versions of the best model fit with five risk attitude subgroups, including two mixed risk lovers, two mixed risk averters, and a second, third, or fourth degree risk-neutral baseline subgroup, allowing us to isolate and contrast the effects of HORA subgroups with a (second, third, or fourth degree) risk-neutral subgroup on WTP for *Fortified*. In each model, homeowners are classified as (i) risk averse, prudent, and temperate (RA-Prud-Temp); (ii) risk averse, imprudent, and temperate (RA-Imprud-Temp); (iii) risk loving, prudent, and intemperate (RA-Prud-Intemp); (iv) risk loving, imprudent, and intemperate (RL-Imprud-Intemp); and (v) n^{th} degree risk-neutral baseline subgroup. In model 1, second degree risk-neutral (2RN) homeowners are taken as the baseline allowing us to make comparisons with both mixed risk averters and mixed risk lovers. Models 2 and 3 adopt third degree risk-neutral (3RN) baselines. Model 2 adopts risk averse and third degree risk-neutral (RA-3RN) subjects as the baseline, allowing a comparison with mixed risk averters. Model 3 adopts risk loving and third degree risk-neutral (RL-3RN) as the baseline, enabling comparison with mixed risk lovers. Models 4-7 are based on fourth degree risk-neutral baselines, in which model 4 adopts risk loving, imprudent, and fourth degree risk-neutral (RL-Imprud-4RN) as the baseline;[26] model 5 takes risk loving, prudent, and fourth degree risk-neutral (RL-Prud-4RN) as the baseline; model 6 uses risk averse, imprudent, and fourth degree risk-neutral (RA-Imprud-4RN) as the baseline; and model 7 adopts risk averse, prudent, and fourth degree risk-neutral (RA-Prud-4RN) baseline. Models 4 and 5 permit comparisons with mixed risk lovers. Models 6 and 7 permit comparisons with mixed risk averters. Table 8 presents the regression results of the seven models with the risk-neutral subgroup taken (and omitted) as a baseline group. Therefore a chi-square statistic to test whether the effects of each mixed risk attitude subgroup against its corresponding risk-neutral baseline differ significantly from zero is inferred.

Homeowners who exhibit RA-Prud-Temp choose a significantly higher ($4,461) WTP for *Fortified* than those who exhibit RA-3RN partially supporting hypothesis 1. Compared to 2RN, RA-Imprud-4RN, and Ra-Prud-4RN, RA-Prud-Temp homeowners' WTP is not statistically different from zero.

Results reported in Model 3 reveal that RL-Imprud-Intemp homeowners are willing to pay $3,195 less

[26]Note that the risk attitude coefficient estimates in model 4 are highly inefficient and unstable due to multicollinearity.

than RL-3RN homeowners and the difference is statistically significant at the 5% level, supporting hypothesis 2.

Results in Table 8 also reveal that RL-Prud-Intemp homeowners consistently choose a higher WTP for *Fortified* than all risk-neutral (and mixed risk) subgroups and the differences ($2,738 and $4,451) are statistically significant in comparison to 2RN and RL-Prud-4RN subgroups but not RL-3RN.

Table 8: Random-effects Tobit regression models with second, third, and fourth degree risk neutral baselines

	Model 1 2RN	Model 2 RA-3RN	Model 3 RL-3RN	Model 4 RL-Imprud-4RN	Model 5 RL-Prud-4RN	Model 6 RA-Imprud-4RN	Model 7 RA-Prud-4RN
Fortified Silver	144	115	118	117	135	147	211
	(179)	(173)	(160)	(176)	(168)	(168)	(156)
35% ins discount	1,162**	1,246**	1,263**	1,274**	1,220**	1,276**	1,297**
	(225)	(218)	(201)	(222)	(211)	(212)	(196)
45% ins discount	2,472**	2,659**	2,553**	2,717**	2,678**	2,637**	2,731**
	(223)	(216)	(199)	(220)	(209)	(210)	(195)
WTP_LUB / Watched video	-81	-611	-1,397	-840	-1,542	-504	-667
	(1,346)	(1,182)	(1,076)	(1,191)	(1,182)	(1,108)	(1,082)
WTP_HUB / No video	1,437	2,115^{+}	1,058	1,372	-756	1,562	1,712
	(1,385)	(1,241)	(1,134)	(1,270)	(1,195)	(1,215)	(1,104)
WTP_HUB / Watched video	2,528^{+}	1,441	1,082	1,156	149	1,582	1,763
	(1,396)	(1,267)	(1,154)	(1,263)	(1,291)	(1,154)	(1,117)
Income	1,366*	801	580	1,105^{+}	1,182^{+}	1,314*	1,089^{+}
	(597)	(650)	(553)	(656)	(641)	(623)	(598)
House size	852	666	949	577	988	275	874
	(647)	(1,231)	(1,063)	(1,223)	(1,218)	(1,173)	(1,177)
RA-Prud-Temp	355	4,461*	-189	21,376	2,140	433	315
	(1,211)	(2,243)	(1,070)	(277,503)	(1,408)	(1,619)	(929)
RA-Imprud-Temp	-1,412	2,764	-2,181	19,661	41	-1,119	-1,391
	(1,881)	(2,476)	(1,558)	(277,505)	(1,827)	(1,963)	(1,527)
RL-Prud-Intemp	2,738^{+}	6,954**	2,146	23,826	4,451**	2,831	2,748*
	(1,631)	(2,425)	(1,364)	(277,505)	(1,727)	(1,805)	(1,299)
RL-Imprud-Intemp	-2,821	1,375	-3,195*	18,547	-339	-2,379	-2,650^{+}
	(1,961)	(2,547)	(1,605)	(277,505)	(1,962)	(2,070)	(1,606)
Constant	-22,493**	-18,502*	-12,859^{+}	-37,858	-21,658*	-17,168*	-19,266*
	(7,958)	(8,257)	(7,340)	(277,637)	(8,677)	(8,361)	(7,995)
Panel-level variance (σ_u)	4,131**	3,326**	3,130**	3,274**	3,477**	3,184**	3,413**
	(385)	(345)	(302)	(343)	(351)	(323)	(315)
Overall variance (σ_e)	1,815**	1,582**	1,589**	1,592**	1,587**	1,577**	1,626**
	(75)	(72)	(66)	(73)	(70)	(70)	(65)
Observations	551	444	498	450	480	450	569
Survey Participants	92	74	83	75	80	75	95

Dependent variable is WTP for precautionary building standards. The first six variables are dummy variables representing attribute levels in the experimental design. Income is the natural log of household income. House size is the natural log of square feet of living space. RA-Prud-Temp = Risk averse, prudent, and temperate; RA-Imprud-Temp = Risk averse, imprudent, and temperate; RL-Prud-Intemp = Risk loving, prudent, and intemperate; RL-Imprud-Intemp = Risk loving, imprudent, and intemperate. Model 1 adopts second degree risk neutral (2RN) as the baseline; Model 2 adopts Risk-averse, third degree risk neutral agents (RA-3RN) baseline; Model 3 adopts Risk-loving third degree risk neutral (RL-3RN) baseline; Model 4 adopts risk loving, imprudent, and fourth degree risk neutral agents (RL-Imprud-4RN) as the baseline; Model 5 adopts risk loving, prudent, and fourth degree risk neutral (RL-Prud-4RN) agents as the baseline; Model 6 adopts risk averse, imprudent, and fourth degree risk neutral (RA-Imprud-4RN) as the baseline; and Model 7 adopts risk averse, prudent, and fourth degree risk neutral (RA-Prud-4RN) as the baseline. The number of participants and observations vary when respondents choose not to answer questions. Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

For completeness, RL-Prud-Intemp homeowners are willing to pay $6,954 and $2,748 more than RA-3RN and RA-Prud-4RN homeowners, with similar characteristics (other covariates). Results in Table 8 also reveal that the level of insurance discount and household income both have significant effects on WTP for *Fortified*, and the level of *Fortified* appears to have no significant effect. A 35% insurance discount fetches between \$1,162 and \$1,297 more in WTP for *Fortified* compared to a 20% insurance discount. This amount more than doubles (\$2,472 to \$2,731) for a 45% insurance discount.

Regarding information friction, Model 1 results in Table 8 show the coefficient on WTP_{HUB} / watched video is positive and statistically significant at the 10% level while WTP_{HUB} / No video and WTP_{LUB} / watched video are not significant, indicating that, with all other variables held constant, homeowners who watched the informational video and assigned to higher WTP payment range choose a (\$2,528) higher WTP than 2RN agents who did not receive the information treatment and were assigned a lower WTP payment range. Notably, we fail to reject a chi-square test that WTP_{HUB} / watched video = WTP_{HUB} / No video (p-value = 0.405) with all other variables held constant. We also find no statistical difference between homeowners with similar HORA treated with WTP_{LUB} / watched video and those treated with WTP_{LUB} / No video, suggesting no effect on information friction on WTP for *Fortified* in our sample. Conversely, we reject the null hypothesis that WTP_{HUB} / watched video = WTP_{LUB} / Watched video (p-value = 0.037), indicating that those assigned a higher WTP payment range selected statistically higher (\$2,609) WTP than those assigned to a lower range. This result confirms the presence of endpoint bias in WTP payment card designs.

Furthermore, results in Table 8 confirm the significant effects of endpoint bias on WTP for *Fortified*. For example, Model 1 results show that homeowners treated with WTP_{HUB} / Watched video choose \$2,528 and \$2,609 higher WTP than those exhibiting 2RN preferences treated with WTP_{LUB} / No video and WTP_{LUB} / Watched video, respectively. Similarly, Model 2 results reveal that homeowners treated with WTP_{HUB} / No video choose \$2,115 and \$2,726 higher WTP than RA-3RN homeowners treated with WTP_{LUB} / No video and WTP_{LUB} / Watched video, respectively. In addition, homeowners treated with WTP_{HUB} / Watched video choose significantly higher WTP (\$2,052) than those treated with WTP_{LUB} / Watched video. Similarly, Model 3 results show that homeowners treated with WTP_{HUB} / No video and WTP_{HUB} / Watched video choose a significantly higher WTP (\$2,455 and \$2,479, respectively) than RA-3RN treated with WTP_{LUB} / Watched video, further supporting endpoint bias, and Model 6 results show an endpoint bias of \$2,086 compared to WTP_{HUB} / Watched video and WTP_{LUB} / Watched video treatments, while that for model 7 is \$2,430.

6.1 Predicted WTP for precautionary building standards

The final step in our analysis is to compare the predicted average WTP among HORA groups across information and payment card range treatment, insurance discount levels, and income levels. This approach has two advantages over the previous analyses. First, it allows us to test our hypotheses across salient subgroups of demographic and experimental variables to further examine their heterogeneous effects on WTP for *Fortified*. In addition, considering WTP by income level is useful for estimating optimal means-tested subsidies that could be used to increase adoption. The predicted average WTP with confidence intervals are based on models 1-3 and 5-7 in Table 8.[27] Following each models' prediction, we also test whether the difference in WTP between all pairwise combinations of predicted groups equals zero using a chi-square test.

6.1.1 Predicted WTP for *Fortified* Bronze and Silver

Figure 3 presents the predicted average WTP and 90% confidence intervals for *Fortified* Bronze and Silver using the six models. Results reveal significant differences in WTP for the level of *Fortified* across some HORA subgroups and corresponding risk-neutral baselines. Homeowners who are RL-Prud-Intemp are willing to pay significantly more than 2RN, RL-3RN, and RL-Prud-4RN homeowners. For example, RL-Prud-Intemp homeowners are willing to pay \$2,738 and \$2,882 more for *Fortified* Bronze and Silver, respectively, than 2RN agents pay for *Fortified* Bronze. Homeowners exhibiting RL-Prud-Intemp preferences pay \$6953 (\$6838) more for *Fortified* Bronze than RL-3RN agents pay for Bronze (Silver), and are also willing to pay \$7068 (\$6953) more for *Fortified* Silver than RL-3RN agents pay for Bronze (Silver). Similarly, RL-Prud-Intemp agents are willing to pay \$4451 (\$4316) more for *Fortified* Bronze than RL-3RN agents WTP for *Fortified* Bronze (Silver), and \$4586 (\$4451) more for *Fortified* Silver than RL-3RN agents offer for Bronze (Silver).

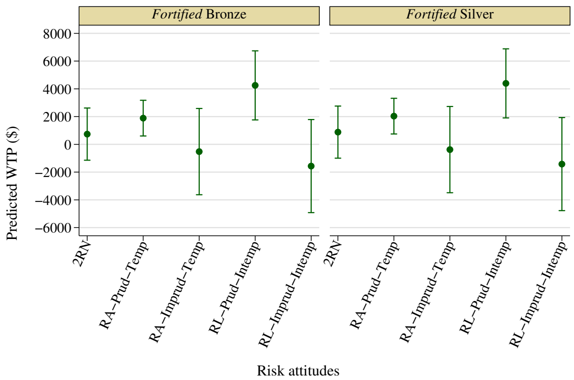
However, no significant differences are evident between WTP for *Fortified* Bronze and Silver offered by 2RN agents and WTP offered by RA-Prud-Temp, RA-Imprud-Temp, or RL-Imprud-Intemp agents. Similarly, we find no significant differences between WTP for *Fortified* Bronze and Silver offered by RA-Prud-Temp or RA-Imprud-Temp agents and RA-3RN, RA-Prud-4RN, or RA-Imprud-4RN agents.

6.1.2 Predicted WTP over information and payment card range

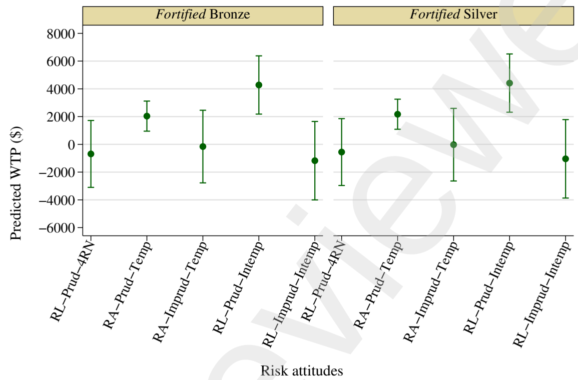
Figure 4 presents predicted average WTP and 90% confidence intervals over the four block-treatments in our experiment (video and payment card range) using the six models. The results highlight the positive correlation between prudence and WTP and the heterogeneous effect of endpoint bias between HORA and second, third, and fourth degree risk-neutral baselines. For example, RL-Prud-Intemp homeowners who were assigned to WTP_{HUB} / No video and WTP_{HUB} / Watched video treatments, on average, choose \$4,175 to \$5,347 higher WTP for *Fortified* than 2RN homeowners assigned to WTP_{LUB} / No video or the WTP_{LUB} / Watched video treatment. In addition, RL-Prud-Intemp homeowners assigned to the WTP_{HUB} / Watched video treatment are willing to pay \$3,828 more than 2RN homeowners treated with WTP_{HUB} / No video.

[27]Prediction are made using observed covariates and then averaged over specific groups or combinations of salient variables; therefore, we are unable to make or depict predictions for a few groups due to lack of observations for the specific combination of HORA and/or salient variables. We exclude predictions based on model 4 because of its extremely poor performance in predicting average WTP because the coefficients of risk attitude are inefficiently estimated and unstable due to multicollinearity.

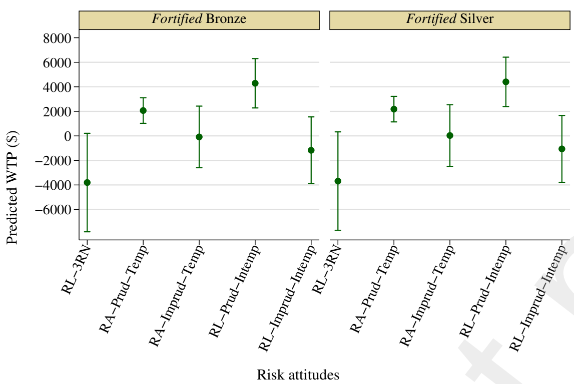
Figure 3: Predicted average WTP for *Fortified* Bronze and Silver by Risk-neutral (RN) baseline



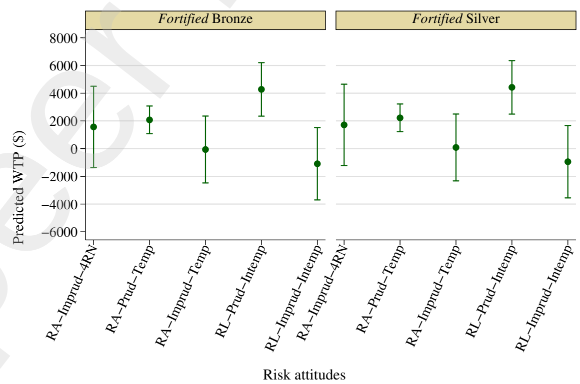
(a) 2^{nd} degree RN



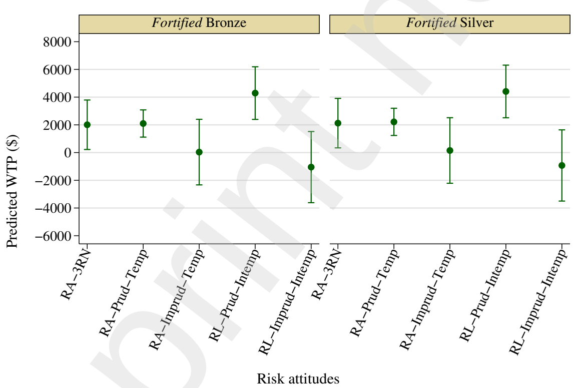
(b) Risk loving - Prudent - 4^{th} degree RN



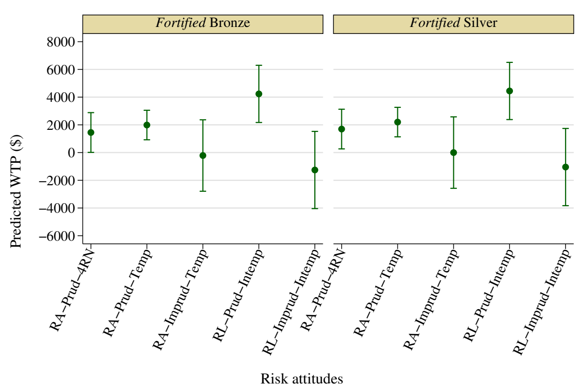
(c) Risk loving - 3^{rd} degree RN



(d) Risk averse - Imprudent - 4^{th} degree RN

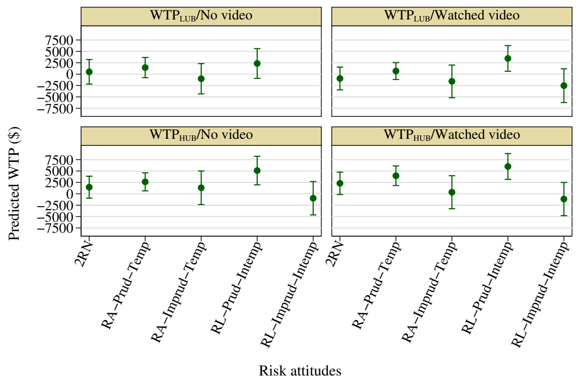


(e) Risk averse - 3^{rd} degree RN

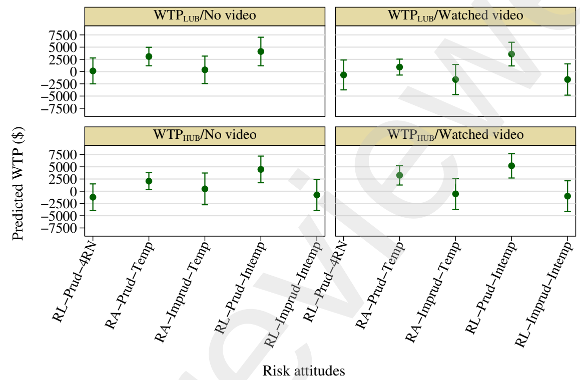


(f) Risk averse - Prudent - 4^{th} degree RN

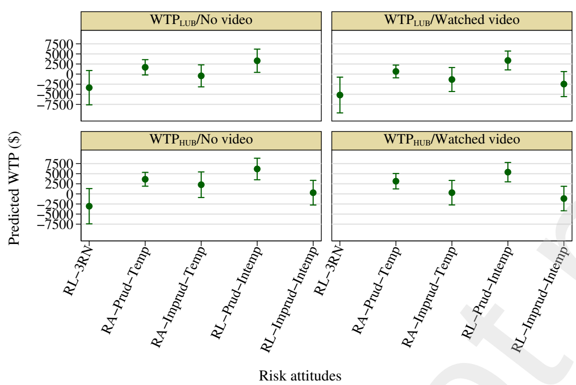
Figure 4: Predicted average WTP for *Fortified* over information and payment card range by Risk-neutral (RN) baseline



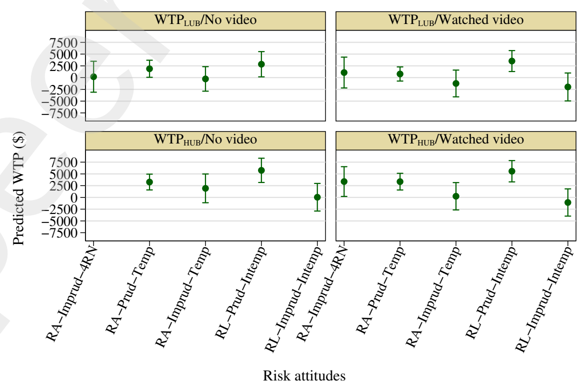
(a) 2^{nd} degree RN



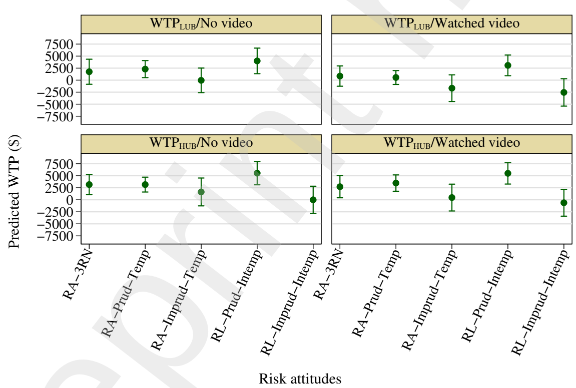
(b) Risk loving - Prudent - 4^{th} degree RN



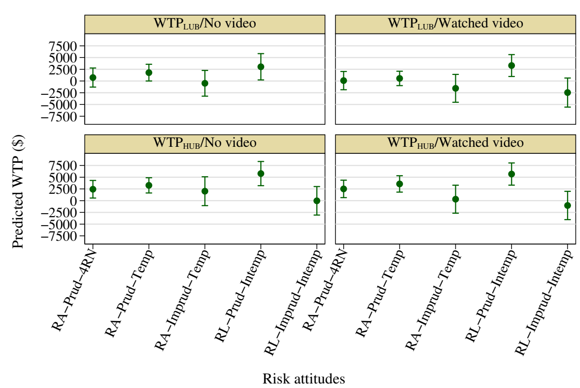
(c) Risk loving - 3^{rd} degree RN



(d) Risk averse - Imprudent - 4^{th} degree RN



(e) Risk averse - 3^{rd} degree RN



(f) Risk averse - Prudent - 4^{th} degree RN

In contrast, RL-Imprud-Intemp homeowners assigned to WTP_{LUB} / No video and WTP_{LUB} / Watched video treatments, on average, choose significantly lower WTP (\$4,258 and \$4,340, respectively) than 2RN homeowners assigned to WTP_{HUB} / No video treatment. The same groups choose a significantly much lower WTP (\$5,349 and \$5,430, respectively) than 2RN homeowners assigned to WTP_{LUB} / Watched video treatment. Similarly, RL-Imprud-Temp homeowners assigned to WTP_{LUB} / No video and WTP_{LUB} / Watched video treatments, on average, choose significantly lower WTP (\$3,939 and \$4,021, respectively) than 2RN homeowners assigned to WTP_{HUB} / Watched video treatment. All other pairwise contrasts between 2RN homeowners and mixed risk categories show no significant difference at a 10% level or less.

Comparing predicted WTP for RL-3RN homeowners with those for mixed risk lovers over information and payment card range treatments, as depicted in Figure 4, reveals that RL-Prud-Intemp homeowners treated with WTP_{HUB} / No video, WTP_{HUB} / Watched video and WTP_{LUB} / Watched video are willing to pay \$9,068, \$8,395, and \$6,342 more, respectively, for *Fortified* than RL-3RN homeowners treated with WTP_{LUB} / No video. Similarly, RL-Prud-Intemp homeowners treated with WTP_{HUB} / No video, WTP_{HUB} / Watched video, WTP_{LUB} / No video, and WTP_{LUB} / Watched video are willing to pay, on average, \$9,679, \$9,006, \$7,564, and \$6,953 more for *Fortified*, respectively, than RL-3RN homeowners treated with WTP_{LUB} / Watched video. Likewise, the same groups are willing to pay, on average, \$6,953, \$6,280, \$4,839, and \$4,227 more, respectively, for *Fortified* than RL-3RN homeowners treated with WTP_{HUB} / No video and \$7,626, \$6,953, \$5,512, and \$4,901 more than RL-3RN homeowners treated with WTP_{HUB} / Watched video. These results confirm that prudence positively impacts WTP to invest in precautionary building codes, revealing a somewhat negative effect of viewing the video on mixed risk lovers' WTP, in line with the results gleaned from the MHT above.

On the other hand, comparing RA-3RN homeowners with mixed risk averters shows that RA-Imprud-Temp homeowners treated with WTP_{LUB} / Watched video choose, on average, \$3,578 lower WTP than RA-3RN homeowners treated with WTP_{LUB} / No video, indicating that providing information on *Fortified* performance relative to conventional house does not compensate for prudence. Homeowners exhibiting RA-Imprud-Temp preferences and treated with WTP_{LUB} / No video and WTP_{LUB} / Watched video choose, on average, \$3,239 and \$4,636 lower WTP, respectively, than RA-3RN homeowners treated with WTP_{HUB} / No video. Likewise, RA-Prud-Temp treated with WTP_{LUB} / Watched video choose a lower WTP (\$2,644 and \$2,668) than RA-3RN homeowners treated with WTP_{HUB} / No video and WTP_{HUB} / Watched video.

In addition, we find that RA-Imprud-Temp treated with WTP_{LUB} / No video and WTP_{LUB} / Watched video choose \$3,236 and \$4,660 lower WTP, respectively, than RA-3RN homeowners treated with WTP_{HUB} / Watched video. Similarly, RL-Imprud-Intemp homeowners treated with WTP_{LUB} / No video and WTP_{LUB} / Watched video choose, on average, \$3,194 and \$4,592 lower WTP, respectively, than RA-3RN homeowners treated with WTP_{LUB} / No video. The results also reveal that RL-Imprud-Intemp agents treated with WTP_{LUB} / No video, WTP_{LUB} / Watched video, WTP_{HUB} / No video, and WTP_{HUB} / Watched video are willing to pay about \$4,252, \$5,649, \$3,194, and \$3,170 lower WTP, respectively, than RA-3RN agents treated with WTP_{HUB} / No video or WTP_{HUB} / Watched video.

In contrast, RL-Prud-Intemp agents treated with WTP_{LUB} / No video, WTP_{HUB} / No video, and WTP_{HUB} / Watched video are willing to pay significantly higher WTP (\$3,543, \$4,601 and \$4,625, respectively) than RA-3RN treated with WTP_{LUB} / Watched video, indicating both information friction and endpoint bias between RL-Prud-Intemp and RA-3RN agents. Similarly, RL-Prud-Intemp agents treated with WTP_{HUB} / No video, WTP_{HUB} / Watched video are willing to pay significantly higher WTP (\$3,204 and \$3,228, respectively) than RA-3RN treated with WTP_{LUB} / No video.

Comparing RL-Prud-4RN with mixed risk lovers reveals that RL-Prud-Intemp agents treated with WTP_{HUB} / No video, WTP_{HUB} / Watched video are willing to pay significantly higher amounts (\$3,695 and \$4,601, respectively) than RL-Prud-4RN treated with WTP_{LUB} / No video. Also, RL-Prud-Intemp agents treated with WTP_{LUB} / No video, WTP_{LUB} / Watched video, WTP_{HUB} / No video, and WTP_{HUB} / Watched video are willing to pay \$5,993, \$4,451, \$5,237, and \$6,143 higher WTP, respectively, than RL-Prud-4RN agents treated with WTP_{LUB} / Watched video. Similarly, RL-Prud-Intemp agents treated with WTP_{LUB} / No video, WTP_{LUB} / Watched video, WTP_{HUB} / No video, and WTP_{HUB} / Watched video are willing to pay \$5,208, \$3,666, \$4,451, and \$5,357 higher WTP than RL-Prud-4RN agents treated with WTP_{HUB} / No video. Furthermore, RL-Prud-Intemp agents treated with WTP_{HUB} / No video are willing to pay \$4,302 higher than a RL-Prud-4RN agents treated with WTP_{HUB} / Watched video. These results suggest information friction among mixed risk lovers. Comparing these results with the MHT results reported in Table 5 for mixed risk loving subgroups reveals that the effects of information friction on RL-Prud-4RN appears to be double that of RL-Prud-Intemp agents, suggesting that all three HORAs contribute to the effect of mixed risk lovers on WTP for precautions.

Comparing all pairs of RA-Imprud-4RN with a mixed risk averter with different combinations of information and payment card range reveals that no pair statistically differs from zero.

Additionally, comparing all pairs of RA-Prud-4RN with a higher mixed risk averter with different combinations of information and payment card range reveals that RA-Prud-Temp agents treated with WTP_{HUB} / No video, and WTP_{HUB} / Watched video are willing to pay \$2,694 and \$2,745 more, respectively, than RA-Prud-4RN agents treated with WTP_{LUB} / Watched video. In contrast, RA-Prud-Temp agents treated with WTP_{LUB} / Watched video are willing to pay \$2,115 less than RA-Prud-4RN agents treated with WTP_{HUB} / Watched video. In addition, RA-Imprud-Temp agents treated with WTP_{HUB} / No video, and WTP_{HUB} / Watched video are willing to pay \$3,103 and \$3,770 less, respectively, than RA-Prud-4RN agents treated with WTP_{HUB} / No video while RA-Imprud-Temp agents treated with WTP_{LUB} / No video, and WTP_{LUB} / Watched video are willing to pay \$3,153 and \$3,821 less, respectively, than RA-Prud-4RN agents treated with WTP_{HUB} / Watched video.

Interestingly, although not theorized in this study, we find that RA-Prud-Temp homeowners treated with

WTP_{HUB} / No video, WTP_{HUB} / Watched video, WTP_{LUB} / No video, and WTP_{LUB} / Watched video are willing to pay \$7,186, \$6,513, \$5,071, and \$4,460 more, respectively, for *Fortified* than RL-3RN homeowners treated with WTP_{LUB} / Watched video. Ra-Prud-Temp homeowners treated with WTP_{HUB} / No video are willing to pay \$5,133 more than a RL-3RN homeowners treated with WTP_{HUB} / Watched video. Also, RA-Imprud-Temp homeowners treated with WTP_{HUB} / No video and WTP_{HUB} / Watched video choose a significantly higher WTP (\$5,490 and \$4,816, respectively) than RL-3RN homeowners treated with WTP_{LUB} / Watched video.

6.1.3 Predicted WTP over insurance discounts

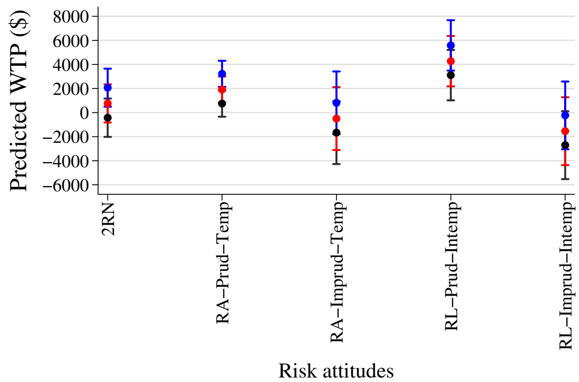
Figure 5 presents predicted average WTP and 90% confidence intervals over insurance discounts using the six models. The results show that a RA-Prud-Temp homeowners are willing to pay \$2,827 more for *Fortified* with 45% discount than a 2RN agent offers for *Fortified* with a 20% discount, suggesting that 2RN agents

undervalue the effects of insurance discounts compared to RA-Prud-Temp homeowners. Comparatively, a 2RN agent is willing to pay \$2,117 more for *Fortified* with a 45% discount compared to an RA-Prud-Temp agent for a 20% discount. No significant statistical difference is evident between RA-Imprud-Temp WTP for *Fortified* with a 45% discount and 2RN WTP for *Fortified* with a 20% discount. We note significant statistical difference between RA-Imprud-Temp WTP for *Fortified* with a 20% discount and 2RN WTP for *Fortified* with a 45% discount, indicating that the latter is willing to pay \$3,884 more, which suggests that 2RN homeowners overvalue the effects of insurance discounts compared to RA-Imprud-Temp homeowners.

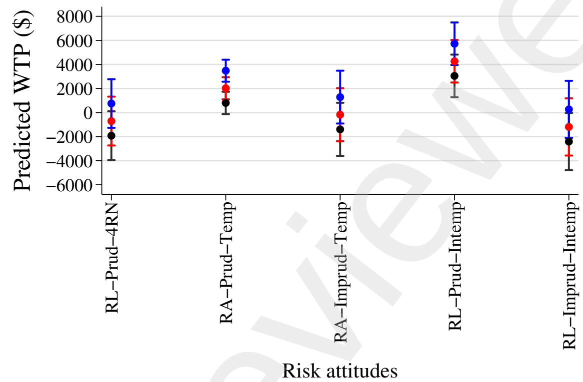
Compared to RL-3RN, RL-Prud-Intemp homeowners are willing to pay between \$ 4,294 and \$9,613 more for *Fortified* for any combination of insurance discounts between the two subgroups. We find no significant statistical difference between WTP for RL-Imprud-Temp and RL-3RN homeowners for any combination of insurance discounts compared. Similarly, comparing RL-Prud-4RN WTP with a 20% discount, RL-Prud-Intemp homeowners are willing to pay \$4,451, \$5,671, and \$7,128 more for *Fortified* with 20%, 35%, and 45% discounts, respectively. The amounts decreases to \$3,231, \$4,451, and \$5,908, respectively, when compared to RL-Prud-4RN WTP with a 35%. Overall, there is no significant difference between WTP of RL-Imprud-Intemp and RL-Prud-4RN homeowners.

We only uncover significant statistical differences when comparing WTP for RA-Prud-Temp at 45% discount with that of RA-3RN, RA-Prud-4RN, and RA-Imprud-4RN at a 20% discount, indicating the former is willing to pay \$2,363, \$3,046, and \$3,070 more, respectively, than the latter. Similarly, RA-Prud-Temp is willing to pay \$2,742, \$2,416, and \$3,756 less for *Fortified* with a 20% discount compared to RA-3RN, RA-Prud-4RN, and RA-Imprud-4RN at a 45%. In addition, an "Ra-Imprud-Temp agent is willing to pay between \$2,480 and \$4,734 less for *Fortified* with a 20% discount compared to RA-3RN, RA-Prud-4RN or RA-Imprud-4RN agents at a 35% (45%) discount, but there is no significant difference in WTP between RA-Imprud-Temp at a 35% (45%) discount and RA-3RN, RA-Prud-4RN, and RA-Imprud-4RN agent at a

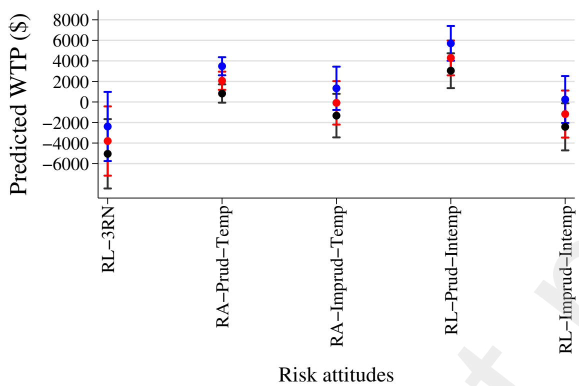
Figure 5: Predicted average WTP for *Fortified* over insurance discount by Risk-neutral (RN) baseline



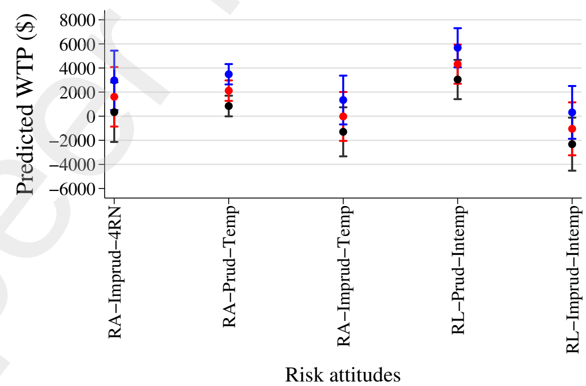
(a) 2^{nd} degree RN



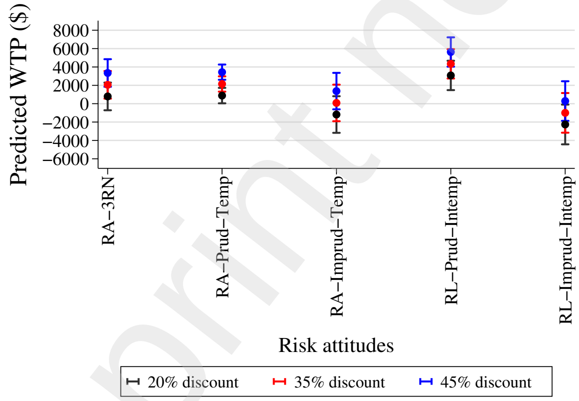
(b) Risk loving - Prudent - 4^{th} degree RN



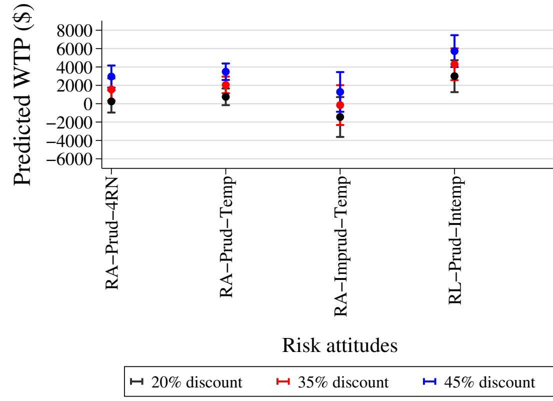
(c) Risk loving - 3^{rd} degree RN



(d) Risk averse - Imprudent - 4^{th} degree RN



(e) Risk averse - 3^{rd} degree RN



(f) Risk averse - Prudent - 4^{th} degree RN

20% discount.

Table 9: Random-effects Tobit regression models with 2^{nd}, 3^{rd}, and 4^{th} degree risk neutral baselines

	Model 1 2RN	Model 2 RA-3RN	Model 3 RL-3RN	Model 4 RL-Imprud-4RN	Model 5 RL-Prud-4RN	Model 6 RA-Imprud-4RN	Model 7 RA-Prud-4RN
Fortified Silver	153	124	126	145	127	157	221
	(181)	(174)	(161)	(169)	(177)	(169)	(157)
35% ins discount	1,164**	1,252**	1,268**	1,224**	1,280**	1,282**	1,303**
	(226)	(219)	(202)	(212)	(223)	(213)	(197)
45% ins discount	2,479**	2,675**	2,565**	2,694**	2,736**	2,653**	2,745**
	(225)	(217)	(200)	(210)	(221)	(211)	(196)
WTP_LUB / Watched video	-76	-413	-1,201	-1,841	-775	-530	-569
	(1,344)	(1,186)	(1,084)	(1,211)	(1,214)	(1,115)	(1,075)
WTP_HUB / No video	2,011	2,945*	1,728	-460	2,216	2,358^{+}	2,217*
	(1,420)	(1,312)	(1,177)	(1,245)	(1,352)	(1,284)	(1,114)
WTP_HUB / Watched video	2,976*	1,636	1,408	255	1,357	1,781	1,824^{+}
	(1,401)	(1,252)	(1,146)	(1,295)	(1,255)	(1,145)	(1,099)
$25^{th} \leq$ percentile of income $<50^{th}$	3,798**	1,202	1,575	2,173^{+}	1,777	2,117^{+}	1,499
	(1,396)	(1,219)	(1,103)	(1,254)	(1,265)	(1,186)	(1,145)
$50^{th} \leq$ percentile of income $<75^{th}$	1,740	839	827	2,808*	1,327	1,779	1,092
	(1,371)	(1,432)	(1,214)	(1,385)	(1,448)	(1,346)	(1,139)
$\geq 75^{th}$ percentile of income	3,219*	2,459^{+}	2,211^{+}	2,713*	2,690*	3,207*	2,709*
	(1,344)	(1,355)	(1,207)	(1,344)	(1,351)	(1,248)	(1,204)
House size	1,068	878	1,002	1,327	1,043	763	1,102
	(743)	(1,210)	(1,040)	(1,233)	(1,215)	(1,158)	(1,182)
Ra-Prud-Temp	1,203	4,472*	-169	2,293	21,111	398	383
	(1,221)	(2,235)	(1,056)	(1,414)	(267,234)	(1,595)	(930)
Ra-Imprud-Temp	-631	3,142	-1,886	-221	19,533	-1,049	-1,078
	(1,928)	(2,516)	(1,553)	(1,861)	(267,236)	(1,960)	(1,543)
Rl-Prud-Intemp	3,193*	6,770**	1,995	4,390*	23,373	2,578	2,539*
	(1,629)	(2,429)	(1,349)	(1,732)	(267,237)	(1,771)	(1,287)
Rl-Imprud-Intemp	-2,317	1,529	-3,139*	-193	18,271	-2,367	-2,466
	(1,951)	(2,537)	(1,598)	(1,978)	(267,237)	(2,073)	(1,591)
Constant	-12,051*	-12,724	-8,338	-13,109	-30,620	-8,303	-10,461
	(6,101)	(8,944)	(7,888)	(9,240)	(267,395)	(8,718)	(8,719)
Panel-level variance (σ_u)	4,078**	3,247**	3,063**	3,455**	3,220**	3,113**	3,354**
	(385)	(344)	(300)	(355)	(344)	(322)	(315)
Overall variance (σ_e)	1,807**	1,567**	1,577**	1,574**	1,577**	1,563**	1,615**
	(75)	(72)	(66)	(70)	(73)	(70)	(65)
Observations	539	432	486	468	438	438	557
Survey Participants	90	72	81	78	73	73	93

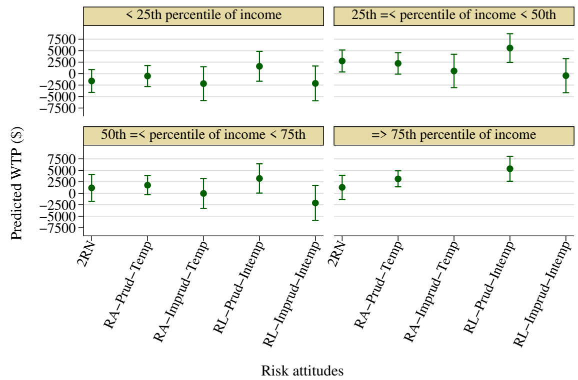
Dependent variable is WTP for precautionary building standards. The first six variables are dummy variables representing attribute levels in the experimental design. Household income is a categorical variable derived as income quartiles and "$\leq 25^{th}$ percentile of income" is the baseline category. House size is the natural log of square feet of living space. Ra-Prud-Temp = Risk averse, prudent, and temperate; Ra-Imprud-Temp = Risk averse, imprudent, and temperate; Rl-Prud-Intemp = Risk loving, prudent, and intemperate; Rl-Imprud-Intemp = Risk loving, imprudent, and intemperate. Model 1 adopts 2^{nd} degree risk neutral (2RN) baseline; model 2 adopts Risk-averse 3^{rd} degree risk neutral (RA-3RN) baseline; model 3 adopts Risk-loving 3^{rd} degree risk neutral (RL-3RN) baseline; model 4 adopts risk loving, imprudent, and 4^{th} degree risk neutral (RL-Imprud-4RN) baseline; model 5 adopts risk loving, prudent, and 4^{th} degree risk neutral (RL-Prud-4RN) baseline; model 6 adopts risk averse, imprudent, and 4^{th} degree risk neutral (RA-Imprud-4RN) baseline; and model 7 adopts risk averse, prudent, and 4th degree risk neutral (RA-Prud-4RN) baseline. Number of participants and observations vary when respondents choose not to answer questions. Standard errors in parentheses. $^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$.

6.1.4 Predicted WTP over income quartiles

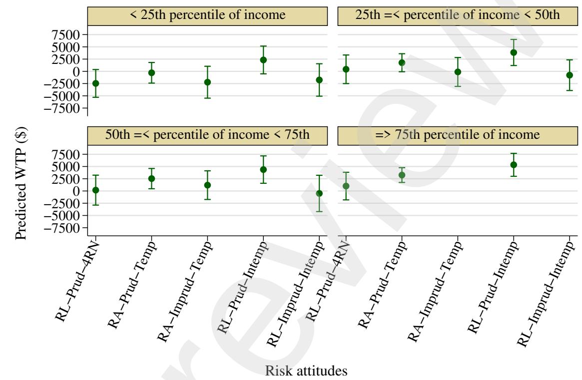
To examine how WTP varies between extremely low to extremely high income levels, we re-estimate the models in Table 8 using household income as a categorical variable composed of household income quartiles. The results are reported in Table 9. Figure 6 shows the predicted average WTP and 90% confidence intervals over household income quartiles applying six models (1-3 and 5-7) in Table 9.

The results show that RA-Prud-Temp homeowners in higher (2^{nd}, 3^{rd}, and 4^{th}) income quartiles are willing to pay \$5,000, \$2,942, and \$4,421 more, respectively, that 2RN agents in the 1^{st} income quartile.

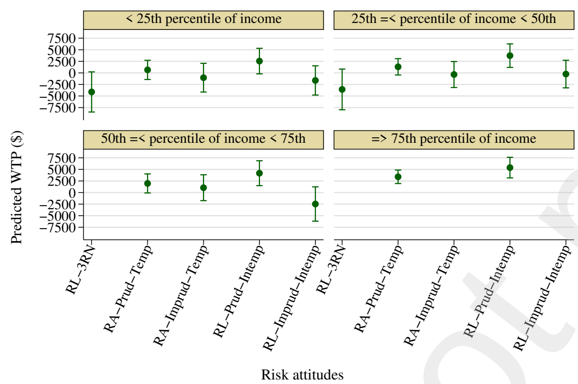
Figure 6: Predicted average WTP for *Fortified* over income quartiles by Risk-neutral (RN) baseline



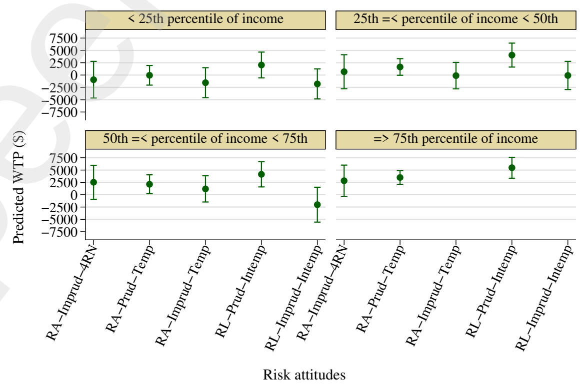
(a) 2^{nd} degree RN



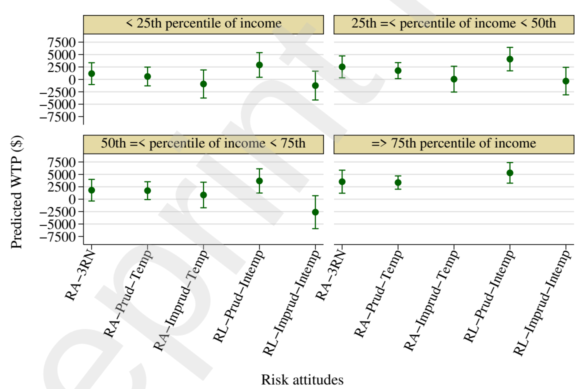
(b) Risk loving - Prudent - 4^{th} degree RN



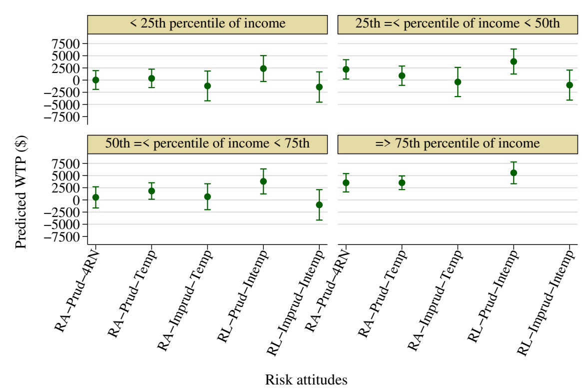
(c) Risk loving - 3^{rd} degree RN



(d) Risk averse - Imprudent - 4^{th} degree RN



(e) Risk averse - 3^{rd} degree RN



(f) Risk averse - Prudent - 4^{th} degree RN

Similarly, RL-Prud-Intemp homeowners in the 1^{st} - 4^{th} income quartiles are willing to pay $3,193, $6,990, $4,933, and $6,411 more, respectively, than 2RN homeowners in the 1^{st} income quartile. In addition, RL-Prud-Intemp homeowners in the 2^{nd} and 4^{th} income quartiles are willing to pay $5,250 and $4,671 more, respectively, than 2RN agents in the 3^{rd} income quartile. The results also show that RL-Imprud-Intemp agents in the 1^{st} income quartile are willing to pay $6,115, $4,057, $5,536 less than 2RN agents in the 2^{nd} - 4^{th} quartiles, respectively.

Generally, RL-Prud-Intemp homeowners in the 1^{st}-4^{th} income quartiles are willing to pay significantly more than RL-3RN in any income quartile, and the differential decreases with the increase in RL-3RN agents' income quartile. For example, RL-Prud-Intemp homeowners in the 2^{nd}-4^{th} income quartiles are willing to pay $7,972, $7,609, and $9,229 more, respectively, than RL-3RN agents in the 1^{st} quartile, and this amount drops to $7,133, $6,770, and $8,390, respectively, when compared to RL-3RN agents in the 3^{rd} quartile. Similarly, RL-Prud-Intemp homeowners in the 2^{nd}-4^{th} income quartiles are willing to pay $3,755 to $7198 more than RL-Prud-4RN agents in the 1^{st}-4^{th} income quartiles.

There is generally no significant difference in WTP between RA-Prud-Temp agents and RA-3RN or RA-Imprud-4RN for any combination of income quartiles. Comparatively, RA-Prud-Temp agents in the 4^{th} income quartile are willing to pay $3,092 more than RA-Prud-4RN agents in the 1^{st} income quartile, while RA-Prud-Temp agents in the 1^{st} income quartile pay $3,787 less than RA-Prud-4RN agents in the 4^{th} quartile. We also find that RA-Prud-Temp agents in the 4^{th} income quartile are willing to pay $3,604 more than RA-Imprud-4RN agents in the 1^{st} quartile. RA-Imprud-Temp agents in the 1^{st} income quartile are willing to pay $3,460 and $4,096 less than RA-3RN agents in the 2^{nd} and 4^{th} quartiles, respectively, and $4,255 less than RA-Imprud-4RN in the 4^{th} income quartile.

Although a full retrofit to the Bronze level costs more than $2,000, it often costs less than $2,000 to retrofit a house to *Fortified* Bronze when the homeowner is already replacing the roof. If the average life of a roof is 25 years, these results suggest that a large percentage of houses could be improved to the Bronze standard at the current (actuarially fair) insurance discounts, without providing subsidies to wealthy homeowners. However, these results also indicate that a complete and faster transition to stronger building standards will require subsidies, such as the Strengthen Alabama Homes (SAH) project. Among the houses that have been retrofitted in the SAH project, the average cost of retrofitting to Bronze is $12,057, of which $10,000 is paid with a grant from the Alabama Department of Insurance. The similarity in WTP between our estimates and the observed outcomes in the SAH program improves our confidence in the WTP estimates, despite the potential limits imposed by a somewhat small sample.

7 Conclusions

We applied theory and conducted field experiments to investigate the associations among and effects of HORA and information friction on homeowners' WTP for precautionary building standards with wind insurance discounts. Our experimental design employed 50-50 model-free risk apportionment lotteries to elicit homeowners' risk attitudes up to the fourth order, and a payment card WTP experiment to estimate WTP for *Fortified* building standards coupled with home insurance premium discounts.

Our theory uncovered new critical bounds for initial probability of loss that allow both risk averters and risk lovers to be prudent and willing to pay more than higher order risk-neutral agents to reduce the probability of loss. Finally, we developed testable conditions comparing mixed risk averters and mixed risk lovers' WTP for *Fortified* to higher order risk-neutral benchmarks.

Our analysis demonstrated strong correlations among HORAs and WTP for precautionary building standards revealing the significant role of thrid order risk attitude. The empirical results are partially consistent with our theoretical predictions based on second, third and fourth degree risk-neutral benchmarks. Specifically, we found that RA-Prud-Temp homeowners choose significantly higher WTP ($4,461) than RA-3RN agents, and RL-Imprud-Intemp homeowners chose significantly lower WTP ($3,195) than RL-3RN agents in line with theory. We also found that RL-Prud-Intemp homeowners consistently chose a significantly higher WTP ($2,738 and $4,451) than second degree and fourth degree risk-neutral agents, consistent with theory, but similar WTP when compared with third degree risk-neutral agents. Surprisingly, we found that prudent risk lovers are willing to pay significantly more than prudent risk averse homeowners relative to corresponding risk-neutral benchmarks.

Our analysis also found strong causal and heterogeneous effects of information friction on WTP for precautionary building standards in the subset of homeowners assigned to a higher WTP payment card range. In this group, WTP was significantly higher for those who watched the informational video. However, additional analysis suggests weak positive effects of information friction on WTP among the subgroup of mixed risk lovers. Specifically, information friction appears to increase WTP among RL-Prud-Intemp homeowners and the effect doubled for fourth degree risk-neutral agents. Further research is required to fully understand this result.

Finally, the results revealed that average WTP estimates are lower than the cost of retrofitting the average house in our sample, however, the marginal cost of retrofitting a roof already being replaced to the *Fortified* standard is less than the estimated WTP for most homeowners, which suggest that a slow transition of the existing housing stock is possible without the use of subsidies or supplemental building codes. A faster transition to precautionary building standards will require government intervention (subsidies) or technical innovation that reduces the cost of windstorm mitigation. Imprudent homeowners at the 25$^{\text{th}}$ percentile of household income may require full subsidies, at a minimum, to willingly adopt *Fortified*. Low WTP for

Fortified designations relative to cost may indicate that homeowners have acute time preferences in terms of the direct and indirect benefits of *Fortified* construction, which include reduced damages, shorter displacement time following a disaster, and the increased resale value of *Fortified* houses. Awondo et al. (2017) find that *Fortified* designations are capitalized into home values, increasing resale value by on average 7%. This benefit alone outweighs the average direct cost and indicates that investing in a *Fortified* designation can often be a sound financial decision.

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Online Appendix 1: Example, WTP Question

Q1. About how much would you be willing to pay to upgrade your current home to the **SILVER Fortification designation** (wind- and water-resistant roof, doors and windows), which would reduce your homeowners insurance premiums by **45%**?

$0

$2,500

$7,500

$10,000

$12,500

$15,000

$17,500

$20,000

$25,000

$30,000

$35,000 or more

Online Appendix 2: Risk attitudes choice task

Suppose you are presented with **two "lottery"** options, **Option A** and **Option B**. Each of the **14 questions** that follow presents a different scenario, where you must carefully compare the probabilities and payoffs of Option A versus those of Option B. For each scenario, **choose the one option** that you would prefer to "play."

***NOTE:** A full circle split into two halves by a line in the middle indicates that there is a 50% chance that the outcome on the left side of the circle will occur, and a 50% chance that the outcome on the right side of the circle will occur.

***NOTE:** All dollar values are positive unless otherwise noted.

***IMPORTANT NOTE:** Your response to one randomly selected question from this section will be used to determine your potential compensation bonus.

The file named "Explanation of Compensation Bonus" provides details on calculating the bonus. Please consider each of the following 14 scenarios carefully and pay close attention to the information contained in each question.

Please watch this short instructional video for a full explanation of how to complete this section: If, after viewing this video, you still have questions about how to complete this section, please contact Dr.

Sebastain Awondo (snawondo@cba.ua.edu).

LOTTERY QUESTIONS VIDEO SCRIPT

You have now reached the second of two sections of this survey which seek to measure your risk preferences. Both of these sections are very important because they contain the questions which will determine the potential amount of your compensation bonus. The bonus can range from \$0 up to \$60.

Each of the 14 questions in this section will ask you to choose between two "lottery" options: Option A and Option B. Each question will ask you to imagine that Option A and Option B are real lotteries that you can play, with each option offering different possible payout combinations.

In the first question, for example, you will see that there is a 100% chance that Option A will pay out \$20, since a full, undivided circle represents a "100% chance." There is a 100% chance that Option B, by comparison, will pay out \$20 + \$10. Based on this information, you must carefully compare Option A and Option B, and choose only one lottery which you would (theoretically) like to play. You may do this by simply dragging your mouse cursor over the top of your preferred Option, and clicking on the graph. You will know that your selection has been recorded by the survey when the graph of your preferred option becomes outlined by a dark shaded box.

So I would choose Option A this way ... and this is how I would choose Option B. Once you have selected your preferred option, click the 'NEXT' button and go onto the next question.

In the second question, you will see that Option A and Option B look slightly different. For Option A, there is now a 50% chance that the payout will be \$20, and a 50% chance that the payout will be equal to \$2 PLUS either \$10 or \$20. So, you see that a straight line which divides a full circle into two halves indicates that either side of the now divided circle has a 50% chance of occurring. You can think of each circle as a 50-50 coin toss, with one half of the circle representing "heads" and the other half representing "tails." For Option B, there is a 50% chance that it will pay out \$25, AND a 50% chance that the payout will be \$27, PLUS \$1 or MINUS \$1.

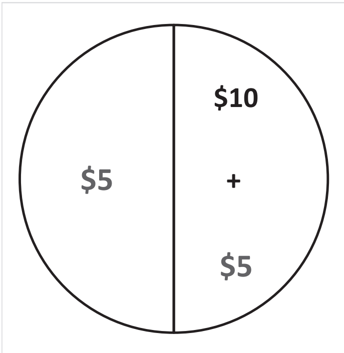
Each of the 14 questions will proceed in this manner, and will pose different options like this for you to choose from. You should note that all dollar values are POSITIVE unless otherwise noted by a negative sign.

Your answer to one randomly selected question from this section of 14 questions will be used to determine a portion of your potential compensation bonus, so all questions do require your response. Please pay close attention to the information presented in each question.

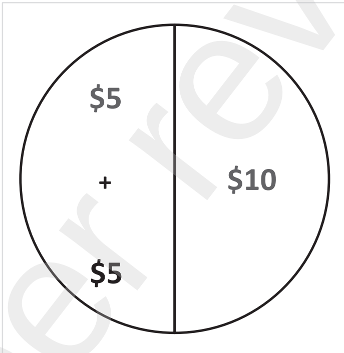
If you would like to go back and change an answer to a previous question within the section, you may use the 'BACK' button.

Task 3 (Table 1): Choose one of the two options below:

OPTION A

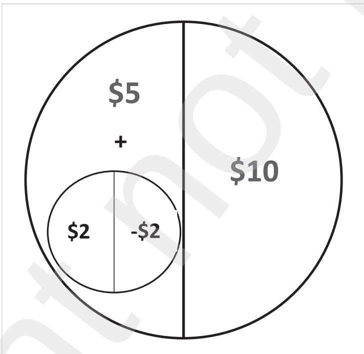


OPTION B

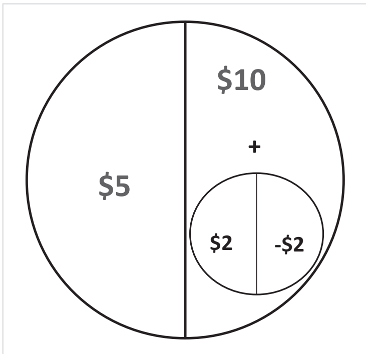


Task 7 (Table 1): Choose one of the two options below:

OPTION A



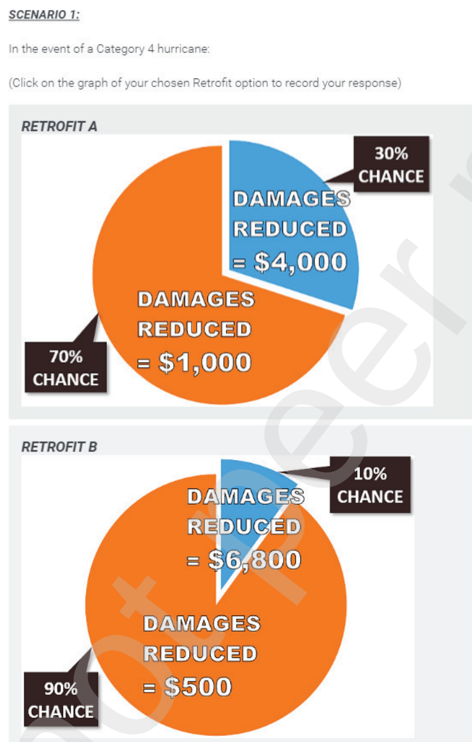
OPTION B



There are 6 steps involved in the calculation of the compensation bonus:

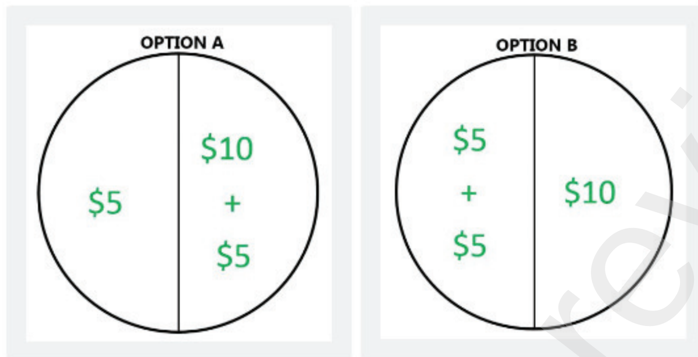
STEP 1: Complete the two (2) sections on the survey which seek to measure your risk preferences.

- The first risk preference section contains twenty-four (24) total questions. Each question asks you to choose between two retrofitting options (Retrofit A and Retrofit B) which, if installed, would fortify your home against windstorm damages. The first question in the section ("Scenario 1"), for example, presents the following retrofit options:



- The second risk preference section contains fourteen (14) total questions. Each question asks you to choose between two hypothetical "lottery" options (Option A and Option B). One sample question from this section presents the following "lottery" options:

Choose one of the two options below:



- *NOTE: When you reach each of two (2) the risk preference sections in the survey, you will be made aware that you are about to begin a section that is tied to the actual compensation bonus.
- *NOTE: You must submit responses to all questions in each of the two (2) risk preference sections.

STEP 2: For both risk preference sections, the survey software calculates the expected value of each option presented in each question.

- *NOTE: "Expected value" is one of the most important concepts in probability. It is defined as the "average value" (or "mean value") of all possible outcomes from a distribution. In simplest terms, expected value is the "best predictor" of a value, when more than one outcome is possible. Expected value is probability-weighted, meaning that the probability of a value occurring is factored into the calculation, along with the value itself. So, expected value is calculated by multiplying the probability of a value occurring by the value itself; this step is repeated for all possible values in the distribution. The sum of all these individual expected values is the expected value for the entire distribution. The following example will help to explain expected value more clearly:

EXAMPLE 2.1:

Imagine you have a 2-sided coin. Suppose that there is a 50% chance that the coin will land "Heads up", and there is a 50% chance that the coin will land "Tails up." Also, imagine that a friend has agreed to pay you $10 if the coin lands "Heads up", and $5 if the coin lands "Tails up." What is the expected value of the coin flip?

__EXPECTED VALUE__ = $[(\text{Prob}_{\text{HEADS}}) \times (\text{Value}_{\text{HEADS}})] + [(\text{Prob}_{\text{TAILS}}) \times (\text{Value}_{\text{TAILS}})]$

__EXPECTED VALUE__ = $[(.50) \times (10)] + [(.50) \times (5)]$

The chances of the coin landing "Heads up" are = 50%.

Your payout when the coin lands "Heads up" is = $10.

The chances of the coin landing "Tails up" are = 50%.

Your payout when the coin lands "Tails up" is = $5.

__EXPECTED VALUE__ = 5 + 2.5

__EXPECTED VALUE__ = ***$7.5***

Based on our calculation, we find that the expected value of the coin flip is = $7.50. This means that your best prediction of the average amount your friend will pay you is $7.50. Note that receiving $7.50 is not an actual possible outcome in the "distribution" ($10 and $5 are the only options). Still, we say that $7.50 is the "expected value", because it is meant to be a predictor of the *__average__* value of the coin flip…it should NOT, however, be viewed as a predictor of the actual dollar amount your friend will pay you!

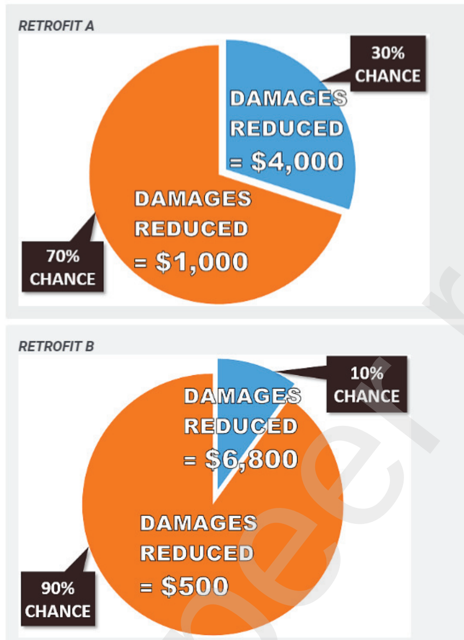
- Using expected value formulas similar to the one shown in the above example, the survey software will calculate an "expected value" for every answer choice in each question in the two risk preference sections. (You will not, however, be able to view these values within the survey.) The example below shows how the expected value of each answer choice would be calculated for Scenario 1 in the first risk preference section (i.e., the "retrofitting" section):

EXAMPLE 2.2:

SCENARIO 1:

In the event of a Category 4 hurricane:

(Click on the graph of your chosen Retrofit option to record your response)

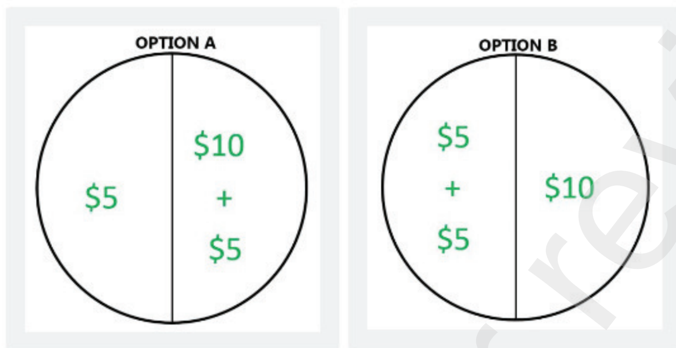


$EXPECTED\ VALUE_{RETROFIT\text{-}A}$	=	[(Prob$_{SUCCESS}$) x (Value$_{SUCCESS}$)]		+	[(Prob$_{FAIL}$) x (Value$_{FAIL}$)]		
$EXPECTED\ VALUE_{RETROFIT\text{-}A}$	=	[(.30) x (4,000)]	+		[(.70) x (1,000)]		
$EXPECTED\ VALUE_{RETROFIT\text{-}A}$	=	1,200	+	700	=	***$1,900***	
$EXPECTED\ VALUE_{RETROFIT\text{-}B}$	=	[(Prob$_{SUCCESS}$) x (Value$_{SUCCESS}$)]		+	[(Prob$_{FAIL}$) x (Value$_{FAIL}$)]		
$EXPECTED\ VALUE_{RETROFIT\text{-}B}$	=	[(.10) x (6,800)]	+		[(.90) x (500)]		
$EXPECTED\ VALUE_{RETROFIT\text{-}B}$	=	680	+	450	=	***$1,130***	

- Expected values are calculated for all questions in the second risk preference section (i.e., the "lottery" section), as well. The example below shows how the expected value of each answer choice would be calculated for a sample question in the second risk preference section:

EXAMPLE 2.3:

Choose one of the two options below:



EXPECTED VALUE$_{OPTION\text{-}A}$ = [(Prob$_{LEFT}$) x (Value$_{LEFT}$)] + [(Prob$_{RIGHT}$) x (Value$_{RIGHT}$)]

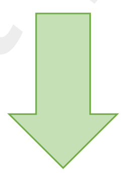
EXPECTED VALUE$_{OPTION\text{-}A}$ = [(.50) x (5)] + [(.50) x (15)]

EXPECTED VALUE$_{OPTION\text{-}A}$ = 2.5 + 7.5 = ***$10***

EXPECTED VALUE$_{OPTION\text{-}B}$ = [(Prob$_{LEFT}$) x (Value$_{LEFT}$)] + [(Prob$_{RIGHT}$) x (Value$_{RIGHT}$)]

EXPECTED VALUE$_{OPTION\text{-}B}$ = [(.50) x (10)] + [(.50) x (10)]

EXPECTED VALUE$_{OPTION\text{-}B}$ = 5 + 5 = ***$10***

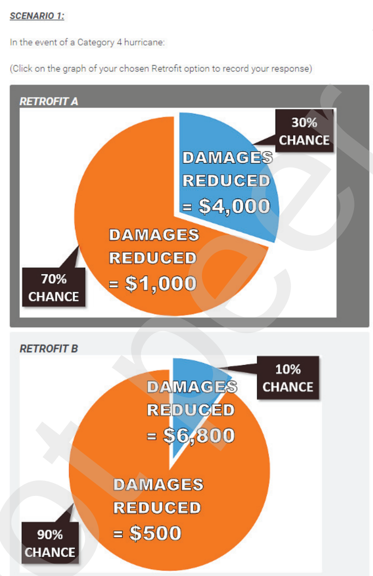


STEP 3: The survey software randomly selects one question from each of the two (2) risk preference sections, to be used in calculating the potential compensation bonus.

- Once you have submitted responses to all questions in both risk preference sections, the survey software will draw, at random, one question from each section. These questions will be used to calculate your potential compensation bonus.
- Out of the twenty-four (24) questions in the retrofitting section, one and only one question will be selected.
- Out of the fourteen (14) questions in the "lottery" section, one and only one question will be selected.
- ACIIR exercises no control over which questions will be selected. The process is completely random, and is executed by the Qualtrics survey software.
- The expected value of your chosen responses on both randomly selected questions will be used to calculate your potential compensation bonus.

EXAMPLE 3.1:

Suppose that the first question in the retrofitting section ("Scenario 1") was randomly selected – out of all 24 retrofitting questions – to be used for calculating your bonus. Also suppose that you selected "Retrofit A" as your answer to Scenario 1.

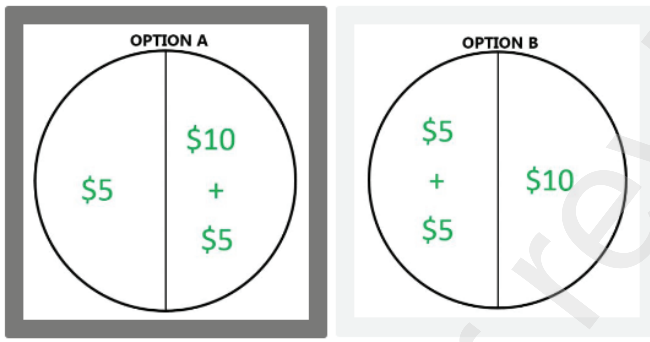


The expected value of answer choice 'A' in Scenario 1 is = $1,900. (This was calculated in **STEP 2, Example 2.2**.) Therefore, ***$1,900*** is one of two values that will be used to calculate your potential compensation bonus.

EXAMPLE 3.2:

Suppose that the sample question we viewed in **STEP 2, Example 2.3** was randomly selected – out of all 14 questions in the "lottery" section –to be used for calculating your bonus. Also suppose that you selected "Option A" as your answer to this question.

Choose one of the two options below:



The expected value of answer choice 'A' in the sample question is = $10. (This was calculated in **STEP 2, Example 2.3**.) Therefore, ***$10*** is one of two values that will be used to calculate your potential compensation bonus.

STEP 4: Expected values for all answer choices are scaled.

- The maximum compensation bonus that ACIIR will provide for survey participants is $60; the minimum compensation bonus that ACIIR will provide for survey participants is $0. In order to align the expected values of answer choices within that range, it is necessary to "scale" the calculated expected values for answer choices in both risk preference sections.
- Scaling is also necessary because ACIIR researchers wanted each risk preference section to contribute equally to the calculation of the compensation bonus. What this means is that the maximum bonus for the first ("retrofitting") section is = $30, and the maximum bonus for the second ("lottery") section is also = $30.
- Using the expected values calculated earlier in **STEP 3, Example 3.1 and Example 3.2**, we can show how this "scaling" would work:

EXAMPLE 4.1:

The expected value to be used from the retrofitting section was $1,900. In order to scale this number, $1,900 is divided by a "scaling factor"; for all questions in the retrofitting section, a scaling factor of 272 was used*. After dividing $1,900 by 272, we calculate that the potential compensation bonus from the retrofitting section is = $6.99. This is rounded to the nearest dollar: $7.

> *NOTE: The selection of 272 as the "scaling factor" is not arbitrary – when the maximum expected value for all possible answer choices in the retrofitting section ($8,160) is divided by 272, the result is $30. Since $30 is the maximum potential compensation bonus available for the retrofitting section, 272 was chosen as the "scaling factor."

The expected value to be used from the "lottery" section was $10. In order to scale this number, $10 is divided by a "scaling factor"; for all questions in the "lottery" section, a scaling factor of 1.5 was used*. After dividing $10 by 1.5, we calculate that the potential compensation bonus from the retrofitting section is = $6.67. This is rounded to the nearest dollar: $7.

> *NOTE: The selection of 1.5 as the "scaling factor" is not arbitrary – when the maximum expected value for all possible answer choices in the lottery section ($45) is divided by 1.5, the result is $30. Since $30 is the maximum potential compensation bonus available for the lottery section, 1.5 was chosen as the "scaling factor."

In order to calculate the full potential compensation bonus, we would simply add the bonus from the retrofitting section to the bonus from the "lottery" section:

$$\text{PotentialBonus}_{\text{TOTAL}} = \text{PotentialBonus}_{\text{RETROFIT}} + \text{PotentialBonus}_{\text{LOTTERY}}$$

$$\text{PotentialBonus}_{\text{TOTAL}} = \$7 + \$7 = \boldsymbol{\$14}$$

STEP 5: Answer the validation question at the end of the survey to receive the final compensation bonus.

- The Alabama State Code and the policies of The University of Alabama Institutional Review Board (IRB) prohibit the usage of gambles, lotteries or raffles as a form of compensation. Therefore, in order for our compensation bonus plan to comply with all legal requirements, we were advised by Legal Counsel and the IRB at The University of Alabama to add in a "validation" question at the end of the survey. This validation question is required to have a right or wrong answer, and must not be subject to random selection. It is the final question in the survey.
- The validation question developed by ACIIR is shown below. In order to answer the validation question correctly, survey participants must be able to properly calculate expected value based on the information provided.

Suppose that you enter a lottery which has a 50% chance of paying out $50, and a 50% chance of paying out $40. What is the *expected value* of the lottery payout?

*NOTE: The way to mathematically calculate the expected value of the situation described above is:

(.50 x 50) + (.50 x 40) = ANSWER

$0 | $40 | $45 | $50 | $90

- When a participant answers the validation question *correctly*, they receive the exact compensation bonus amount which was calculated from their randomly selected answer choices in each risk preference section. (This is the reason why this document has constantly referred to the calculation of the "*potential*" compensation bonus.) For example: the participant from **STEP 4, Example 4.1** above would receive exactly $14 as their compensation bonus if they were to answer the validation question correctly. Together with the base compensation amount of $40, the total compensation for this participant would be = ***$54*** ($40 + $14 = $54). Please note that the $14 calculated here is only an example which is being used to demonstrate our general method for calculating compensation bonuses; in reality, a participant's particular compensation bonus can range from $0 to $60.
- When a participant answers the validation question *incorrectly*, they do *not* receive the compensation bonus amount which was calculated from their randomly selected answer choices in each risk preference section. Instead, they will receive a "flat rate" bonus equal to exactly $10. Together with the base compensation amount of $40, the total compensation for participants who answer the validation question incorrectly is equal to exactly ***$50*** ($40 + $10).
- *NOTE: All participants who submit responses to all required survey questions are entitled to receive base compensation equal to exactly $40. This base compensation value does not change, and is not related to any particular answer choices made within the survey.

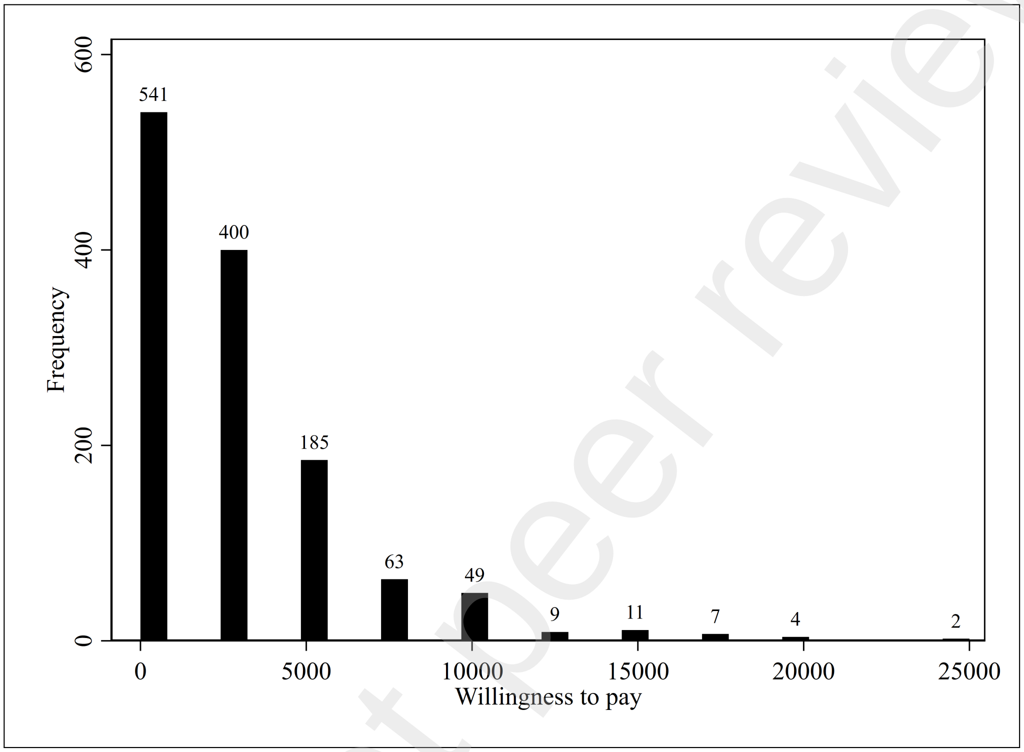
STEP 6: View and confirm the compensation amount.

- Once you have submitted your response to the validation question, the final screen in the survey will display the compensation bonus amount and the total compensation amount which you are entitled to receive.
- By downloading the "Online Incentive Form" from our website (http://aciir.culverhouse.ua.edu/research/), completing the form, and mailing it to our office, you will allow us to begin processing your compensation payment. This payment will be processed by the Accounts Payable office at The University of Alabama and will take the form of a one-time, lump-sum check mailed to the address which you provide.
- Upon competing and submitting the survey, you will also receive an immediate email confirmation from ACIIR which will list your specific compensation amount. This confirmation will serve as a "receipt" for you to keep for future documentation.

Online Appendix 3

In this appendix, we present additional tables of empirical results that are mentioned in the paper. First, Figure A1 shows the distribution of WTP responses.

Figure A1: Distribution of WTP responses



Next, we present results from the specification and robustness tests mentioned in the article. Tobit models could be biased if the left-censor limit depends on the same distribution as the uncensored observation. We address this concern by estimating Cragg's model. Cragg's model is a two-equation system. The first equation estimates the probability of being above the censoring limit (zero in our analysis), and the second equation is a truncated regression on the uncensored observations. Table A1 presents results from the pooled Tobit model. Table A2 presents results of a Probit model from Stage 1 of Cragg's model. Table A3 presents results of the truncated regression model in Stage 2.

Results from the truncated model show strong similarities to those reported in the random-effects Tobit model in terms of sign, level of significance, and overall magnitude of coefficients. Thus, we are satisfied using the Tobit model in our analysis.

Table A1: Pooled Tobit regression models

	Model 1	Model 2	Model 3	Model 4	Model 5
Fortified Silver	98	99	157	150	152
	(315)	(302)	(273)	(269)	(267)
35% ins discount	1,199**	1,143**	1,137**	1,136**	1,140**
	(389)	(374)	(339)	(333)	(331)
45% ins discount	2,208**	2,200**	2,136**	2,138**	2,140**
	(388)	(372)	(337)	(332)	(330)
WTP_{LUB} / watched video	-516	-221	-894*	-944*	-1,128**
	(451)	(429)	(396)	(390)	(391)
WTP_{HUB} / no video	808^{+}	816^{+}	270	201	120
	(448)	(436)	(386)	(380)	(378)
WTP_{HUB} / watched video	2,162**	2,094**	1,958**	1,983**	1,724**
	(460)	(436)	(392)	(387)	(391)
Hurricane risk perception		281**			
		(90)			
Female		-652*			
		(315)			
Income		1,358**	1,196**	1,170**	1,209**
		(203)	(177)	(174)	(174)
House size		1,200**	1,100**	1,052**	1,160**
		(311)	(272)	(274)	(275)
Safe choices			253**	111	221*
			(96)	(97)	(102)
Prudent choices				635**	653**
				(105)	(105)
Temparate choices					-450**
					(131)
Constant	-722	-25,214**	-22,206**	-22,899**	-23,305**
	(440)	(3,049)	(2,605)	(2,601)	(2,594)
Utility curvature()	5,188**	4,782**	4,150**	4,074**	4,044**
	(149)	(140)	(124)	(122)	(121)
Observations	1,271	1,187	1,065	1,065	1,065

Note: Dependent variable is WTP for precautionary building standards. Model 1 is based on the attribute levels in the experimental design. Models 2, 3, 4 and 5 include additional controls and higher order risk attitudes. Hurricane risk perception is the number of category three hurricanes the respondent expects will affect her community in the next 50 years. Income is the natural log of household income. Female is a dummy variable equal to one if respondent is female. House size is the natural log of square feet of living space. Safe/Prudent/Temperate choices is the number of choices indicating respondent is risk averse/prudent/temperate. Number of observations varies when respondents choose not to answer questions. Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A2: Cragg stage-one: Probit regression models

	Model 1	Model 2	Model 3	Model 4	Model 5
Fortified Silver	-0.030	-0.045	-0.022	-0.022	-0.021
	(0.072)	(0.077)	(0.082)	(0.083)	(0.083)
35% ins discount	0.238**	0.261**	0.297**	0.304**	0.305**
	(0.087)	(0.093)	(0.100)	(0.101)	(0.101)
45% ins discount	0.326**	0.365**	0.400**	0.410**	0.412**
	(0.088)	(0.094)	(0.100)	(0.101)	(0.102)
WTP_{LUB} / watched video	-0.210*	-0.148	-0.251*	-0.290*	-0.321**
	(0.100)	(0.106)	(0.114)	(0.116)	(0.117)
WTP_{HUB} / no video	0.048	0.094	-0.097	-0.147	-0.159
	(0.101)	(0.109)	(0.113)	(0.114)	(0.114)
WTP_{HUB} / watched video	0.487**	0.511**	0.540**	0.564**	0.532**
	(0.108)	(0.116)	(0.126)	(0.128)	(0.130)
Hurricane risk perception		0.087**			
		(0.022)			
Female		-0.185*			
		(0.080)			
Income		0.327**	0.337**	0.342**	0.350**
		(0.051)	(0.052)	(0.053)	(0.053)
House size		0.310**	0.343**	0.331**	0.356**
		(0.077)	(0.080)	(0.082)	(0.084)
Safe choices			0.112**	0.070*	0.089**
			(0.028)	(0.030)	(0.031)
Prudent choices				0.167**	0.170**
				(0.031)	(0.031)
Temparate choices					-0.081*
					(0.040)
Constant	-0.035	-6.160**	-6.519**	-6.815**	-6.936**
	(0.096)	(0.766)	(0.776)	(0.795)	(0.802)
Observations	1,278	1,194	1,068	1,068	1,068

Note: Dependent variable is a dummy variable = 1 if WTP ¿ 0. Model 1 is based on the attribute levels in the experimental design. Models 2, 3, 4 and 5 include additional controls and higher order risk attitudes. Hurricane risk perception is the number of category three hurricanes the respondent expects will affect her community in the next 50 years. Income is the natural log of household income. Female is a dummy variable equal to one if respondent is female. House size is the natural log of square feet of living space. Safe/Prudent/Temperate choices is the number of choices indicating respondent is risk averse/prudent/temperate. Number of observations varies when respondents choose not to answer questions. Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A3: Cragg stage-two: Truncated regression models

	Model 1	Model 2	Model 3	Model 4	Model 5
Fortified Silver	450	526	448	454	445
	(646)	(566)	(415)	(415)	(412)
35% ins discount	1,757	692	918	861	925
	(1,084)	(796)	(584)	(591)	(587)
45% ins discount	4,162**	2,713**	2,688**	2,559**	2,603**
	(1,092)	(783)	(576)	(582)	(579)
WTP_{LUB} / watched video	624	904	-896	-599	-803
	(1,236)	(882)	(685)	(676)	(680)
WTP_{HUB} / no video	2,709**	1,938*	2,174**	2,163**	2,070**
	(972)	(867)	(616)	(617)	(611)
WTP_{HUB} / watched video	2,250*	2,019*	1,769**	1,908**	1,621**
	(966)	(819)	(568)	(574)	(584)
Hurricane risk perception		-118			
		(181)			
Female		516			
		(596)			
Income		575	493	451	520^{+}
		(427)	(308)	(307)	(308)
House size		621	314	424	529
		(669)	(465)	(470)	(472)
Safe choices			-346*	-337*	-209
			(154)	(150)	(162)
Prudent choices				355^{+}	413*
				(190)	(192)
Temparate choices					-410^{+}
					(215)
Constant	-2,727^{+}	-11,803^{+}	-6,429	-7,969	-9,000^{+}
	(1,606)	(7,052)	(4,808)	(4,966)	(4,980)
Utility curvature()	5,071**	4,771**	3,708**	3,729**	3,708**
	(353)	(305)	(205)	(205)	(203)
Observations	553	595	555	561	561

Note: Dependent variable is WTP for precautionary building standards. Model 1 is based on the attribute levels in the experimental design. Models 2, 3, 4 and 5 include additional controls and higher order risk attitudes. Hurricane risk perception is the number of category three hurricanes the respondent expects will affect her community in the next 50 years. Income is the natural log of household income. Female is a dummy variable equal to one if respondent is female. House size is the natural log of square feet of living space. Safe/Prudent/Temperate choices is the number of choices indicating respondent is risk averse/prudent/temperate. Number of observations varies when respondents choose not to answer questions. Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Finally, only homeowners who had indicated in an earlier question that their house is currently not built to IBHS *Fortified* standards were directed to answer the WTP section of the survey, raising potential sample selection problems. Even though homeowners were randomly assigned to a block of the experimental design, we further examine the robustness of our results by estimating Heckman 2-stage selection models.

Results of the sample selection models, reported in Table A4, are also highly consistent with the previous results in terms of sign, level of significance, and relative magnitude of coefficients.

Table A4: Heckman two-stage selection models

	Model 1	Model 2	Model 3	Model 4	Model 5
Fortified Silver	237	267	271	265	263
	(225)	(214)	(214)	(213)	(212)
35% ins discount	513^{+}	469^{+}	477^{+}	480^{+}	490^{+}
	(284)	(270)	(269)	(268)	(266)
45% ins discount	$1,491^{**}$	$1,466^{**}$	$1,481^{**}$	$1,478^{**}$	$1,486^{**}$
	(281)	(267)	(267)	(266)	(264)
WTP_LUB / Watched video	-159	-236	-170	-159	-307
	(340)	(317)	(317)	(316)	(318)
WTP_HUB / No video	$1,165^{**}$	865^{**}	942^{**}	$1,007^{**}$	906^{**}
	(322)	(310)	(308)	(307)	(308)
WTP_HUB / Watched video	858^{**}	$1,013^{**}$	$1,035^{**}$	$1,082^{**}$	858^{**}
	(316)	(297)	(297)	(296)	(305)
Hurricane risk perception		-61			
		(70)			
Female		185			
		(228)			
Ln(Income)		301^{*}	298^{*}	339^{*}	366^{*}
		(148)	(147)	(147)	(147)
House size		202	158	345	356
		(263)	(260)	(266)	(265)
Safe choice			-117	-142^{+}	-54
			(77)	(77)	(83)
Prudent choice				275^{**}	277^{**}
				(105)	(105)
Temperate choice					-293^{**}
					(105)
Constant	$3,414^{**}$	-1,333	-813	-3,949	-3,664
	(423)	(2,651)	(2,595)	(2,831)	(2,816)
High education	0.38^{**}	0.40^{**}	0.40^{**}	0.40^{**}	0.40^{**}
Risk literacy	-0.62^{**}	-0.49^{**}	-0.49^{**}	-0.49^{**}	-0.49^{**}
House age	-0.01^{**}	-0.01^{**}	-0.01^{**}	-0.01^{**}	-0.01^{**}
House size	0.32^{**}	0.36^{**}	0.36^{**}	0.36^{**}	0.36^{**}
Distance to Coast	0.10^{**}	0.11^{**}	0.11^{**}	0.11^{**}	0.11^{**}
Prudent choice	0.19^{**}	0.19^{**}	0.19^{**}	0.19^{**}	0.19^{**}
Constant	-2.78^{**}	-3.30^{**}	-3.30^{**}	-3.30^{**}	-3.30^{**}
mills lambda	-696.44	-746.83	-717.54	101.69	-99.96
Observations	1137	1097	1097	1097	1097

Note: Dependent variable is WTP for precautionary building standards. Model 1 is based on the attribute levels in the experimental design. Models 2, 3, 4 and 5 include additional controls and higher order risk attitudes. Hurricane risk perception is the number of cat-3 hurricanes the respondent expects will affect her community in the next 50 years. Income is the natural log of household income. Female is a dummy variable equal to one if respondent is female. House size is the natural log of square feet of living space. Safe/Prudent/Temperate choices is the number of choices indicating respondent is risk averse/prudent/temperate. Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$