A Market-Based Measure of Ambiguity Aversion: Housing Prices Under Rising Seas *

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Abstract

We examine how ambiguity aversion shapes real estate market responses to long-run sea-level rise (SLR) risk. We link theory and empirics to quantify ambiguity aversion, and explore how this parameter impacts real estate markets and raises homeowners' willingness to invest in climate change adaptation. Using a novel dataset of projected inundation times for over two million coastal homes, we show that housing prices reflect both expected SLR risk and uncertainty across climate scenarios. We estimate an ambiguity aversion parameter, and find that this shifts probability weights toward worst-case scenarios, substantially increasing the weight on the most extreme SLR projections. Our paper provides the first market-based estimates for ambiguity aversion parameters in the field. We further use our model and estimates to provide new estimates for very long-run discount rates.

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1. Introduction

Standard economic models often assume agents make decisions under risk, where all relevant probabilities are known. However, in many real-world settings, decision-makers face model uncertainty, where the true probabilities of key events are unknown or disputed due to ambiguity across different potential models, misspecification about a given model, or both. Ambiguity aversion can generate first-order welfare effects, altering savings decisions, investment behavior, and policy design (Hansen, 2014).[1] One of the most policy-relevant domains where parameter uncertainty plays a critical role is climate change, and particularly sea-level rise (SLR).

Future SLR projections vary widely across different Representative Concentration Pathways (RCPs), reflecting uncertainty in emissions, ice sheet dynamics, and geophysical feedback mechanisms. For example, median projections under RCP2.6 and RCP8.5 can diverge by several feet, with first-year inundation estimates for coastal properties spanning a century or more (Kopp et al., 2014; DeConto and Pollard, 2016; Rodziewicz et al., 2022). Moreover, the plausibility of these scenarios are themselves highly uncertain as scenario developers and modelers do not provide probability distributions for these scenarios, despite the different scenarios being labeled as "business as usual," "most likely," or "least likely." This deep uncertainty matters: economic agents making location and investment decisions must evaluate risks that depend not only on expected SLR outcomes, but also on the ambiguity surrounding them. A highly ambiguity-averse decision-maker may react more strongly to the worst-case SLR projections, potentially discounting future real estate values or avoiding coastal investments altogether, while a less ambiguity-averse agent might take a more measured approach (Barnett, 2023; Ilut and Schneider, 2023). The extent to which markets capitalize both SLR risk and ambiguity remains an open empirical question with direct implications for climate adaptation and policy design.

This paper proposes a novel empirical approach to disciplining the ambiguity aversion parameter in decision-making, especially in the context of climate-related risks. Our

[1] A large and growing literature studies decision-making under such settings with parameter uncertainty, ambiguity, and robust control, recognizing their critical implications for economic planning and policy (Ilut and Schneider, 2023; Ilut and Valchev, 2023). In such environments, agents internalize the possibility of having competing models, leading to cautious behavior, precautionary actions, and non-trivial distortions in asset pricing and macroeconomic outcomes.This concern has motivated a broad theoretical literature in economics and finance that builds on the foundations of multiple priors models (Gilboa and Schmeidler, 1989), robust control (Hansen and Sargent, 2001, 2008, 2020), and smooth ambiguity preferences (Klibanoff et al., 2005; Hansen and Miao, 2018), among others. These frameworks prescribe how economic agents can account for model uncertainty, where they do not trust any single probability distribution, but instead evaluate choices using a set of possible models and act in a way that is robust against worst-case scenarios.

approach parallels that of Giglio et al. (2021), who use real estate market data to infer the discount rates relevant for evaluating long-run climate change mitigation. Just as discount rates observed in market transactions provide guidance on the appropriate social discount rate for climate policy, we argue that the degree of ambiguity aversion reflected in real estate prices offers a way to empirically discipline the ambiguity preferences that should be incorporated into climate-economy models. If real estate markets capitalize not only the expected SLR risk but also the uncertainty surrounding it, we can use these pricing patterns to infer the degree of ambiguity aversion implicit in economic behavior.

Our strategy involves three key steps. First, we develop a simple theoretical model to illustrate the role of ambiguity aversion in pricing uncertain climate risks. The model formalizes the relationship between ambiguity aversion and the capitalization of risk and uncertainty in asset prices. The model provides a clear asset-pricing equation under ambiguity aversion that can be estimated in the data.

Second, we construct a new high-resolution dataset that combines proprietary property transaction records with detailed geospatial SLR projections. Unlike global SLR estimates, local SLR is highly heterogeneous due to differences in topography, land subsidence, tidal variation, and ocean dynamics. Accurately assessing a property's inundation risk requires integrating localized elevation data, hydrologic connectivity, and regional sea-level projections rather than relying on broad global trends. We begin with the universe of Corelogic transaction data, and for each property in our dataset, we carefully calculate its expected first year of inundation under different RCP scenarios by integrating local elevation data with probabilistic SLR projections, following the methodology outlined in Rodziewicz et al. (2022). Finally, using this extensive data set we estimate how housing markets capitalize both SLR risk and uncertainty following an approach similar in spirit to Baldauf et al. (2020). Linking directly to our theoretical model, we explore the relationship between housing prices and the expected first year of inundation, capturing risk, as well as the variance in the first year of inundation across climate scenarios, capturing uncertainty. Our main results are as follows.

First, by linking these estimates to theoretical models of decision-making under ambiguity, we derive an implied ambiguity aversion parameter for market participants. Consistent with the model, we find that an increase in SLR uncertainty leads to an additional discount in house prices. More importantly, the empirical estimates allows us to estimate a market-based ambiguity aversion parameter which we find to be approximately 0.045. To give a quantitative interpretation to this value, this degree of ambiguity aversion distorts a uniform prior that puts equal probability weights ($p_1 = p_2 = p_3 = 1/3$) across three scenarios (RCP 2.6, RCP 4.5, RCP 8.5) towards a much more pessimistic distribution that puts much more probability weight on the worst-case scenario ($q_1 \approx 17\%, q_2 \approx 32\%, q_3 \approx 51\%$, i.e., the weight on the worst-case scenario RCP 8.5 increases from 1/3 to more than 1/2). These estimates provide strong evidence that uncertainty about climate risks is a first-order concern in asset valuation and highlight the need to incorporate ambiguity aversion into (asset pricing) models of long-run risk and robust climate policy. Moreover we provide some of the first estimates of ambiguity aversion parameters in the field, which can help guide theory and disipline models.

Second, our estimates of the capitalization of SLR risk (or the "SLR beta") provide a unique opportunity to revisit a foundational question in climate economics: what is the appropriate discount rate for long-run climate damages (Weitzman, 2013)? The choice of discount rate plays a central role in climate policy models, directly influencing estimates of the social cost of carbon and optimal mitigation strategies (Giglio et al., 2021). Our framework is well-suited for this estimation, as it relies on durable housing assets whose long-run exposure to SLR risk is carefully projected under different climate scenarios. We find that properties expected to be inundated 100 years earlier sell at approximately an 8.8% to 10.5% discount, which, through a deterministic present value calculation, implies relatively low long-run discount rates: our baseline estimate is about 2.34% per year. This estimate is lower than the 4% rate typically used in DICE models (Nordhaus, 2013) and roughly aligns with prior empirical estimates from UK and Singapore real estate markets (Giglio et al., 2015, 2021) of 2.6% over the 100-year horizon. The lower discount rate implied by our market-based approach suggests that future climate damages are valued (at least in the US coastal housing market) more heavily than previously thought.

Our framework also allows us to gauge the incremental willingness to adapt by raising a home's elevation, capturing how ambiguity aversion shifts homeowners' valuations. For instance, for a house currently at 1 ft above the inundation threshold, the baseline willingness-to-adapt is estimated at $126,917; when ambiguity aversion is factored in, this figure rises to $130,574—a nontrivial increase of about $3,657. As current elevation increases from 1 ft to 6 ft, the additional willingness-to-adapt declines—from roughly $3,600 down to around $554—reflecting diminishing marginal benefits of further elevation gains. This quantification is, to our knowledge, the first market-based estimate linking empirically derived discount rates and ambiguity aversion to adaptation costs, highlighting that ambiguity aversion substantially influences asset valuations under long-run climate-related risks.

1.1. Related Literature

Our paper is related to several strands of the economic and finance literature. To the best of our knowledge, our paper is the first to quantify ambiguity aversion based on market transaction data and projections from scientific models.

We contribute to the broader discussion on the economic valuation of long-run climate impacts, offering an asset-pricing-based complement to theoretical approaches in the valuation of the social costs of carbon (Weitzman, 2012; Golosov et al., 2014; Nordhaus, 2017; Cai and Lontzek, 2019; Giglio et al., 2021; Barrage and Nordhaus, 2024) and empirical estimates of the economic costs and consequences of climate change (Colacito et al., 2018; Hsiang et al., 2017; Burke et al., 2018). Our paper contributes to the growing literature on real estate and climate risk and the consequences of sea-level rise for various assets (Bernstein et al., 2019; Baldauf et al., 2020; Murfin and Spiegel, 2020; Painter, 2020; Goldsmith-Pinkham et al., 2023; Bakkensen and Barrage, 2022; Bakkensen et al., 2025) by quantifying how markets price not just climate-related sea-level rise risk but also uncertainty. Furthermore, an extensive climate finance literature has highlighted the implications of climate change for various assets along diverse dimensions (Hong et al., 2019; Ilhan et al., 2021; Kruttli et al., 2021; Seltzer et al., 2020; Alok et al., 2020; Krueger et al., 2020; Bansal et al., 2019; Barnett, 2019; Choi et al., 2020; Engle et al., 2019; Giglio et al., 2021; Bolton and Kacperczyk, 2021b,a) to which we contribute a novel market-based analysis of ambiguity aversion.

Our work also contributes to the important work on uncertainty analysis and the application of dynamic decision theory. As noted previously, this literature includes work on multiple priors (Gilboa and Schmeidler, 1989), model misspecification (Anderson et al., 2003; Maccheroni et al., 2006; Hansen and Sargent, 2007; Cerreia-Vioglio et al., 2021), and smooth ambiguity (Klibanoff et al., 2009; Hansen and Miao, 2018; Ilut and Schneider, 2023). There is also a growing literature exploring uncertainty analysis as it pertains to climate change (Kelly and Kolstad, 1999; Crost and Traeger, 2010; Lemoine and Traeger, 2012; Brock and Hansen, 2018; Barnett et al., 2020; Rudik, 2020; Barnett et al., 2021; Barnett, 2023; Barnett et al., 2023a). Prior work has attempted to quantify ambiguity aversion using survey-based methods, such as eliciting imprecise probabilities or presenting hypothetical choice experiments (Bhandari et al., 2024; Ilut and Schneider, 2023). While informative, these approaches are limited by hypothetical bias and framing effects. Work by Brenner and Izhakian (2018) provides one of the few market-based measures of ambiguity aversion based on high frequency return volatility, woth a recent application of the methodology to climate ambiguity (Rocciolo et al., 2024). Instead, we take a market-based approach integrated with scientific model projections. By examining how housing markets capitalize both expected SLR risk and uncertainty in inundation timing, we provide the first revealed-preference estimate of ambiguity aversion related to climate change. Hence, our paper helps address a key gap in the literature on robust decision-making under uncertainty, the pricing of climate risk in real estate markets, and the empirical discipline of ambiguity aversion—specifically but not limited to the context of climate-related risks.

The remainder of the paper is structured as follows. Section 2 presents a simple theoretical model of ambiguity aversion in real estate markets. Section 3 describes our dataset and empirical strategy, highlighting the integration of CoreLogic property transactions with localized SLR projections. Section 4 presents our empirical results, quantifying the extent to which real estate prices reflect SLR risk and uncertainty. Section 5 discusses the implications of our findings for climate policy, particularly in calibrating dynamic, general equilibrium optimal control models augmented by ambiguity aversion. Section 6 concludes.

2. A simple asset pricing model with ambiguity aversion

In this section we build a model of housing valuation with climate risk and ambiguity. We use the framework to derive relationships between home values, projected climate damages and ambiguity.

Environment Consider a homebuyer who evaluates a coastal housing unit that faces uncertainty about future SLR. The buyer evaluates three possible climate scenarios: a good scenario (s_1) where SLR progresses slowly, a "middle-of-the-road" scenario s_2, and a worst scenario (s_3) where SLR advances rapidly. The buyer has a reference probability distribution (baseline belief) that assigns probability weights p_i to scenario i. A more pessimistic agent who is more concerned about climate risks places a higher probability mass on scenarios 2 and 3 (in a first order stochastic dominance sense).

Consider a robust control problem of the form:

$$\min_{q} \left\{ E_q[v] + \xi D_{\mathrm{KL}}(q \| p) \right\},$$

where v as the log value of housing that is subject to SLR risk, and $v_1 > v_2 > v_3$. The solution to the minimization problem yields a worst-case distortion in the probability weights. The buyer has a baseline prior $p = (p_1, p_2, p_3)$ that puts benchmark probability weights on the three scenarios. Ambiguity aversion distorts the prior p to distorted probability weights $q = (q_1, q_2, q_3)$ that reflects the buyer's robustness concern about the worst case scenario. The expectation term $E_q[v] = \sum_i q_i v_i$ captures the homebuyer's perceived value of the house, given their worst-case distorted beliefs q. The Kullback-Leibler (KL) divergence term, $D_{\mathrm{KL}}(q \| p)$, which penalizes deviations of q from the reference beliefs

p, captures ambiguity averse preferences and is given by

$$D_{\mathrm{KL}}(q\|p) = \sum_i q_i \log\left(\frac{q_i}{p_i}\right).$$

This term quantifies the information cost of distorting the probability weights away from the baseline beliefs. The parameter ξ controls how much the buyer dislikes ambiguity, or not knowing the precise likelihood of future states of the world. A high ξ means the buyer is less ambiguity averse and does not significantly adjust their beliefs, while a low ξ implies strong ambiguity aversion and a greater tendency to overweight the worst-case scenario. In the extreme case where $\xi \to \infty$, the buyer does not deviate from the prior at all and behaves as a standard expected utility maximizer.

Worst-case distorted probability weights Taking the first-order conditions with respect to q yields the following optimal probability weights:

$$q_i^* = \frac{p_i \exp\left(-\frac{v_i}{\xi}\right)}{\sum_{j=1}^{3} p_j \exp\left(-\frac{v_j}{\xi}\right)}.$$

The solution shows that the distorted probabilities q_i^* are a weighted version of the baseline probabilities p_i, where the weights are given by $\exp(-v_i/\xi)$. This is often referred to as "exponential tilting." Since the valuation of the house in the worst case is lowest ($v_3 < v_2 < v_1$), the ambiguity-averse buyer puts more weight on the worst case ($q_3^* > p_3$). The strength of this adjustment depends on $1/\xi$. If $1/\xi$ is large, the buyer significantly increases their weight on the bad scenario relative to the prior ($q_3^* \to 1$ as $1/\xi \to \infty$). If $1/\xi$ is small, they largely retain their original beliefs ($q^* \to p$ as $1/\xi \to 0$).

Ambiguous asset pricing To analytically characterize how ambiguity aversion affects housing prices, we assume a simple parametrization for the valuation of the house as a linear function of SLR risk:

$$v_i = \bar{v} - \beta S_i, \quad i \in \{1, 2, 3\}.$$

where the SLR risk ranks according to:

$$S_1 < S_2 < S_3.$$

The term $\bar{v}$ represents the amenity value of the house absent climate risk, S_i is a measure of SLR risk under scenario i, and β captures how strongly house prices respond to SLR exposure (the "SLR beta").

Remark 1. The linearity of v in S simplifies our analysis, and can be partially justified by the empirical observation that the log of housing prices are approximately linear in the projected first year of inundation, once amenities are controlled for (see Figure 4). The linearity can be microfounded as follows. Consider a house that, in the absence of SLR risk, yields housing utility flow between period $t = 0$ and a terminal period $T_{\max}$. However, with SLR risk, the housing utility flow will stop as soon as the house is permanently inundated by the rising seas. Denote the first period of inundation under SLR scenario i by T_i. Suppose the homeowner discounts the future at rate ρ. Then the present discounted value of the housing unit in scenario i is given by $v_i = \frac{1}{\rho}(1 - \exp(-\rho T_i \wedge T_{\max}))$. Let $S_i \equiv (T_{\max} - T_i)^+$. Then the housing valuation can be approximated linearly by $v_i \approx \alpha - \beta S_i$, where $\alpha \equiv \frac{1}{\rho}(1 - \exp(-\rho T_{\max})$ and $\beta \equiv \exp(-\rho T_{\max})$.[2]

Substituting this linear valuation structure into the belief adjustment equation and solving for the ambiguity-adjusted expectations, we obtain

$$q_i^* = \frac{p_i \, e^{\beta S_i/\xi}}{\sum_j p_j \, e^{\beta S_j/\xi}} \approx p_i \left[1 + \frac{\beta}{\xi}\left(S_i - \bar{S}\right)\right] \tag{1}$$

where $\bar{S}$ is the average SLR risk under the benchmark prior p:

$$\bar{S} \equiv \sum_j p_j S_j.$$

Again, this equation implies that if $S_i > \bar{S}$ (SLR risk is higher in scenario i on average), then ambiguity aversion will tilt the probability weight more towards scenario i ($q_i > p_i$). Clearly, the distortion is stronger if the buyer is more ambiguity averse (higher $1/\xi$). It is also stronger if the SLR beta is larger (more positive β).

With distorted weights q^*, the ambiguity-adjusted housing valuation $V \equiv E_q[v]$ is given by

$$V \approx \underbrace{\bar{v}}_{\text{invariant of SLR}} - \underbrace{\beta \overbrace{\Big(\sum_i p_i S_i\Big)}^{\text{avg } \bar{S}}}_{\text{SLR capitalization term}} \underbrace{- \frac{1}{\xi}\beta^2 \overbrace{\sum_{i<j} p_i p_j (S_i - S_j)^2}^{\text{uncertainty } \sigma_S^2}}_{\text{ambiguity capitalization term}}. \tag{2}$$

The first hedonic term represents the intrinsic amenity value of the house. The second term represents the capitalization of the average SLR risk $\bar{S} \equiv \sum_i p_i S_i$ based on the buyer's

[2] The approximation is reasonable in our context. For example, with $T_{\max} = 2301 - 2001$ (our SLR projection ends in 2300 and the first year in our data is 2001), $T = 2273 - 2001$ (the median projected first year of inundation due to SLR under RCP 4.5 is 2273), $\rho = 2\%$, the value of v_i is 49.783, which is well approximated by 49.807.

baseline belief. The third term introduces an ambiguity discount, which depends on the variance of the SLR projections across scenarios, weighted by the baseline probabilities:

$$\sigma_S^2 \equiv \sum_{i<j} p_i p_j (S_i - S_j)^2 = \sum_i p_i (S_i - \bar{S})^2,$$

the ambiguity aversion parameter ξ, and the SLR beta β. A more ambiguity-averse buyer, characterized by a higher $1/\xi$, applies a larger discount to the uncertainty across the scenarios. Similarly, a larger SLR beta implies a larger ambiguity capitalization term.

This equation provides a direct mapping between market pricing of SLR uncertainty and ambiguity aversion. If buyers are ambiguity neutral, house prices should only reflect expected SLR risk, and the last term vanishes. However, if buyers are ambiguity averse, properties with greater variation in SLR projections experience larger price discounts.

Heterogeneity Is it reasonable to expect all homebuyers to be so sophisiticated with respect to scientific projections of SLR? In fact, it is well documented that a significant portion of US populations are not worried about global warming, or even do not believe that global warming is happening (Howe et al., 2015). Furthermore, this "optimism" manifests in the lack of capitalization of SLR risk in housing prices in areas with low degree of worry or belief in global warming (Baldauf et al., 2020; Bakkensen et al., 2025).

Hence, we enrich the model by introducing heterogeneity among homebuyers. Suppose there are two types of homebuyers: optimists and pessimists (or realists). The pessimists' behaviors are as described above. However, the optimists do not believe that climate change will lead to an increase in sea levels, and hence their housing valuation does *not* depend or SLR projections:

$$V^{\text{opt}} = \bar{v}.$$

Taking the difference in valuations between pessimists (2) and optimists yields:

$$V^{\text{pes}} - V^{\text{opt}} = -\beta \bar{S} - \frac{1}{\xi} \beta^2 \sigma_S^2. \tag{3}$$

This equation shows that the difference in housing valuations between pessimists and optimists consists of two components. The first term reflects the standard SLR capitalization effect, meaning that pessimists discount home values according to their expected exposure to SLR. The second term is the ambiguity discount, which depends on both the spread in SLR risk across scenarios and the pessimists' belief weights.

Equation (3) provides the key empirical link between market pricing and ambiguity aversion. The first term allows us to estimate β, the SLR capitalization rate, while the second term enables the estimation of ξ, the ambiguity aversion parameter. In the next sections, we will estimate ξ using observed variation in house prices and uncertainty in SLR projections across climate scenarios. The coefficient from our main estimates will uncover these parameters by leveraging variation in house prices, SLR risk, and uncertainty across different climate belief groups.

3. Empirical analysis

3.1. Data construction

Our analysis is based on high-resolution property transaction data from CoreLogic, which provides extensive mortgage and real estate transaction records spanning 2001 to 2016. By integrating CoreLogic's comprehensive property records with state-of-the-art SLR modeling, we construct a uniquely detailed dataset that allows for an in-depth analysis of how climate change risk is transmitted to housing markets. This dataset includes detailed property characteristics such as sale prices, transaction dates, number of bedrooms and bathrooms, building size, lot size, elevation, and year built. The availability of precise geolocation coordinates for each property enables us to merge these records with sea-level rise (SLR) projections and construct property-specific inundation risk estimates.

To estimate the first year of inundation for each property, we follow the methodology detailed in Rodziewicz et al. (2022). This process involves multiple steps. First, we determine property-specific elevations by matching each property's coordinates with NOAA's Digital Elevation Models (DEMs). These elevation values are adjusted to a consistent vertical datum and account for differences in land height relative to sea level. Unlike simple elevation-based assessments, we incorporate NOAA's Sea-Level Rise Viewer shapefiles, which delineate areas projected to be hydrologically connected to the ocean. This ensures that properties behind levees, dunes, or other protective barriers are not misclassified as vulnerable to near-term SLR.

These property-specific elevations are then integrated with well known SLR projections developed by DeConto and Pollard (2016). These projections estimate the timing of inundation under three Representative Concentration Pathways (RCPs): RCP2.6 (low emissions, slow SLR), RCP4.5 (moderate emissions, moderate SLR), and RCP8.5 (high emissions, accelerated SLR). The projections incorporate global and local uncertainties in future sea-level rise, accounting for ice sheet loss dynamics, thermal expansion, and land subsidence. The resulting property-level SLR inundation timing estimates range from 2050 to 2300, with uncertainty bands capturing projections from the 10th to the 90th percentile.

Figure 2 illustrates how we construct the projections of the first year of inundation for each property. The solid lines represent the median SLR projections for RCP2.6, RCP4.5, and

RCP8.5. For each property, its elevation (represented for a single house by the horizontal solid line) determines the first year of inundation. Taking the RCP4.5 scenario as an example, the intersection of the horizontal line with the median SLR curve for RCP4.5 determines the first year ($T_{RCP4.5}$) that the property will be permanently inundated under the median projection. The same method is applied for the RCP2.6 and RCP8.5 scenarios, yielding the corresponding first years of inundation $T_{RCP2.6}$ and $T_{RCP8.5}$.

As an example, Figure 3 plots the actual local SLR projections for the city of Miami. Again, the solid lines represent the median SLR projections for RCP2.6, RCP4.5, and RCP8.5, while the dotted lines plot the corresponding 10th and 90th percentile projections under each scenario.

Beyond physical exposure to SLR, we analyze how buyers' perceptions of climate risk influence housing transactions. We incorporate county-level climate opinion data from the 2014 Yale Climate Opinion Survey (Howe et al., 2015), which provides estimates of the percentage of residents who believe climate change is occurring. This dataset, based on over 13,000 survey responses, serves as a proxy for buyers' climate awareness at the time of purchase. By linking this measure to property transactions, we evaluate how climate beliefs impact pricing, demand, and market behavior.

To control for broader economic and demographic trends, we merge our dataset with county-level statistics from the U.S. Census Bureau, including population density, median income levels, and local economic indicators. These controls help disentangle the effects of SLR risk from other economic factors affecting property values.

We restrict our analysis to single-family properties from 17 major coastal metropolitan statistical areas (MSAs) (Figure 1). To reduce the influence of extreme outliers, we exclude transactions with sale prices outside the $50,000–$10,000,000 range and winsorize key housing variables, including house price, building size, elevation, and age, at the 1st and 99th percentiles.

Table 1 provides summary statistics for the properties in our dataset. The average home sale price is $464,496 (std: $539,648), with a median price of $325,500. Houses typically have 3.25 bedrooms and 2.31 bathrooms, with an average building size of 2,049.8 square feet. The average property elevation is 82.11 feet above sea level, but 10 percent of homes sit below 6.8 feet, highlighting the range of exposure to coastal flooding. SLR projections suggest substantial variation in the first year of inundation across properties and climate scenarios. Under RCP2.6, the average projected inundation year is 287 years from the base year of 2010, while under RCP8.5, it drops to 234. Uncertainty in these estimates increases under more extreme climate scenarios, with projected standard deviations ranging from 13.6 years (RCP2.6) to 86.5 years (RCP8.5).

3.2. Specification

To estimate the impact of sea-level rise (SLR) risk and uncertainty on housing prices, we employ the following empirical specification. This specification follows Baldauf et al. (2020), who analyze how housing markets capitalize exposure to climate risk. We extend their framework by incorporating our novel measure of SLR uncertainty at the house level, capturing the variation in projected inundation timing across climate scenarios.

$$\begin{aligned}\log V_{i,c,t} = \alpha_1 \text{SLR Risk}_i + \alpha_2 \text{SLR Uncertainty}_i + \beta_1(\text{Pessimist}_c \times \text{SLR Risk}_i) \\ + \beta_2(\text{Pessimist}_c \times \text{SLR Uncertainty}_i) + X_{i,c,t}\Gamma + \theta_{Z\times D} + \tau_t + \varepsilon_{i,c,t}.\end{aligned} \tag{4}$$

The dependent variable $\log V_{i,c,t}$ represents the log of the value (the sale price) of property i in county c at time t. Note that $|\beta_1|$ maps to the SLR capitalization parameter β in our model. Furthermore, as discussed in more details below, $\frac{|\beta_2|}{\beta_1^2}$ will be scaled and mapped to the model's ambiguity aversion parameter $1/\xi$.

SLR risk measure Consistent with the model, the variable SLR Risk$_i$ is defined as

$$\text{SLR Risk}_i \equiv (2301 - T^{\text{median}}_{\text{RCP }4.5,i})^+,$$

where $T^{\text{median}}_{\text{RCP }4.5,i}$ is the median projected first year of permanent inundation under the RCP 4.5 scenario. We normalize 2301 as the upper bound for SLR Risk because our sea-level rise projections extend to 2300, beyond which we do not have model estimates for individual properties. This means that all properties with $T^{\text{median}}_{\text{RCP }4.5,i} > 2300$ are grouped into a single category, assigned an SLR Risk of zero. This specification assumes that the economic effects of inundation risk diminish beyond this threshold, as properties projected to be safe until at least 2301 are unlikely to be perceived as exposed to meaningful near-term risk.[3] Note that with 2301 being the terminal year of SLR projection and 2001 as the first year of our data, the implied terminal period T_{max} in the model is $2301 - 2001 = 300$.

Our SLR risk measure is significantly more fine-tuned than those used in prior studies. For example, in much of the existing literature, SLR risk is measured using a binary indicator that equals one if a house is projected to be inundated with three feet or with six feet of SLR (Bernstein et al., 2019; Baldauf et al., 2020; Bakkensen and Barrage, 2022; Bakkensen et al., 2025). While useful, such a binary measure provides no information

[3] Quantitatively little changed by taking this assumption. Even with an extremely low discount rate of 2% (we will directly estimate long-run discount rates in Section 4), the value of a home 275 years into the future will be less than 1% of the purchase price. While this choice is reasonable given the long horizon and significant discounting of distant climate risks, we will later conduct sensitivity analyses where we vary the normalization year to alternative cutoffs, such as 2250 or 2290.

about the timing of inundation. A house expected to be submerged in 2050 is treated the same as a house expected to be submerged in 2150, even though the latter faces little to no economic risk in the foreseeable future. Our approach, by contrast, assigns each property a continuous, property-specific measure of inundation timing, allowing us to differentiate between near-term and long-term risk. This enables a more precise assessment of how markets price SLR exposure, making our analysis much richer than existing studies that rely on static thresholds.

SLR uncertainty measure The variable SLR Uncertainty$_i$ measures the ambiguity in SLR projections and is constructed as

$$\text{SLR Uncertainty}_i \equiv (T^{\text{median}}_{\text{RCP 2.6},i} - T^{\text{median}}_{\text{RCP 8.5},i})^2.$$

The indicator Pessimist$_c$ is set to one if the fraction of residents in county c who express concern about climate change in the Yale Climate Opinion Survey exceeds the sample median. The model includes property-level controls such as building age, elevation, number of bedrooms and bathrooms, and square footage. County-level controls include median income, population, and GOP vote share in the last presidential election. Fixed effects $\theta_{Z\times D}$ control for unobserved heterogeneity at the ZIP code $\times$ distance-to-coast bin level, while year fixed effects τ_t absorb broader market trends.[4]

Identification relies on the granular property-level variation in SLR risk and uncertainty, which are computed using precise elevation data and local sea-level rise projections. Unlike global SLR forecasts, localized projections incorporate differences in land subsidence, hydrologic connectivity, and ocean dynamics. This ensures that SLR exposure varies meaningfully across properties within the same region, even after accounting for fixed effects.

A typical concern is that housing prices may reflect omitted factors correlated with both SLR risk and broader market conditions. We address this by controlling for an extensive set of observable characteristics at both the property and county levels. Property-level controls include building age, elevation, number of bedrooms, number of bathrooms, and building square footage. County-level controls include average county income, county population for the year of transaction, and GOP voter share in the last presidential election. In some specifications, these controls are also interacted with SLR Risk$_i$, allowing us to account for potential heterogeneity in how these characteristics influence the capitalization of SLR exposure.

[4]Following Baldauf et al. (2020); Bakkensen et al. (2025), we use nonlinear bins for the distance from the East Coast: 0 – .01 miles, .01 – .02 miles, .02 – .08 miles, .08 – .16 miles, and more than .16 miles.

Additionally, we exploit heterogeneity in climate beliefs to provide further evidence that our estimates capture market perceptions of SLR risk rather than unobserved confounders. If properties in counties with greater climate concern (as measured by the Yale Climate Opinion Survey) exhibit stronger price responses to the same level of SLR risk or uncertainty, this suggests that beliefs about climate change, rather than purely omitted economic fundamentals, drive differences in capitalization effects. This heterogeneity provides an additional check on the causal interpretation of our findings by isolating variation in price sensitivity that aligns with differences in expectations about climate risk.

3.3. Results

Table 2 presents our core findings on how housing markets capitalize SLR risk and uncertainty. The empirical specification follows equation (4), where we estimate the effect of SLR Risk (the projected timing of inundation) and SLR Uncertainty (the variability in first-year inundation across climate scenarios) on house prices.

3.3.1 SLR beta

Column (1) begins with a baseline estimate of SLR Risk. The coefficient is small and not statistically significant, suggesting that, on average, variation in the timing of inundation does not strongly influence prices. However, in column (2), where the sample is restricted to counties with above-median climate concern (Pessimist counties), the coefficient becomes significantly negative. This indicates that in regions where buyers are more concerned about climate change, homes with earlier projected inundation years are discounted more heavily, consistent with prior findings in Baldauf et al. (2020).

Figure 4 provides a visual counterpart to this result. The bin scatter plot shows the relationship between SLR Risk and log house price, after controlling for the full set of property and county-level characteristics. The downward slope of the fitted line confirms the negative price response observed in column (2), reinforcing the finding that home values decline as inundation dates become nearer in climate-conscious regions.[5]

Column (3) introduces an interaction term between SLR Risk and Pessimist, allowing us to test whether properties in climate-concerned regions exhibit differential price sensitivity to inundation timing. The interaction coefficient is

$$\hat{\beta}_1 = -0.00105$$

[5]Notably, this bin scatter specification employs more stringent fixed effects—ZIP × distance bin × year fixed effects—ensuring that the variation exploited is within highly localized markets and further reducing concerns about omitted variable bias.

and statistically significant at the 1% level. This implies that in pessimist counties, a house expected to be inundated 10 years earlier sells for approximately 1% less, while a house expected to be inundated 100 years earlier sells for 10% less, relative to an otherwise comparable home.[6]

3.3.2 Capitalization of scenario uncertainty

Columns (4)–(6) introduce SLR Uncertainty, our novel measure capturing ambiguity in the timing of inundation. Column (4) suggests that SLR Uncertainty has little effect on prices on average, but in column (5), where the sample is restricted to Pessimist counties, the coefficient on SLR Uncertainty is negative and significant. This suggests that ambiguity aversion plays a role in climate risk pricing, particularly in areas where homebuyers are predisposed to worry about climate change.

Figure 5 illustrates this effect using a bin scatter plot of SLR Uncertainty vs. log house price, with the same full set of controls and more stringent fixed effects. The downward slope of the fitted line confirms that greater ambiguity in SLR projections correlates with lower property values, consistent with column (5). The comparison between Figures 4 and 5 underscores that both SLR Risk and SLR Uncertainty influence pricing, but uncertainty effects emerge more clearly in markets where climate risks are salient.

Column (6) presents our key specification, interacting both SLR Risk and SLR Uncertainty with the Pessimist indicator. The coefficient on Pessimist × SLR Risk remains negative and significant at the 5% level:

$$\hat{\beta}_1 = -0.0008869.$$

More importantly, the coefficient on Pessimist × SLR Uncertainty is

$$\hat{\beta}_2 = -0.0000029,$$

also significant at the 5% level. The negative sign suggests that in Pessimist counties, an increase in SLR Uncertainty leads to additional price discount. The sign provides evidence that markets penalize ambiguity itself, not just expected risk.

This pattern of results is crucial for our quantification of ambiguity aversion. Under standard expected utility, homebuyers should care about the expected year of inundation but should be indifferent to variance in that projection unless they exhibit ambiguity

[6]To put in context, Bernstein et al. (2019); Bakkensen et al. (2025) estimate that homes projected to be inundated at six feet of SLR sell for approximately 6-7% less than otherwise comparable homes that remain above water. However, these estimates cannot be directly compared to our estimate, because these papers have no information about the timing of 6ft of SLR.

aversion. The fact that SLR Uncertainty commands a price discount—especially in climate-concerned regions—suggests that ambiguity aversion is an important factor in climate risk pricing. The next section formalizes this interpretation by estimating the implied ambiguity aversion parameter based on market responses to uncertainty.

4. Market-based estimate of the long-run discount rate

Our framework provides a unique opportunity to revisit the debate on what are appropriate long-run discount rates in climate economics, as we can estimate the discount rate against long-run SLR risk using our data. In our model, the parameter β captures the sensitivity of house prices to shifts in the expected first year of inundation due to sea-level rise. Our empirical estimates of $\hat{\beta}_1$ range between 0.0008869 and 0.0010489, implying that, all else equal, a property with an expected inundation date 100 years earlier sells at an 8.8% to 10.5% lower price.

What long-run discount rates do these numbers suggest? Let us focus on the more conservative estimate of the SLR beta $\beta = |\hat{\beta}_1| = 0.0008869$. Recall from Remark 1 that the SLR beta is derived from $\beta = \exp(-\rho T_{\max})$. With $T_{\max} = 2301 - 2001$, the implied discount rate is $\rho = \frac{-\log 0.0008869}{300} \approx 2.34\%$.

Hence, our analysis provides an independent, market-based way to calibrate the long-run discount rate for climate damages, a key input in climate policy models. To put in perspective, previous empirical work based on UK and Singapore housing data (Giglio et al., 2015, 2021) suggest a discount rate of about 2.6% for the 100-year horizon, while the discount rate typically used in DICE models is 4% (Nordhaus, 2013). A lower discount rate suggests a (much) larger social cost of carbon and underscores the importance of our approach in integrating market-based estimates with theoretical models of long-run climate damages.

5. Market-based estimate of the ambiguity aversion parameter

We now use the empirical estimates of β_1 and β_2 from Column 6 of Table 2 to infer the ambiguity aversion parameter $1/\xi$ in equation (3) of the model:

$$V^{\text{pes}} - V^{\text{opt}} = -\beta \bar{S} - \frac{1}{\xi}\beta^2 \sigma_S^2$$

where

$$\bar{S} = \sum_{i=1}^{3} p_i S_i \quad \text{and} \quad \sigma_S^2 = \sum_{i=1}^{3} p_i (S_i - \bar{S})^2.$$

Assume a uniform baseline prior (i.e., $p_1 = p_2 = p_3 = \frac{1}{3}$). Furthermore assume that the middle scenario approximates the average of the two extremes ($T_2 \approx \frac{T_1+T_3}{2}$ and hence $S_2 \approx \frac{S_1+S_3}{2}$, as $S_i \equiv 2301 - T_i$).[7] Then we obtain $\bar{S} \approx S_2$, and the variance further simplifies to

$$\sigma_S^2 \approx \frac{1}{6}(S_1 - S_3)^2, \tag{5}$$

since the deviations of S_1 and S_3 from S_2 are symmetric. This reduction means that instead of including all six terms—S_1, S_2, S_3, $(S_1 - S_2)^2$, $(S_2 - S_3)^2$, and $(S_3 - S_1)^2$—our specification needs only two key terms: the median inundation time S_2 and the squared difference $(S_1 - S_3)^2$. This simplification streamlines the empirical implementation, allowing us to map (3) to our econometric specification (4).

As mentioned before, the coefficient estimate on *Pessimist × SLR Risk* is $|\hat{\beta}_1| = 0.0008869$, which is the empirical counterpart of β in (3). Similarly, the coefficient estimate on *Pessimist × SLR Uncertainty* is $\hat{\beta}_2 = -0.0000029$, which corresponds to the ambiguity discount term in equation (3). Notably, SLR Uncertainty appears negatively in both the empirical estimates and the theoretical expression, reinforcing the consistency between the structural model and the data.

From equations (3) and (5), we have:

$$\frac{1}{\xi} \approx 6\frac{|\hat{\beta}_2|}{(\hat{\beta}_1)^2} = 6\frac{0.0000029}{0.0008869^2} \approx 22.12$$

or equivalently:

$$\xi \approx 0.045$$

What does this value mean for the distortion of belief from p_1 to q_1 due to ambiguity aversion? Using equation (1), and plugging in the average value of T in our sample, we get a distortion of probability that increases the weight on the worst-case scenario RCP 8.5 from the baseline of 1/3 to about 1/2 (see Table 4). This distortion implies that market participants assign disproportionately higher probability weight to the worst-case climate scenario than an unbiased prior would suggest. In economic terms, this shift means that homebuyers in coastal markets act as if they believe extreme sea-level rise outcomes are significantly more likely than indicated by scientific projections alone. This finding provides the first known market-based estimate of probability distortion due to ambiguity aversion, quantifying how uncertainty reshapes expectations and influences asset pricing in a way that is economically significant for climate risk valuation and policy design.[8]

[7]This approximation is reasonable. Figure 6 plots the histogram of $S_2 - \frac{S_1+S_3}{2}$, which has a substantial concentration of mass at 0.

[8]Our estimate of $1/\xi \approx 22$ can be mapped to a risk aversion parameter of approximately 23 in a recursive

6. Application: Willingness to adapt to SLR

Our framework also allows us to quantify, for the first time to our knowledge, the role of ambiguity aversion in adaptation decisions by linking empirically estimated discount rates and ambiguity parameters to homeowners' willingness to raise their property's elevation. We have in mind the adaptation technology of raising a house on stilts (Fried, 2022). In the model, this technology simply maps to an increase in the house's elevation above the sea level.[9] Under our model, the housing utility flow is normalized to 1 until inundation occurs at time T, so that the value of the house is given by

$$V(T) = \frac{1 - e^{-\rho T}}{\rho}.$$

Sea-level rise is modeled as

$$\mathcal{S}_t = \mathcal{S}_0 e^{\mu t}, \quad \mathcal{S}_0 = 1,$$

and for a house with current elevation h, the inundation time is

$$T(h) = \frac{1}{\mu} \log\left(1 + \frac{h}{\mathcal{S}_0}\right).$$

A homeowner can raise the elevation by increasing h, and the marginal willingness to adapt is given by $\frac{\partial V(h)}{\partial h} = \frac{(\mathcal{S}_0+h)^{-\frac{\rho}{\mu}-1}}{\mu}$. Similarly, the willingness to raise elevation by 1 unit is captured by the difference $V(h+1) - V(h)$.

As a baseline, we set $\rho = 2.4\%$ (as previously derived from our SLR capitalization estimates) and set the rat of SLR to be $\mu_1 = 1.60\%$, $\mu_2 = 1.75\%$, and $S_3 = 1.97\%$ (calibrated to average inundation timings under the RCP2.6, RCP4.5, and RCP8.5 scenarios given the average house elevation in the data). We obtain some quantitative predictions for the cost of adaptation. Table 5 summarizes our preliminary estimates: columns 2, 3, and 4 show the willingness to raise the current elevation by 1 ft as a percentage of the current house value, while columns 5, 6, and 7 report the corresponding dollar amounts based on an average house price of \$464,000. For example, for a house with a current elevation of 1 ft, the baseline probability weights imply a willingness to raise elevation by 1 ft of approximately

preference setting. This follows from the well-documented mathematical equivalence between ambiguity aversion in robust control models and risk aversion in Epstein-Zin recursive utility frameworks (Hansen and Sargent, 1995; Skiadas, 2003). This transformation suggests that ambiguity aversion plays a significant role in asset pricing, as a risk aversion parameter of this magnitude is notably high—well beyond typical values used in macro-finance models, where risk aversion often ranges between 2 and 10 (Duffie and Epstein, 1992; Maenhout, 2004).

[9] We can also alternatively consider a version of the exercise where the decision maker is a local authority that is considering building a sea wall.

27.2% of its value, while under distorted probability weights (reflecting ambiguity aversion) this increases to 28.08%—a difference of about 0.79 percentage points (or roughly $3,657). This is the first time, to the best of our knowledge, that the role of ambiguity aversion in adaptation decisions can be quantified using empirically estimated discount rates and ambiguity parameters.

7. Dynamic model (work in progress)

In Appendix A, we provide a dynamic model that analyzes how ambiguity aversion shapes housing investment and adaptation decisions under stochastic SLR risk. Homeowners or policymakers choose adaptation investments, such as raising elevation, while accounting for model uncertainty over emissions pathways, climate sensitivity, and sea-level response. The model incorporates ambiguity-averse preferences that distort prior beliefs toward worst-case scenarios, with the degree of distortion governed by our estimated ambiguity aversion parameter.

By embedding these estimates into a recursive optimization framework, we plan to quantify how uncertainty affects the value of climate adaptation. The model will provide a structured approach to assessing long-term housing investments under climate risk. Such a quantitative characterization of climate change is not possible in the static or modular settings commonly explored in the literature which cannot capture the dynamic, long-run nature of climate change or the interconnected general equilibrium feedbacks resulting from optimal policy choices. The resulting valuations derived in this setting provide a more complete, global quantification of climate consequences, rather than local approximations that are ill-suited for capturing consequences of nonlinear settings such as those coming from climate change and model uncertainty consequences. Moreover, by linking our dynamic general equilibrium model to the empirical estimates provided in this paper, we provide one of the first set of valuations of the consequences and uncertainties associated with climate change that are founded on empirically-estimated quantitative model parameters, particularly with regards to the degree of model uncertainty aversion. See the appendix for preliminary details.

8. Conclusion

Our findings provide direct empirical evidence that ambiguity aversion plays a significant role in how housing markets capitalize climate risks. By linking observed house price discounts to uncertainty in sea-level rise projections, we quantify the degree to which market participants exhibit aversion to ambiguous climate outcomes. The estimated ambiguity aversion parameter, ξ, varies with assumed prior beliefs, but our benchmark estimates suggest that homebuyers in climate-conscious markets apply substantial discounts to properties with greater uncertainty in their inundation timing. This highlights the importance of considering not just expected climate risks, but also the uncertainty surrounding those risks when assessing asset prices and policy interventions. Future research could explore how these effects evolve over time as more information about climate change becomes available and whether markets adjust their responses dynamically to new scientific projections and policy signals.

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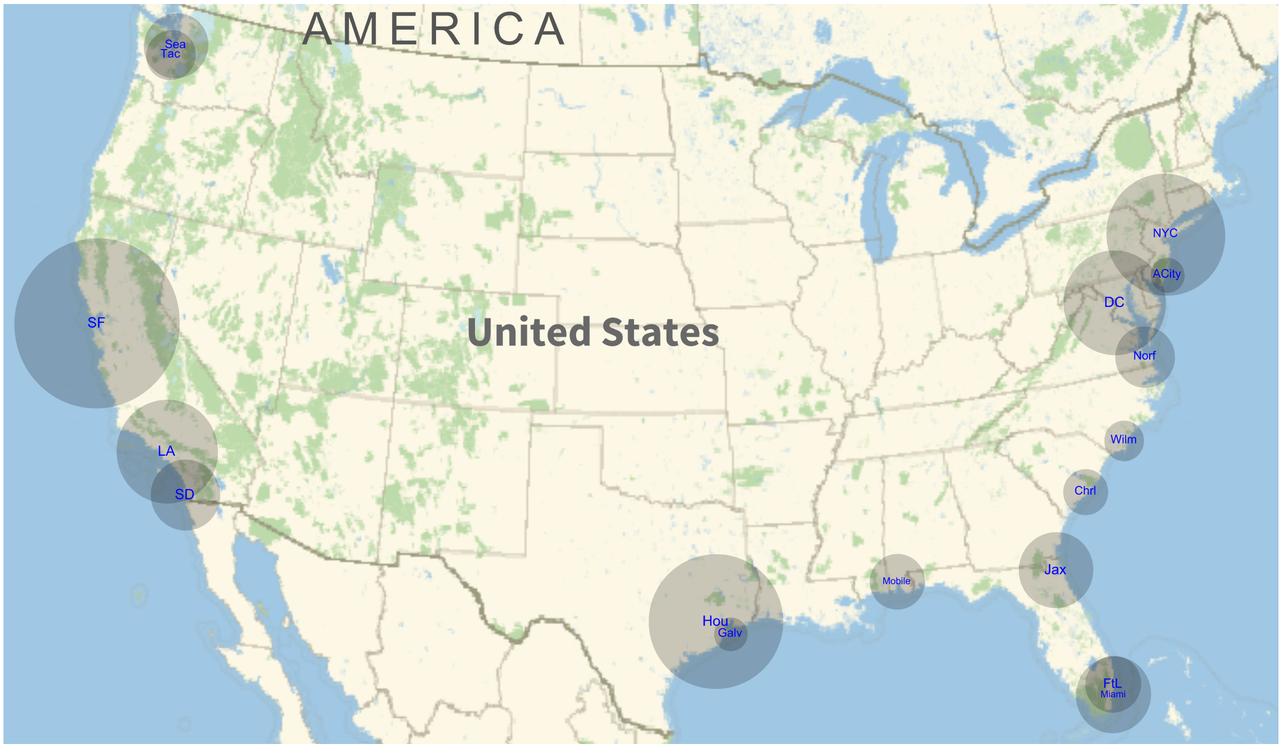

Figure 1: Geographic coverage: Our sample (of more than 2 million housing transactions) covers 17 major coastal metropolitan statistical areas (MSAs). Each MSA's circle radius is proportional to the sample size in that MSA.

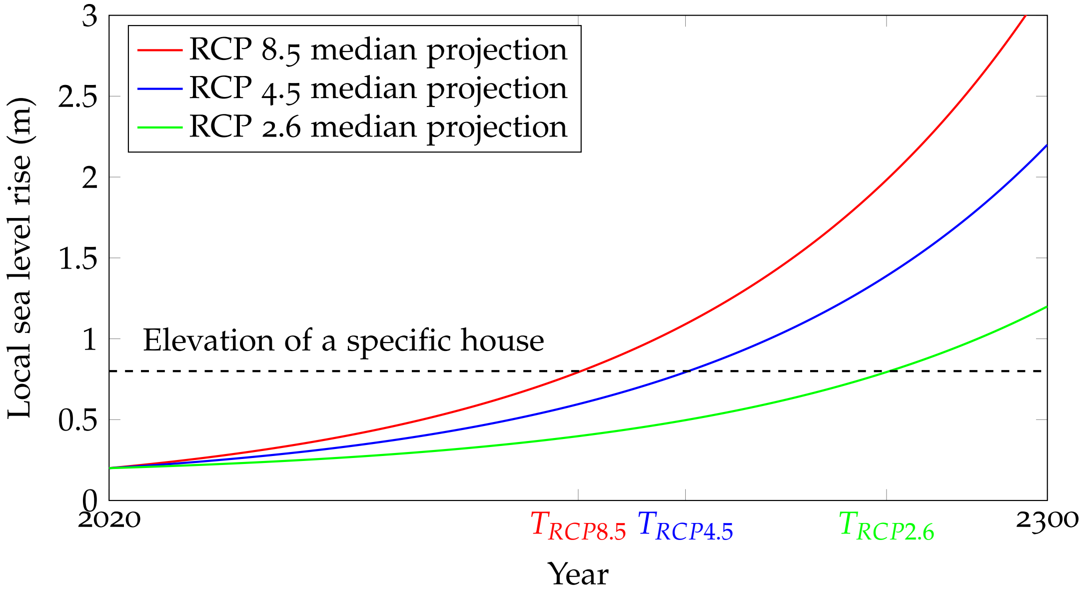

Figure 2: Illustration of how we construct each property's first year of inundation T using the median projection of local SLR under each climate scenario (RCP 2.6, 4.5, or 8.5)

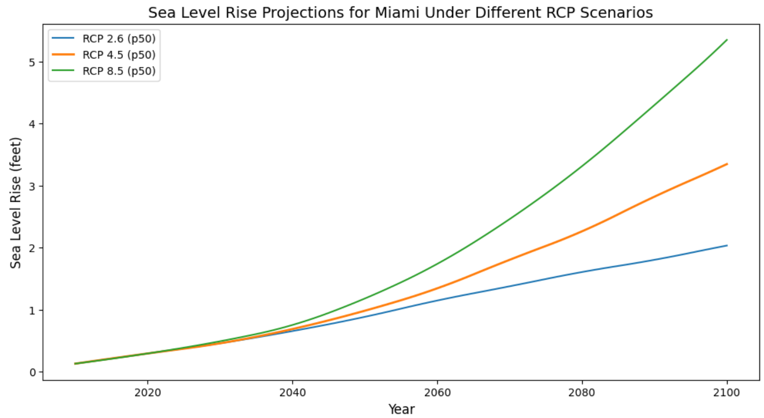

Figure 3: Example of local SLR projections under different scenarios for the city of Miami.

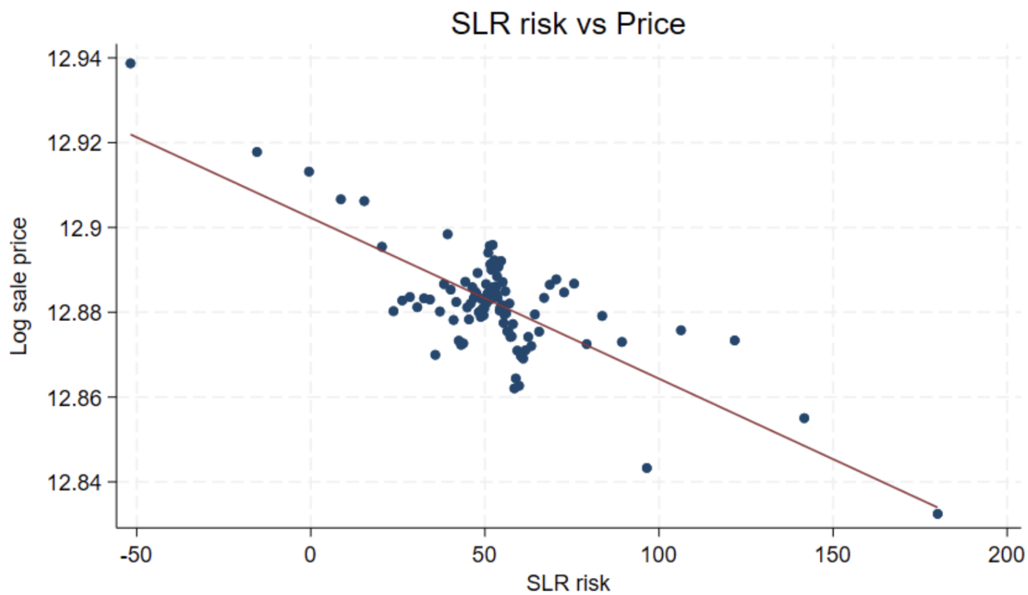

Figure 4: Bin scatter of SLR Risk and Log of House Sale Price, after controlling for property controls (building age, elevation, number of bedrooms, number of bathrooms, building square footage), the house's county controls (average county income and county population for the year of transaction, and GOP voter share in the last presidential election), and ZIP by distance to coast bin by sale year fixed effects.

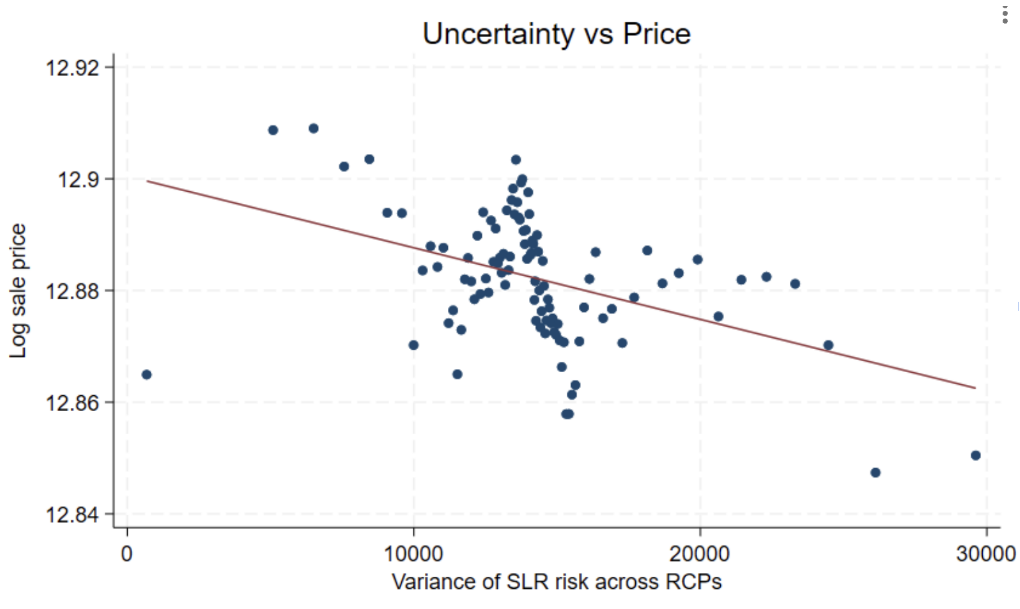

Figure 5: Bin scatter of SLR Uncertainty ($:= (T^{\text{median}}_{\text{RCP 2.6}} - T^{\text{median}}_{\text{RCP 8.5}})^2)$) and Log of House Sale Price. The controls and fixed effects include those described in the caption of Figure 4 and additionally the interactions of the controls with *SLR Risk*.

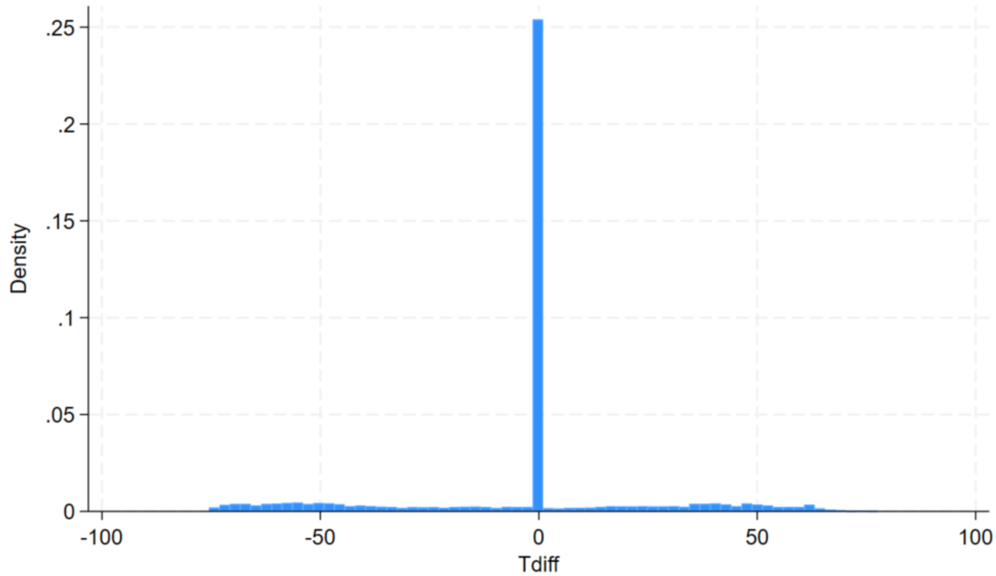

Figure 6: Histogram of $S_{RCP4.5} - \frac{S_{RCP2.6}+S_{RCP8.5}}{2}$.

Housing characteristics						
	Mean	Std	p10	p50	p90	N
House sale price ($)	464,496.00	539,648.10	117,000.00	325,500.10	879,000.40	2,278,863
Number of bedrooms	3.25	0.88	2.00	3.00	4.00	2,449,749
Number of bathrooms	2.31	1.04	1.00	2.00	4.00	2,680,114
Building square feet	2,049.80	975.59	1,082.00	1,824.00	3,284.00	2,628,989
Property elevation (feet)	82.11	106.91	6.80	32.53	260.61	2,100,303
House age (years)	39.29	28.36	1.00	39.00	78.00	2,172,837
First year of SLR inundation, median projection undereach RCP scenarios, up to 2300						
	Mean	Std	Corr	$T_{rcp2.6}$	$T_{rcp4.5}$	$T_{rcp8.5}$
$T_{rcp2.6}$	2,297.27	23.52	$T_{rcp2.6}$	1.0000		
$T_{rcp4.5}$	2,273.39	56.30	$T_{rcp4.5}$	0.5113	1.0000	
$T_{rcp8.5}$	2,244.11	78.03	$T_{rcp8.5}$	0.3438	0.8422	1.0000
$\sigma_T = T_{rcp2.6} - T_{rcp8.5}$	53.16	73.34				
σ_T^2	8205.05	12735.54				

Table 1: Summary statistics of key selected variables.

	log House Sale Price					
	(1)	(2)	(3)	(4)	(5)	(6)
SLR Risk	0.0001455	-0.0003327**	0.0000290	0.0001901	-0.0002081	0.0002067
	(0.0001305)	(0.0001464)	(0.0007480)	(0.0001208)	(0.0001555)	(0.0007598)
SLR Uncertainty				-0.0000006	-0.0000012*	0.0000017
				(0.0000007)	(0.0000007)	(0.0000012)
Pessimist # SLR Risk			-0.0010489***			-0.0008869**
			(0.0003752)			(0.0003575)
Pessimist # SLR Uncertainty						-0.0000029**
						(0.0000012)
Sample	Full	Pessimist	Full	Full	Pessimist	Full
Controls	Y	Y	Y	Y	Y	Y
Controls interacted			Y			Y
FE	ZxD Y	ZxD Y	ZxD Y	ZxD Y	ZxD Y	ZxD Y
N	1058703	488638	1058703	1058703	488638	1058703
R2	0.807	0.810	0.808	0.807	0.810	0.808

Table 2: Capitalization of SLR risk and of its ambiguity across climate scenarios (RCPs). The dependent variable is the log of house sale price. *SLR Risk* is defined as 2301 minus the first year of permanent inundation due to SLR under RCP 4.5 median projection. *SLR Uncertainty* measures the variation of SLR median projections under the worst and the best climate scenarios (i.e., $:= (T^{\text{median}}_{\text{RCP 2.6}} - T^{\text{median}}_{\text{RCP 8.5}})^2$). *Pessimist* indicates whether the housing transaction takes place in a county where the fraction of respondents in Yale Climate Opinion Survey stating that they are worried about global warming is above the sample median. Columns 2 and 5 are restricted to the *Pessimist* $= 1$ subsample. $Z \times D$ indicates ZIP code $\times$ distance to coast bin fixed effects, and Y indicates sale year fixed effects. *Controls* refer to property controls (building age, elevation, number of bedrooms, number of bathrooms, building square footage) and the house's county controls (average county income and county population for the year of transaction, and GOP voter share in the last presidential election). *Controls interacted* indicates that the controls are interacted with *SLR Risk*. Standard errors in parentheses are clustered at the ZIP code level; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

	log House Sale Price				
	(1)	(2)	(3)	(4)	(5)
Pessimist # SLR Risk	-0.0011316***	-0.0010575***			
	(0.0003646)	(0.0003648)			
Pessimist # SLR Uncertainty	-0.0000025**	-0.0000027**			
	(0.0000012)	(0.0000012)			
Pessimist (happening) # SLR Risk			-0.0006350*		
			(0.0003531)		
Pessimist (happening) # SLR Uncertainty			-0.0000030**		
			(0.0000012)		
Pessimist (timing) # SLR Risk				-0.0002942	
				(0.0003943)	
Pessimist (timing) # Uncertainty				-0.0000041***	
				(0.0000013)	
Pessimist (worried buyer) # SLR Risk					-0.0001747
					(0.0001916)
Pessimist (worried buyer) # Uncertainty					-0.0000019**
					(0.0000009)
Controls	Y	Y	Y	Y	Y
Controls interacted	Y	Y	Y	Y	Y
FE	ZxDxY	ZxDxYxB	ZxD Y	ZxD Y	ZxD Y
N	1056084	1041216	1058703	1058703	1056248
R2	0.836	0.847	0.808	0.808	0.808

Table 3: Robustness checks. *Pessimist (happening)* (or *Pessimist (timing)*) indicate whether the housing transaction takes place in a county where the fraction of respondents in Yale Climate Opinion Survey stating that they believe global warming is happening (or global warming will start to harm people in the U.S. within ten years, respectively) is above the sample median. *Pessimist (worried buyer)* indicates whether the buyer in the transaction comes from a county where the fraction of respondents in Yale Climate Opinion Survey stating that they are worried about global warming is above the sample median. $Z \times D \times Y$ (or $Z \times D \times Y \times B$) indicates ZIP by distance to coast bin by sale year fixed effects (ZIP by distance to coast by sale year by number of bedroom fixed effects, respectively). The rest are as in Table 2. For brevity, uninteracted terms (SLR Risk and SLR Uncertainty) are not shown.

Scenario	Baseline belief (p_i)	Worst-case belief (q_i^*)	Change (pp)
RCP2.6 (Best)	33.3%	$\sim 17\%$	-16
RCP4.5 (Mid)	33.3%	$\sim 32\%$	-1
RCP8.5 (Worst)	33.3%	$\sim 51\%$	$+17$

Table 4: Belief distortion from ambiguity aversion

	Willingness to raise elevation by 1ft (% of current house value)			Willingness to raise elevation by 1ft ($, based on average house price)		
Current house elevation (ft)	Baseline prob weights	Distorted prob weight	Difference (pp)	Baseline prob weights	Distorted prob weight	Difference
1	27.29%	28.08%	0.79%	$126,917	$130,574	$3,657
2	9.51%	9.89%	0.38%	$44,217	$45,991	$1,774
3	4.78%	5.01%	0.24%	$22,221	$23,317	$1,097
4	2.84%	3.00%	0.16%	$13,213	$13,968	$755
5	1.87%	1.99%	0.12%	$8,681	$9,236	$554
6	1.31%	1.40%	0.09%	$6,097	$6,523	$425
7	0.97%	1.04%	0.07%	$4,493	$4,830	$337
8	0.74%	0.80%	0.06%	$3,434	$3,708	$274
9	0.58%	0.63%	0.05%	$2,700	$2,927	$227
10	0.47%	0.51%	0.04%	$2,173	$2,364	$191

Table 5: Model-implied willingness to raise elevation by 1 ft, expressed both as a percentage of current house value (columns 2–4) and in dollars (columns 5–7), based on an average house price of $464,000 in our sample.

Appendix

A. Dynamic Model with Policy Choice

In this section, highlight an important application of the estimated uncertainty aversion parameter from our empirical analysis. Specifically, we derive a social valuation of climate change adaptation investment by constructing and solving a dynamic general equilibrium model of house prices subject to inundation resulting from a stochastic SLR process. Given the significance of housing as both a financial asset and durable consumption good, this novel quantitative framework highlights the importance of our analysis to the literature focused on the social costs of climate change by incorporating the first-order implications of model uncertainty identified and quantitatively validated by our empirical estimation. In what follows, we outline the model and derive key theoretical results, and will provide the computational results for different numerical examples in future work.

A.1. Housing

Our stylized model is focused on the pricing of the housing stock of an individual homeowner. In our framework, we assume consumption is proportional to the housing stock H_t owned by our homeowner, less investment in additional housing stock, such that

$$C_t = H_t \left(\alpha - i_t\right)$$

where i_t is the fraction of "output" from housing invested in building new housing "capital". The evolution of the log of the housing stock $\log H_t = h_t$ is determined by investment, adjustment costs, and Brownian shocks

$$dh_t = \left(\mu_h + \Gamma \log\left(1 + \phi i_t\right) - \frac{1}{2}|\sigma_h|^2\right) dt + \sigma_h \cdot dW_t$$

where μ_h is the housing stock depreciation rate and (Γ, ϕ) are adjustment cost parameters.

We assume the per period (instantaneous) contribution to preferences, or utility function $U(\cdot)$, is of the risk neutral form over consumption C_t, exponentially discounted at the subjective rate of discount ρ. Thus preferences are given by

$$U(C_t) = C_t = H_t \left(\alpha - i_t\right)$$

Critically for our analysis, we introduce the additional component for our house price valuation which is the potentially negative consequences associated with climate change and sea-level rise. We elaborate on these dynamics and the consequences in what follows.

A.2. Climate Change and Seal-Level Rise

The sea-level rise dynamics for our model are based on three geoscientific ingredients:

1. An affine relationship between carbon emissions and changes in atmospheric temperature known as the Transient Climate Response to cumulative carbon Emissions (TCRE).

2. An exogenous (to the household) emission pathway corresponding to the implied atmospheric temperature outcome of a given IPCC RCP scenario.

3. A semi-empirical dual model of sea-level rise dynamics that reflects the long-term trend and rapid-response effect of climate change on sea-level rise.

In general form, we denote the sea-level rise (SLR) dynamics as follows:

$$dS_t = \mu_S(S_t)dt + \sigma_S(S_t)dW_t$$

We assume that climate change and sea-level rise are relevant to our house price valuations as their is a potential for catastrophic flooding from sea-level rise that inundates the home and drives the value of the house to zero. Therefore, our preferences are alter to account for this risk as follows

$$U(C_t) = C_t = H_t\,(\alpha - i_t)\,\mathbb{I}_{S\leq\bar{S}}$$

The price of the house in our model will reflect the likelihood of this potentially catastrophic risk occurring.[10] Importantly, there is significant uncertainty about the climate change pathway we are on, the magnitude of sea-level rise we will experience, and the resulting economic consequences from the different possible realizations we could experience along these dimensions. As such, we augment our framework to account for such model uncertainty in what follows.

A.3. Model Uncertainty

We allow for model uncertainty broadly conceived in our framework by applying the toolset of dynamic decision theory as via continous-time smooth ambiguity as developed in

[10] While the technical mathematical representation for jump arrival intensity function is a Dirac delta function, for computational purposes can approximate this with a smooth function which builds up to a probability of (approximately) one by $\bar{S}$ for the jump to occur:

$$\mathcal{I}(S;\bar{S},\underline{S}) \;\; = \;\; r_1\left(\exp\left(\frac{r_2}{2}(s-\bar{s})^2\right)-1\right)\mathbb{I}_{s\leq\underline{s}}$$

We can use scientific projections of SLR and inundation times to calibrate these parameter values.

Hansen and Miao (2018) and applied in Barnett et al. (2020) and Barnett et al. (2023b). We consider ambiguity as it relates to the models of climate change and sea-level rise dynamics. Specifically, we assume there are a range of potential climate sensitivity values β_f values, emissions trajectories $(\bar{E}, \delta)$, and sea-level rise response values (a, b). For tractability, we consider a discrete set of each values of the form

$$\begin{aligned} \beta_{f,\ell}, \qquad & \ell \in \{1, \ldots, \mathcal{L}\} \\ \left(\bar{E}_j, \delta_j\right), \qquad & j \in \{RCP2.0, \ldots, RCP8.5\} \\ \left(a_i, b_i\right), \qquad & i \in \{1, \ldots, \mathcal{I}\} \end{aligned}$$

We denote a given model in our setting by $\theta(m)$ where

$$\begin{aligned} \theta(m) &= \left(\beta_{f,\ell}, \bar{E}_j, \delta_j, a_i, b_i\right) \\ m &= (\ell, j, i) \\ m &\in \{(1, RCP2.0, 1), \ldots, (\mathcal{L}, RCP2.0, 1), \\ & \quad (1, RCP2.0, 2), \ldots, (\mathcal{L}, RCP2.0, 2), \\ & \quad \ldots \\ & \quad (1, RCP8.5, \mathcal{I}), \ldots, (\mathcal{L}, RCP8.5, \mathcal{I})\} \end{aligned}$$

The number of models m in our framework is therefore given by $\mathcal{M} = \mathcal{L} \times \mathcal{J} \times \mathcal{I}$ where $\mathcal{L}$ is the number of TCRE parameters, $\mathcal{J}$ is the number of RCP emissions scenarios, and $\mathcal{I}$ is the number of sea-level rise response values. We denote the prior probability weighting for a given model $\theta(m)$ by $\pi(m)$, and assume an equal-weighted probability across the different potential models so that $\pi(m) = 1/\mathcal{M}$, $\forall m \in \{1, \ldots, \mathcal{M}\}$.

This preference structure brings uncertainty concerns inside the house price valuation and decision maker's problem by applying, as opposed to model averaging or sensitivity analysis comparisons often done in the literature. To do this requires that we make two adjustments to our framework as currently given. First, the dynamic evolution of the climate change and sea-level rise state variables are adjusted to account for the set of possible alternative models considered by the decision-maker. This adjustments leads to the evolution of the state variables being given as follows

$$\begin{aligned} dY_t &= \sum_{m=1}^{\mathcal{M}} \pi(m) \left(\bar{E}(m) - \delta(m) Y_t\right) \beta_f(m) dt + \sigma_Y dW_t \\ dS_t &= \sum_{m=1}^{\mathcal{M}} \pi(m) a(m) Y_t dt + \sum_{m=1}^{\mathcal{M}} \pi(m) b(m) \left(\bar{E}(m) - \delta(m)\right) \beta_f(m) dt \\ & \quad + \sum_{m=1}^{\mathcal{M}} \pi(m) b(m) \varsigma dW_t + \sigma_S dW_t \end{aligned}$$

Second, we augment the preferences and optimization problem of the decision-maker to include a penalization term over which the planner can optimize "reasonable" worst-case models to inform their sagacious optimal policy decisions. The penalization is a measure of model discrepancy, in our case the Kullback-Leibler or relative entropy distance measure, scaled by a parameter ξ which constrains the model distortion minimization of the decision-maker. Specifically, the preferences of the planner are now of the form

$$\max_{i_t} \min_{\tilde{\pi}(m)} H_t (\alpha - i_t) \mathbb{I}_{S \leq \underline{S}} + \xi \sum_{m=1}^{M} \tilde{\pi}(m) (\log \tilde{\pi}(m) - \log \pi(m))$$

With these components, we can now characterize the planner's optimization problem and provide it's recursive representation through a Hamilton-Jacobi-Bellman equation.

A.4. Model Solution

The HJB equation, as well as corresponding FOC for investment in the housing stock and optimal model distortions, are given in the following form

$$\begin{aligned}
\rho V(h, Y, S) &= \min_{\tilde{\pi}, g} \max_{i_t} (\alpha - i_t) H_t + \xi \sum_{m=1}^{M} \tilde{\pi}(m) \log \frac{\tilde{\pi}(m)}{\pi(m)} + \xi \mathcal{I}(Y)(1 - g + g \log g) - g \mathcal{I}(S) V \\
&\quad + V_h \left(\mu_h + \Gamma \log (1 + \phi i_t) - \frac{1}{2} |\sigma_H|^2 \right) + \frac{1}{2} V_{hh} |\sigma_H|^2 \\
&\quad + V_y \sum \tilde{\pi}(m) \beta_f(m) (\bar{E}(m) - \delta(m) Y) + \frac{1}{2} V_{yy} |\varsigma|^2 \\
&\quad + V_s \sum_{m=1}^{\mathcal{M}} \pi(m) \left(a(m) Y_t + b(m) \beta_f(m) \left(\bar{E}(m) - \delta(m) \right) \right) + \frac{1}{2} V_{ss} \left(|\sigma_Y|^2 + |\sigma_S|^2 \right) \\
g &= \exp(\frac{1}{\xi} V(h, Y, S)) \\
\tilde{\pi}(m) &\propto \pi(m) \exp \left(-\frac{1}{\xi} \left([V_y + b(m) V_s] \beta_f(m) (\bar{E} - \delta(m) Y) + V_s \left(a(m) Y_t \right) \right) \right) \\
i_t &= \frac{v_h \Gamma}{H_t} - \frac{1}{\phi}
\end{aligned}$$

We can solve this model computationally, and examine the distorted probabilities resulting from g and $\tilde{\pi}(m)$ to understand the implications of ambiguity aversion for housing prices, as well as their implications for the optimal housing investment choice i_t. Of particular interest to us is determining the social value of adaptation in response to climate change induced SLR risk. To derive this, we can augment the model in the following ways: first, we incorporate a cost of adaptation investment that enters the consumption-output market clearing condition; and second we allow for the adaptation investment to alter the SLR state which determines the time to inundation for the house with decreasing returns to scale benefits. With this additional model richness, we can follow the methodology put forth in Barnett et al. (2023a) and derive the social value of adaptation investment based upon the impact so social welfare from an additional unit increase of adaptation investment. We leave this analysis for future work, providing a rich application of our ambiguity aversion parameter estimate derived earlier in our analysis.

A.5. Climate Change and Seal-Level Rise - Calibration

The climate dynamics of the model are based on two main components. First, we assume an affine relationship between carbon emissions and changes in atmospheric temperature known as the Transient Climate Response to cumulative carbon Emissions (TCRE).[11] We use a stochastic version of this approximate relationship, so that the evolution of atmospheric temperature Y_t is given by

$$dY_t = E_t \beta_f dt + \varsigma dW_t$$

where β_f is the TCRE parameter, E_t is per period emissions, and ς is the volatility loading of temperature on the Brownian motion W_t.

For the second component, we assume emissions follow a pathway that is exogenous to the household[12], which are given by the functional form

$$E = e(y) = \bar{e} - \delta y$$

The values $\bar{e}$ and δ are estimated to match temperature outcomes implied by the IPCC's RCP Scenarios. We discuss the uncertainty about which RCP scenario governs the climate change dynamics when we elaborate on the planner's preferences.

The consequences of climate change are reflected by sea-level rise in our model. Specifically, we assume that the level of sea-level depends upon the magnitude of climate change experienced based on the following dynamics

$$\begin{aligned} dS_t &= aY_t dt + b dY_t + \sigma_S dW_t \\ &= (a - b\delta\beta_f) Y_t dt + b\bar{E}\beta_f dt + b\varsigma dW_t + \sigma_S dW_t \\ &\approx b\left(\bar{E}\beta_f dt + \varsigma dW_t\right) \end{aligned}$$

[11]This approximation follows from Matthews et al. (2009); Friedlingstein et al. (2019), and others.

[12]The assumption of exogenously given emissions is based on the fact that our analysis focuses not on global production choices that impact climate change in a measurable way, but instead on individual house prices in response to given climate change outcomes.

This specification comes from the semiempirical dual model specification proposed and estimated by Vermeer and Rahmstorf (2009) where the term $aY_t dt$ reflects the long-term trend of climate change on sea-level rise and the second term bdY_t captures the rapid-response effect, on geoscientific time-scales.

The last approximate expression allows for three specific uncertainty: the SLR sensitivity (b), the climate sensitivity (β_f), and the emissions pathway ($\bar{E}$).