Climate Risk, House Prices, and Neighborhood Dynamics [Preliminary and Incomplete]*

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Abstract

We provide observational evidence that climate risks impacted economic behavior *earlier* and *more significantly* than conventional discourse and research suggests. Using a novel dataset with residential property-level measures of climate risk exposures, we document a significant association between climate risks and house prices and ownership patterns as early as 2006. Within a census block, and using a repeat-sales design, one percent of extra expected future climate losses is associated to a 4% permanent price discount to a house, far larger than the frictionless rational expectations benchmark. Adding rich hedonic controls, to flexibly capture time-varying fundamental demand, alters the timing of the climate discount to appear around 2016, and reduces the cumulative effect from 4% to (conservatively) 2%, still significantly larger than benchmark magnitudes. Riskier properties are disproportionately sold from owner-occupants to landlords, suggesting a potential role for financial constraints.

JEL classification:
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1 Introduction

Scientists, social scientists, and journalists now largely agree that climate change poses tremendous challenges to society. Faced with increasingly frequent extreme weather events and the prospect of future risks, people's ability to prepare and adapt to the effects of climate change has taken a central role. Accordingly, many contemporary economic effects of climate change risks stem from these adaptations, rather than the direct impact of climate itself. Many current empirical debates center around quantitative *magnitudes*. How large are the economic impacts of adaptation to climate risk? When do the mechanics of adaptation begin taking hold? Who have been the winners and losers to climate change adaptation, and to what degree?

This paper tackles these questions in the context of local residential real estate markets. Relative to the extant literature, our study differs in its risk measurement and empirical design. We explore a new dataset estimating various climate risks at the property level. The granularity of this dataset allows us to control for highly localized factors (Census block-by-time fixed effects) and a property fixed effect. The combination of this data and methodology serves two roles. First, the data captures variation in climate risk due to structure-level heterogeneity in building materials (e.g., wood, brick, concrete, etc.), design (e.g., the existence of a basement, attic, etc.), and upkeep. By controlling for a block-by-time fixed effect, our climate risk measure is purged of most geography-related climate risks, and our housing transactions are purged of any time-varying geographic demand. The remaining risk variation includes the aforementioned materials, design, and upkeep. Second, including a property fixed effect brings the analysis close to a "repeat sales" method. This eliminates any time-invariant (including unobservable) factors that are correlated with our climate risk measures but drive valuation differences for other reasons. Overall, our empirical design analysis allows us to shed light on when climate risks became salient, at least in terms of their economic impacts, and to confidently attribute these impacts to climate risk exposures, as opposed to other local factors or other house-level valuation-relevant factors.

Our risk measures also permit some novel economic interpretations not possible in other settings. For instance, a unique feature of our dataset is its estimation of climate-related loss projections in dollar units, allowing for economically-meaningful quantitative statements.

In addition, we are able to distinguish conceptually between the effects of aggregated climate losses versus disaggregated perils. Finally, our data distinguishes between expected losses versus downside risks (although we do not yet fully explore this feature of our data). There are important drawbacks to our data—we must trust a proprietary black-box estimation of climate riskiness and we cannot control for *all* hedonic factors as these are critically important drivers of within-block risk variation. Nevertheless, we believe that our approach brings important contributions to the literature.

Our main result is that climate risk strongly permeates housing markets. In a baseline specification that includes property and block-by-time fixed effects, which controls for arbitrary time-invariant demand factors and any time-varying geographic demand factors, we find that climate-risky properties start to become discounted significantly as early as 2006. Relative to pre-2006 prices, a house in 2024 with a 1% higher estimated climate damages (per year) garners a 4% price discount. We also find a significant change to ownership structure: around the same time (starting 2006), riskier properties become significantly less likely to be owner-occupied—a 2 percentage point drop in owner-occupancy per 1% of expected climate losses. We interpret this as evidence of landlords entering climate-risky markets and putting those properties for rent.

We then control flexibly for some additional important time-varying fundamental demand factors to obtain estimates that are more likely causal as opposed to simply correlational. In particular, climate-safer properties tend to be slightly larger and newer, and so a growing demand for larger and newer houses, beginning in 2006, could potentially explain our baseline result. We address this concern by including, in addition to the property and block-by-time fixed effects from our baseline specification, time-specific loadings on hedonic variables like property size and age. Augmenting our specification with such hedonic controls cuts our baseline results by between 0 to 50%: a 1% higher expected climate damage impounds between a 2-4% price discount, depending on the method. Given our setting is highly controlled, we interpret this as causal evidence of a quantitatively large climate-risk discount. What changes most when accounting for these hedonic controls is the timing of the discount, which then shows up in around 2016, closer to the timing assumed in the existing literature.

How should one interpret our finding of a greater than one-for-one decline in house prices

to climate risk exposure? While the frictionless rational-expectations benchmark is a one-for-one price decline, several standard frictions suggest the potential for an amplified price response. First, housing markets are largely segmented, and so a property's idiosyncratic risks may be priced by its owner-specific risk preferences. In that case, risk aversion suggests that a 1% expected loss should garner a larger-than-1% price discount. While property insurance can potentially mitigate this effect of risk aversion, caps on payouts and gaps in coverage imply that the risk aversion effect should not be eliminated. Second, when a property switches from being owner-occupied to being rented, as we document, the house loses its owner-occupancy premium. One potential microfoundation for this premium would be tenant moral hazard (shirking on upkeep and improvements is value-destroying). One reason why high-risk properties could become rental properties is simply that climate-resilience may be a normal good; if richer households move out of such houses, then poorer, wealth-constrained houses must move in, suggesting owner-occupancy would be less likely. And third, as neighborhood changes kick off, agglomeration effects may take hold. For instance, as poorer households move in, or existing properties become vacant, or as a neighborhood becomes disproportionately tenant-occupied, its desirability decreases to other potential movers. Despite all these forces, it may still be surprising that our effects are 2-4 times larger than the frictionless rational benchmark. The fact that our risk measure is conveniently quoted in percentage terms allows us, for the first time, to engage in this discussion.

In addition to the large magnitude, readers might be surprised to find that changes begin in 2006, in our specifications without hedonic controls for size and age. This is quite early in the process of rising climate awareness and does not coincide with existing measures of the largest climate-relevant events. For example, Engle et al. (2020) find, using newspaper articles, that 2009 was the year with the largest quantity of climate-relevant news, followed by the period from 2014-16. Using Yale opinion surveys since 2008, Marlon et al. (2022) finds that much of the change in opinions regarding climate change has been more recent (e.g., 2016-present). On the firm and institutional investor side, 2016 is a commonly-cited inflection point for the rise of ESG investing and changes to firms' cost of capital (Ilhan et al. 2023; Gormsen et al. 2024). And the literature on house prices and sea-level-rise (SLR) risks only finds effects, if at all, starting in the mid-2010s (Keenan et al. 2018; Bernstein et al. 2019;

Baldauf et al. 2020; Murfin and Spiegel 2020; Keys and Mulder 2020; Bernstein et al. 2022). Based on this literature, our estimates of an early timing could be mismeasurement: the 2006 timing could simply reflect an increasing demand for newer and larger properties; once accounted for via hedonic controls, the measured timing of climate-risk discounts shifts to around 2016, more consistent with the literature above.

But another explanation is that the 2006 timing is real climate awareness by households, despite limited discussion in the academic literature. The Kyoto Protocol became effective in February 2005; although the US was not part of it, this constituted international news. Hurricane Katrina, one of the most severe and costly hurricanes of all time, struck in August 2005. Katrina was a high-profile event in the US that may have shifted overall climate views (see literature cited below). In 2006, the popular documentary "An Inconvenient Truth" was released, which may have played a role in environmental awareness (Nolan 2010). Beyond these specific events, Brulle et al. (2012) and Carmichael and Brulle (2017) conduct a more systematic analysis of public opinion data for the years 2002-2010 and 2001-2013, respectively, identifying several factors driving shifts in climate perceptions. These papers find that reported climate concerns starting rising in 2005 and peaked in 2007, broadly consistent with our results.[1]

Related literature. We primarily contribute to a large existing literature relating climate change risks to housing markets. Most closely related is a literature investigating sea-level-rise (SLR) risk (Keenan et al. 2018; Bernstein et al. 2019; Baldauf et al. 2020; Murfin and Spiegel 2020; Keys and Mulder 2020; Bernstein et al. 2022). These papers construct property-level variation in SLR risk, due to elevation, coastal distance, and other geological factors, controlling for other house characteristics, to identify the impact of flood risk on housing markets.[2] There is some disagreement on the existence and magnitude of an effect on housing, with Murfin and Spiegel (2020) notably finding zero effect of SLR risk on prices through 2017. To the extent the other papers find an effect, they all agree that it appeared later in the sample (e.g., 2013 or even later).

[1] Sparse evidence is available on climate-related views for years in the early 2000s and prior, partly due to data availability. This is not to say that people were unaware of climate risks in these early years. In one study, Krosnick et al. (2000) finds that the 1997 efforts by Clinton administration to build support for the Kyoto Protocol sparked a change in climate-related perceptions, especially among Democrats.

[2] Note that SLR risk may affect household choices in other dimensions, like the stock market, as well (Ilhan 2020).

Our study differs in several respects. Most importantly, our methodology differs, as discussed in the introduction. Second, we go beyond flood risk and examine all climate-related risks (e.g., wildfires, tornadoes, earthquakes, and more), allowing us to study a larger geographic sample of housing markets beyond the coastal areas. Third, our risk measure is conveniently reported in percentage units, allowing us to quantify an economically-meaningful elasticity. Finally, our results differ. Not only do we find a large impact of climate risk on house prices, we also shed light on the timing of the effect. And with the exception of Bernstein et al. (2022), who study partisan sorting, we also examine transactions and residential sorting.

Another literature has measured the impact of disasters on local house prices (McKenzie and Levendis 2010; Ortega and Taspınar 2018; Pollack and Kaufmann 2022; Ellen and Meltzer 2024).[3] These results are often highly localized, for instance the impact of Florida hurricanes on Florida house prices, and struggle to separate the direct effect of the disaster from the effect of future climate risks.[4] A notable exception is Addoum et al. (2024), which demonstrates a persistent decline in Boston house prices following New York's Hurricane Sandy.

A commonly-held view is that climate risk perceptions shift after a climate disaster. For instance, a survey-based literature shows that personal experiences modulate climate risk perceptions (Egan and Mullin 2012; Akerlof et al. 2013; Deryugina 2013; Shao 2017; Bergquist and Warshaw 2019). Relatedly, but in observational data, disaster insurance premia may increase following a disaster realization, and these higher premia can be impounded in house prices (Nyce et al. 2015; Keys and Mulder 2024). Given the coincidence of our effects and the arrival of Hurricane Katrina, such a belief-updating view may be at work. Similar to Addoum et al. (2024), we show our results are not mechanically due to Katrina in a localized sense—in fact, excluding states directly impacted only modestly changes the magnitude of our estimates. But Katrina was a high-profile event, which may have been a broader signal to consumers' attention to climate damages, inducing a belief update.

[3] For surveys on the housing market effects of climate change perceptions, see Schuetz (2024) and Contat et al. (2024).

[4] Some research also examines the ex-post effect of a disaster like Hurricane Katrina on households directly harmed, e.g., Gallagher and Hartley (2017) and Deryugina et al. (2018). But again, this differs from our goals. We wish to obtain the impact of *climate risk*, which requires looking at households not directly harmed and identifying effects ex-ante.

2 Data

We combine two data sources both from CoreLogic: one on climate risks at the property level (single snapshot) and another on housing-market transactions and property characteristics. We take only the properties that have a unique property identifier: CoreLogic Integrated Property (CLIP), which is used to merge the two data.

2.1 Climate Data

Data on climate risks come from CoreLogic's Climate Risk Data, which are a one-time snapshot of structure-level measures of exposures to various climate risks, computed using CoreLogic's proprietary algorithms.

The actual data are at a structure level. This can be more disaggregated than properties for properties that contain multiple structures, for example with a main home and a stand-alone garage buildings. CoreLogic computes an importance ranking, which we use to only take the climate risk scores for the primary structure, e.g., only the climate risk for the main home in our example. The resulting data we use is therefore unique at the property level.

The main measure of climate risk exposure we use is the Average Annual Loss (AAL), which is the fraction of the property value that is expected to be lost due to climate events from CoreLogic's simulations in a given year.

The main composite risk is the union of nine individual climate events, or "perils." These include three separate earthquake-related perils (fire, shake and sprinkler leakage, and tsunami), wildfire, inland flood, severe convective storm, winter storm, hurricane storm surge, and hurricane wind.[5]

CoreLogic provides AAL for the current condition, as well as projections for future years of 2030, 2040 and 2050. For each of the future years, they provide projections under varying climate scenarios following the Representative Concentration Pathways (RCP). RCPs are hypothetical scenarios of varying intensity of climate change described by the the expected changes in radiative forcing values by year 2100. CoreLogic provides projected AAL under three of the four original pathways: Under RCP 2.6, CO_2 concentration eventually falls to

[5] In what follows, we drop the earthquake perils related to leakage and tsunami, due to very sparse coverage.

and stays at around 400 parts per million (ppm); RCP 4.5 is the intermediate scenario; and under RCP 8.5, emissions continue to rise.

Importantly, AAL captures not only the climate change risk but the exposure of a particular property to such climate change. For example, flood risk can increase for an entire neighborhood due to rising temperatures, but the damage to a property can be higher if that property has a lower first floor height or if it has a basement. For another example, wildfire risk can increase for a larger geographic area, but the risk can accompany a higher expected loss for a property that is built from more combustible building material.

2.2 Housing Market Data

Data on housing-market prices and characteristics come from CoreLogic's Real Estate Data, and in particular their Property Basic data based on assessment records and Owner Transfer data based on transaction deed records.

We take all arms-length, resale transactions available in the Owner Transfer data for 2000-2020, with property ID variable (CLIP), transaction price, transaction date, Census block in which the property is located, and an indicator for whether the purchase was for owner occupation. Using the CoreLogic ID variable CLIP, we obtain property characteristics including square footage from the Property Basic and Historical Property Basic data, also from CoreLogic. There are 74 million unique properties that are resold within 2000 and 2024.

2.3 Summary Statistics

Table I shows the cross-sectional distribution of AALs for various perils, as well as a "Composite AAL" that sums across perils. Based on the cross-sectional means of AAL, the largest perils are severe convective storm, inland flood, hurricane wind, and hurricane storm surge (the two hurricane peril AALs are missing for approximately half the properties, which we believe corresponds to a negligible risk for those properties). The smallest risk by far is earthquake (fire following), followed by winter storm and wildfire. The mean Composite AAL is 0.25% per year. For all the perils in Table I, AAL is significantly right-skewed, with a significant fraction of very low-loss properties and small fraction of much higher-loss

properties. For instance, the median inland flood AAL is 0% per year, but its 99th percentile is 0.92% per year. A similar right-skewed pattern holds for the Composite AAL.

The perils are geographically distributed as one might expect. Figure XXXVIII displays maps for the geographic distribution of AALs, by peril and for the composite version. For instance, wildfire risk is concentrated in the west of the US; severe convective storms—which involve winds, tornadoes, and hail—primarily hit the mid-west; winter storms mainly in the north and northeast; hurricane-related damages are on the eastern and southeastern coasts. Interestingly, the Composite AAL (panel A) has a very even distribution throughout the US.

To quantify the determinants of AAL variation, Table IIa shows the R^2 of AAL in various fixed effects specifications. About 60% of the variation in AALs is driven by Census blocks and peril types. As mentioned, the residual variation within-block is what we hope to exploit. Note also that the addition of scenario and timeframe fixed effects interacted with block and peril only increases the explanatory power by 1% or so. This reveals that, roughly speaking, the CoreLogic climate model scales a baseline property-level AAL by come common factor to obtain AALs at different scenarios and timeframes. For this reason, most of our results simply fix the scenario at its intermediate value (the RCP 4.5 scenario) and the timeframe at its long-horizon value (the 2050 timeframe). By contrast, significant variation is captured by heterogeneity across perils: the R^2 rises from about 11% to about 60% when including an interaction of peril with block, versus using block fixed effects alone. Comparing Composite AAL to transaction prices, Table IIb shows that prices are much better explained by geography (tract or block fixed effects) than AAL.[6]

Going beyond their means, Table IIc shows the variance-covariance matrix of AALs across properties for the 8 perils for which there are future projections. (In this case, to compute a full covariance matrix, we set any missing values of peril-specific AALs to zero.) Using variances as a proxy for importance, by far the two largest perils are inland flood and hurricane storm surge, followed by wildfire, convective storm, and hurricane wind. Relative to the variances of these perils, the others pale in comparison. Additionally, the covariances between perils tend to be very small, with the exception of the two hurricane-related perils.

[6]When refining fixed effects from tract to block, the explained variation increases much more for AAL than it does for transaction prices, suggesting that running our specifications with tract fixed effects, rather than block fixed effects, would be a useful alternative, something we are exploring in ongoing work.

What drives the peril-specific risks? Tables III-IX display results from regressing peril-specific AAL (as well as other moments of loss risk beyond the average) onto block fixed effects and property characteristics, such as first-floor height, ground elevation, and dummies for the inclusion of various materials in the property structure (e.g., steel, timber, concrete, etc.). Judging by the R-squareds, Census blocks explain the majority, and often much more, of the variation in climate-related losses. But important variation remains within Census blocks, and this variation appears to co-move in sensible ways with structure characteristics. For instance, Table IV shows that, controlling for block fixed effects, flood-related AAL is negatively related to first-floor height, ground elevation, and the use of "solid" materials like steel, concrete, masonry, and timber. While we only include a coarse set of property characteristics, and only linearly, the takeaway from these tables is that important within-block variation seems related to details of the building and structure. Our main analysis below also employs block fixed effects, so it is important to keep this in mind.

These summary statistics support the following interpretation of the data. Each property is primarily exposed to a single climate peril, if any, with floods, hurricanes, and convective storms being the most important economically. The climate risks to houses in a local region are largely similar, but the property-level exposures can differ significantly, due to variation in construction materials, property design, and upkeep. Ultimately, we seek to isolate these sources of variation from the localized climate-related risks.

Finally, we explore the correlations between standard hedonic variables and Composite AAL in Tables X-XI. The results show that high-AAL properties tend to be smaller (in terms of both square-footage and number of bedrooms) and older. As an example, Table X shows that, within Census block, a property that is 10% larger in square-footage has on average a 0.00234% lower Composite AAL—meaning that modest differences in AAL can potentially be associated to large price differences, through significant differences in property size. Given that larger properties and newer constructions tend to be more valuable on average, our "repeat-sales" style procedure (comparing a house to its own previous transaction) can help to purge these time-invariant valuation issues and identify climate discounts. Furthermore, to correct for potentially "time-varying demand" related to these basic hedonics, but having nothing to do with climate risks, we also control for them directly in some specifications below.

3 Empirical Framework

CoreLogic's property-level climate risk exposure measure varies between properties that may be exposed to similar climate risk. We therefore estimate the gradient of house price along this property-level exposure (AAL), comparing within Census blocks, and use the change in this slope to infer the impact of rising climate-change awareness on house prices.

We first estimate the raw slope of transacted house prices against Composite AAL (which adds losses across all perils) projected for the 2050 horizon under the intermediate scenario (RCP 4.5) with Census block fixed effects, year by year. For property i in block b that has a transaction in year t, we estimate

$$\log P_{it} = \alpha_{bt} + \sum_s \beta_s D_{st} \times X_i + \sum_s \phi_s D_{st} \times A_i + \nu_{it} \tag{1}$$

where α_{bt} is a block-by-time fixed effect, A_i is Composite AAL, X_i are hedonic controls (such as square-footage, number of bedrooms, or age), and D_{st} represents a dummy for year t (equals 1 when $s = t$). We are interested in time-series pattern in the AAL coefficients $\{\phi_t\}$.

One difficulty in interpreting the year-to-year variation is that the set of properties being transacted can be different in each year, as opposed to the climate-risk discount rising over time. The problem is that, by construction, certain value-relevant characteristics are driving our AAL variation (e.g., the presence of basements, carpet versus hardwood floors, and other such characteristics), and the prevalence of these characteristics in housing transactions can be changing over time for reasons unrelated to climate perceptions. Suppose, for example, that houses with basements have higher AAL but are also generally less valued in the market, in a time-invariant way. If the propensity of homes with basements to transact is time-invariant, then there would be a constant downward bias in all of the $\{\phi_t\}$ coefficients. This problem is minor, in the sense that the time-series pattern of the $\{\phi_t\}$ remains preserved. However, if the propensity of homes with basements to transact is rising over time, then even the time-series pattern will be affected: the (negative) bias in the estimates of $\{\phi_t\}$ would be rising over time, a pattern which mimics that of a growing climate risk discount. We attempt to correct for this issue below.

What cannot be addressed in the specifications that follow is the time-varying bias that arises if the demand for basements is time-varying. However, we do try to address

time-varying demand, to some extent, by including some important and standard hedonic controls (the X_i variables), similarly to the "raw" cross-sectional approach in (1).

To address some of these concerns about time-varying compositional effects and some types of time-varying demand, we implement a "repeat-sales" approach as our core method. We estimate:

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \beta_s D_{st} \times X_i + \sum_s \phi_s D_{st} \times A_i + \nu_{it}, \tag{2}$$

where γ_i is a property fixed effect, α_{bt} is a block-by-time fixed effect. The connection between the two-way fixed-effects framework here (property and year fixed effects) and the traditional repeat-sales methodology is noted for example in Gao and Wang (2007).

The same repeat-sales specification can also accommodate other outcome variables. For property i traded at time t, define its homeownership status $H_{it} \in \{0,1\}$. The year-by-year slope on block-residualized AAL for homeownership status, for example, is given by:

$$H_{it} = \gamma_i + \alpha_{bt} + \sum_s \beta_s D_{st} \times X_i + \sum_s \phi_s D_{st} \times A_i + \nu_{it}. \tag{3}$$

As mentioned, specifications (2)-(3) are similar to "repeat sales" analyses. To understand this, consider, for comparison, the simpler regression

$$\log P_{it} = \gamma_i + \alpha_t + \nu_{it}, \tag{4}$$

which delivers via α_t a repeat-sales house price index. By including a property fixed effect in (4), we are effectively considering how housing valuations change over time within a given property. Analogously, by putting the property fixed effect in (2)-(3), we are effectively considering how the impact of climate risk exposures changes over time within a given property. Even though a given property may not transact so often, by putting the linear structure on how properties are impacted by AAL, a large enough dataset allows us to estimate ϕ_s reliably using this within-property variation. Akin to the standard logic in favor of repeat-sales indexes, our ability to look within property is helpful to control for unobserved cross-sectional quality differences that are correlated with climate risk exposures.

As an alternative for robustness, we also implement the analysis in two stages. Consider first residualizing Composite AAL by block fixed effects:

$$A_i = \alpha_b + \varepsilon_i \tag{5}$$

and then estimating

$$\log P_{it} = \gamma_i + \alpha_t + \sum_s \beta_s D_{st} \times X_i + \sum_s \phi_s D_{st} \times \varepsilon_i + \nu_{it} \tag{6}$$

where γ_i is a property fixed effect, α_t is a time fixed effect, and ε_i are the residuals from equation (5). The results of (6) and (2) should mechanically be identical in a balanced panel; but if some properties transact more than others, the results could potentially differ.

4 Empirical Results

4.1 Main Results

Figure I plots the coefficients $\{\phi_t\}$ from equation (1), with no hedonic controls, which is the equivalent of a cross-sectional regression year by year. Most evident in the figure is a stark drop from 2007 to 2010 for the sensitivity of log price to AAL, which is persistently present thereafter. Quantitatively, $\phi_{2010} - \phi_{2007} \approx -2$, representing a 2% price drop per 1% of climate risk exposure. This is a preview of our main result, that climate concerns had a sizable impact on housing markets and potentially relatively early on. Note also that there is a negative coefficient pre-2007, suggesting some validity to the type of story above that high-AAL properties have characteristics that are value-reducing.

Figure II repeats the same raw analysis but including log square-footage as a hedonic control, with time-varying loadings. While the time-series patterns between Figures I-II are broadly similar, taking out this single hedonic control for size completely eliminates the non-zero coefficients pre-2005. Thus, high-AAL properties tend to be smaller, which itself garners a discount, and this size discount was the primary driver of any non-zero difference in pricing pre-2005.

Figure III plots coefficients $\{\phi_t\}$ from equation (2), which is the repeat-sales specification that corrects for time-varying compositional effects in the market. The effects are substantially larger in magnitudes. Again, around the onset of 2006, there begins a steady decline in the ϕ_t, the sensitivity of log price to AAL. This decline continues until 2010, after which the coefficient remains permanently depressed. Quantitatively, the cumulative

decline is $\phi_{2010} - \phi_{2005} \approx -4$, significantly larger than the raw analysis from the previous figure. Note also that the repeat-sales version has eliminated the positivity of the pre-2005 coefficients, suggesting the property fixed effect has indeed eliminated the biases caused by some unobservable value-enhancing characteristics that simultaneously drive AAL. In addition, the pattern in the $\{\phi_t\}$ coefficients is smoother, and measured better statistically, in this repeat-sales version, suggesting that some random variation due to time-varying compositional effects may have been at play in Figures I-II.

Figure IV repeats the analysis in the two-stage regression (6). The results are almost identical to the one-stage approach in Figure III, suggesting that the impact of heterogeneous transaction rates is limited (since that is the only way the two analyses could produce different results). In subsequent analyses, we therefore explore only the one-stage approach.

We next examine owner-occupancy. Figure XIV plots coefficients $\{\phi_t\}$ from equation (3). Interestingly, although the outcome variable is different (here: an indicator for owner-occupant buyer), the pattern in the coefficients largely mimics that of the coefficients of the log price outcome. In particular, high-AAL properties are increasingly likely to be non-owner-occupied starting around 2005, with the change continuing for several years. We measure no difference in owner-occupancy for high- and low-AAL properties prior to 2005. Quantitatively, a 1% higher AAL translates to a 1.5% decline in owner-occupancy by 2010. Like the price regressions, this effect remains permanently thereafter, increasing if anything.

Our baseline repeat-sales methodology controls for time-invariant demand for property "fundamentals" but does not correct for time-varying demand for these fundamentals. We can partially explore this channel by augmenting our baseline specification with transaction-year dummies interacted with hedonic controls for property age, square footage, and the number of bedrooms.

Figure VI displays the loadings on AAL for our repeat-sales specification with these hedonic controls. There are some important similarities and differences. Broadly speaking, consistent with our earlier results, we continue to see a gradually-building climate risk discount, although the cumulative magnitude by 2024 is only about a -2% discount per 1% AAL (in contrast to our baseline result of -4%). However, the timing of a climate discount now emerges significantly later, beginning in about 2016.

A key difference when including hedonic controls is that they are not available for every property, meaning the sample of properties shrinks from about 45 million to 28 million in moving from Figure III to the hedonic-controlled result in Figure VI. How much of the change in our estimates can be accounted for by the different sample? Figure IX shows loadings on AAL, without hedonic controls, but restricting to properties that do have hedonic controls populated in our data. Notice that the cumulative climate discount for this sample is also about -2% per 1% AAL, although the discount emerges between 2006-2010 as in the non-hedonic specification.

Therefore, we conclude that the timing of the estimated climate discount is sensitive to accounting for time-varying demand, but the quantitative magnitude of the cumulative discount is less so. A climate discount impounded beginning around 2016 is also more in line with existing research.

We note that a particular time-varying demand pattern is required to explain our results. Recall that climate-safer properties are larger and newer. Increasing demand for larger, newer properties, between the years 2006-2010, is required to explain our baseline climate effect from Figure VI. To further confirm this hypothesis, Figure XIII displays the coefficients on the hedonic controls (logSqFt_i, dummies for Bedrooms_i, and dummies for bins of BuiltYear_i). Between 2005-2010, a strongly increasing pattern is visible on the square-footage loading. And over the entire sample, a strongly increasing pattern appears for the loadings on newer properties.

Finally, Figures XV, XXI, and XVII repeat the analyses above after restricting the sample to single-family homes (to avoid potential confounds from apartment buildings). The results are very similar to the ones discussed for the whole sample.

Taken together, this core set of results suggests a large effect of climate risk on housing markets, which persists to date. If we ignore the potential for an increasing demand for larger, newer properties, the climate risk discount begins in 2005, much earlier than previously thought. Accounting for this potential time-varying demand for fundamentals, the climate risk discount begins in around 2016, in line with some existing studies. Overall, the effect is a 2-4% discount per 1% of AAL.

A back-of-the-envelope calculations suggests quantitatively sizable effects at the aggregate level. Given the cross-sectional mean AAL of 0.25% from Table I, a price change of

between (−4,−2) per unit of AAL implies a 0.5-1% lower level of house prices due to climate risk. Similarly, the same type of calculation implies a 0.5% lower owner-occupancy due to climate risk. Of course, such back-of-the-envelope calculations ignore reallocation and general equilibrium effects, which would imply they overstate or understate, respectively, the true aggregate effect.

4.2 Robustness: Hurricane Katrina

Given the main shift in estimated climate risk pricing occurs starting around 2005, the change might be due to the direct impact of Hurricane Katrina, which struck southeastern US in August 2005. To explore this possibility, we re-run the main specification excluding Alabama, Louisiana and Mississippi, which are the three states that were directly affected by Katrina.

Results are shown in Figure XXII, for both log prices and owner occupation. The results are remarkably similar to our baseline results: the timing of the decline is still around 2004-05, the pattern of decline over several years remains largely the same (though slightly more drawn out for prices), and the cumulative effects are quantitatively of similar magnitude.

While these results are meant to control for the direct effect of Katrina, they do not necessarily rule out an indirect role for Katrina. As mentioned in the introduction, a prominent hypothesis, supported by survey data and even some observational studies, is that extreme weather events may raise climate awareness and alter risk perceptions. The fact that Katrina was a large-scale, high-profile event may have caused a shift in climate risk perceptions nationwide. In that sense, our results are completely consistent with Katrina playing a role, through changing household beliefs.

4.3 Robustness: Foreclosure Crisis

Given the shift in 2005, our results could be due to the housing market crisis that triggered the Great Recession. Figure XXIIIA plots the count of REO sales—a proxy for foreclosures—over time, increasing sharply starting around 2007.

Figures XXIIIB and XXIIIC run raw cross-sectional and repeat-sales regressions com-

paring REO sale likelihood against within-block AAL. Properties with higher climate-risk exposure within blocks experienced higher REO sale likelihoods starting around 2007 but revert back to a null relationship by around 2012.

4.4 Peril-specific analysis

We can repeat the same repeat-sales analysis but with peril-specific AALs rather than composite AALs. Doing so helps us explore two issues. First, do peril-specific exposures garner a discount over and above the an overall composite risk exposure? Second, do different risks become salient at similar or different times?

Figures XXIV-XXX display the results from this analysis. We re-run the one-stage, repeat-sales analysis from equation (2), but with two modifications. Rather than only the Composite AAL A_i, we project transaction prices onto both a peril-specific AAL A_i^p (for $p =$ earthquake, hurricane, flood, etc.). We plot the time series of coefficients on A_i^p, which recall are conditional on property and block-by-time fixed effects. In all of these regressions, we include the hedonic controls for square-footage, number of bedrooms, and age.

While these estimates are much noisier than the Composite AAL estimates, we do see climate risk discounts for hurricane storm surge, hurricane wind, inland floods.[7]

5 Conclusion

Using a novel property-level dataset on climate risk exposures, exploiting only within-block variation in exposures, and employing a new repeat-sales-style methodology, we show that climate risk impounded a significant discount on house prices. Depending on the methodology, this discount began appearing in either 2006 (ignoring time-varying demand for house size and age, but accounting for all time-invariant demand factors and

[7]Some words of caution apply to these analyses. The estimated discount for winter storm perils seems unrealistically large, probably because it is a "small" risk, which according to the diagonals in Table IIc has a small exposure magnitudes. In such cases with small risks, covariances to other perils and fundamental variables like size and age are non-trivial relative to the peril-specific variances, meaning that the estimated coefficient on the peril in question likely picks up these other exposures. The perils less subject to these potential issues are wildfire, hurricane storm surge, inland flood, and convective storm, all of which have more stable and reasonable estimates for peril-specific risk discounts.

time-varying geographic demand) or 2016 (with flexible hedonic controls). At exactly the same time, climate-risky houses began being disproportionately sold to landlords rather than owner-occupants. Both effects are permanent, consistent with an interpretation that climate risk perceptions shifted earlier than the literature has appreciated.

References

Addoum, J. M., P. Eichholtz, E. Steiner, and E. Yönder (2024): "Climate change and commercial real estate: Evidence from Hurricane Sandy," *Real Estate Economics*, 52, 687–713.

Akerlof, K., E. W. Maibach, D. Fitzgerald, A. Y. Cedeno, and A. Neuman (2013): "Do people "personally experience" global warming, and if so how, and does it matter?" *Global Environmental Change*, 23, 81–91.

Baldauf, M., L. Garlappi, and C. Yannelis (2020): "Does climate change affect real estate prices? Only if you believe in it," *The Review of Financial Studies*, 33, 1256–1295.

Bergquist, P. and C. Warshaw (2019): "Does global warming increase public concern about climate change?" *The Journal of Politics*, 81, 686–691.

Bernstein, A., S. B. Billings, M. T. Gustafson, and R. Lewis (2022): "Partisan residential sorting on climate change risk," *Journal of Financial Economics*, 146, 989–1015.

Bernstein, A., M. T. Gustafson, and R. Lewis (2019): "Disaster on the horizon: The price effect of sea level rise," *Journal of Financial Economics*, 134, 253–272.

Brulle, R. J., J. Carmichael, and J. C. Jenkins (2012): "Shifting public opinion on climate change: an empirical assessment of factors influencing concern over climate change in the US, 2002–2010," *Climatic change*, 114, 169–188.

Carmichael, J. T. and R. J. Brulle (2017): "Elite cues, media coverage, and public concern: an integrated path analysis of public opinion on climate change, 2001–2013," *Environmental Politics*, 26, 232–252.

Contat, J., C. Hopkins, L. Mejia, and M. Suandi (2024): "When climate meets real estate: A survey of the literature," *Real Estate Economics*, 52, 618–659.

Deryugina, T. (2013): "How do people update? The effects of local weather fluctuations on beliefs about global warming," *Climatic Change*, 118, 397–416.

Deryugina, T., L. Kawano, and S. Levitt (2018): "The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns," *American Economic Journal: Applied Economics*, 10, 202–233.

Egan, P. J. and M. Mullin (2012): "Turning personal experience into political attitudes: The effect of local weather on Americans' perceptions about global warming," *The Journal of Politics*, 74, 796–809.

Ellen, I. G. and R. Meltzer (2024): "Heterogeneity in the recovery of local real estate markets after extreme events: The case of Hurricane Sandy," *Real Estate Economics*.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel (2020): "Hedging climate change news," *The Review of Financial Studies*, 33, 1184–1216.

Gallagher, J. and D. Hartley (2017): "Household finance after a natural disaster: The case of hurricane Katrina," *American Economic Journal: Economic Policy*, 9, 199–228.

Gao, A. and G. Wang (2007): "Multiple transactions model: a panel data approach to estimate housing market indices," *Journal of Real Estate Research*, 29, 241–266.

Gormsen, N. J., K. Huber, and S. S. Oh (2024): "Climate capitalists," Tech. rep., National Bureau of Economic Research.

Ilhan, E. (2020): "Sea level rise and portfolio choice," Available at SSRN 3743046.

Ilhan, E., P. Krueger, Z. Sautner, and L. T. Starks (2023): "Climate risk disclosure and institutional investors," *The Review of Financial Studies*, 36, 2617–2650.

Keenan, J. M., T. Hill, and A. Gumber (2018): "Climate gentrification: from theory to empiricism in Miami-Dade County, Florida," *Environmental Research Letters*, 13, 054001.

Keys, B. J. and P. Mulder (2020): "Neglected no more: Housing markets, mortgage lending, and sea level rise," Tech. rep., National Bureau of Economic Research.

——— (2024): "Property Insurance and Disaster Risk: New Evidence from Mortgage Escrow Data," Tech. rep., National Bureau of Economic Research.

Krosnick, J. A., A. L. Holbrook, and P. S. Visser (2000): "The impact of the fall 1997 debate about global warming onAmerican public opinion," *Public Understanding of Science*, 9, 239.

Marlon, J. R., X. Wang, P. Bergquist, P. D. Howe, A. Leiserowitz, E. Maibach, M. Mildenberger, and S. Rosenthal (2022): "Change in US state-level public opinion about climate change: 2008–2020," *Environmental Research Letters*, 17, 124046.

McKenzie, R. and J. Levendis (2010): "Flood hazards and urban housing markets: The effects of Katrina on New Orleans," *The Journal of Real Estate Finance and Economics*, 40, 62–76.

Murfin, J. and M. Spiegel (2020): "Is the risk of sea level rise capitalized in residential real estate?" *The Review of Financial Studies*, 33, 1217–1255.

Nolan, J. M. (2010): ""An inconvenient truth" increases knowledge, concern, and willingness to reduce greenhouse gases," *Environment and Behavior*, 42, 643–658.

Nyce, C., R. E. Dumm, G. S. Sirmans, and G. Smersh (2015): "The capitalization of insurance premiums in house prices," *Journal of Risk and Insurance*, 82, 891–919.

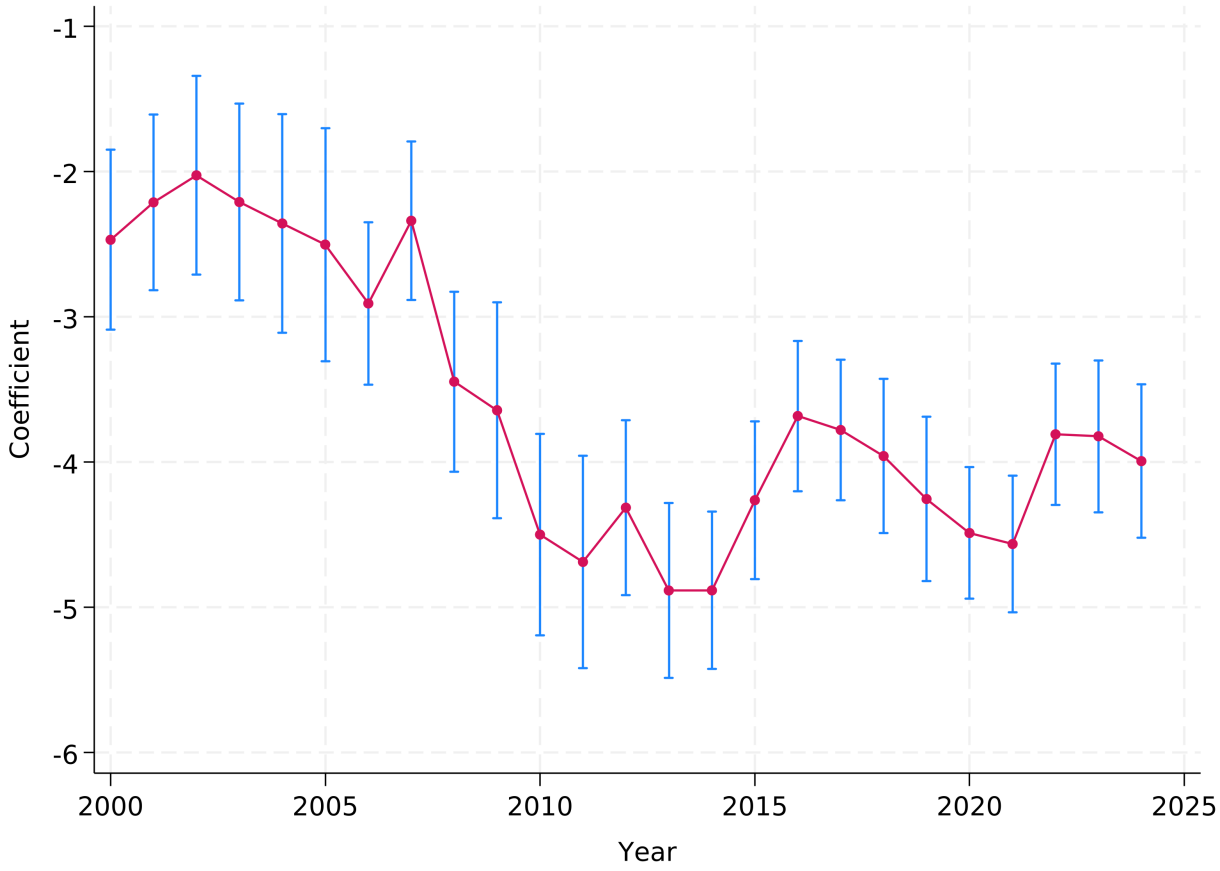
Ortega, F. and S. Taspinar (2018): "Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market," *Journal of Urban Economics*, 106, 81–100.

Pollack, A. B. and R. K. Kaufmann (2022): "Increasing storm risk, structural defense, and house prices in the Florida Keys," *Ecological Economics*, 194, 107350.

Schuetz, J. (2024): "How will US households adjust their housing behaviors in response to climate change?" *Real Estate Economics*.

Shao, W. (2017): "Weather, climate, politics, or God? Determinants of American public opinions toward global warming," *Environmental Politics*, 26, 71–96.

FIGURE I
PRICE AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: RAW

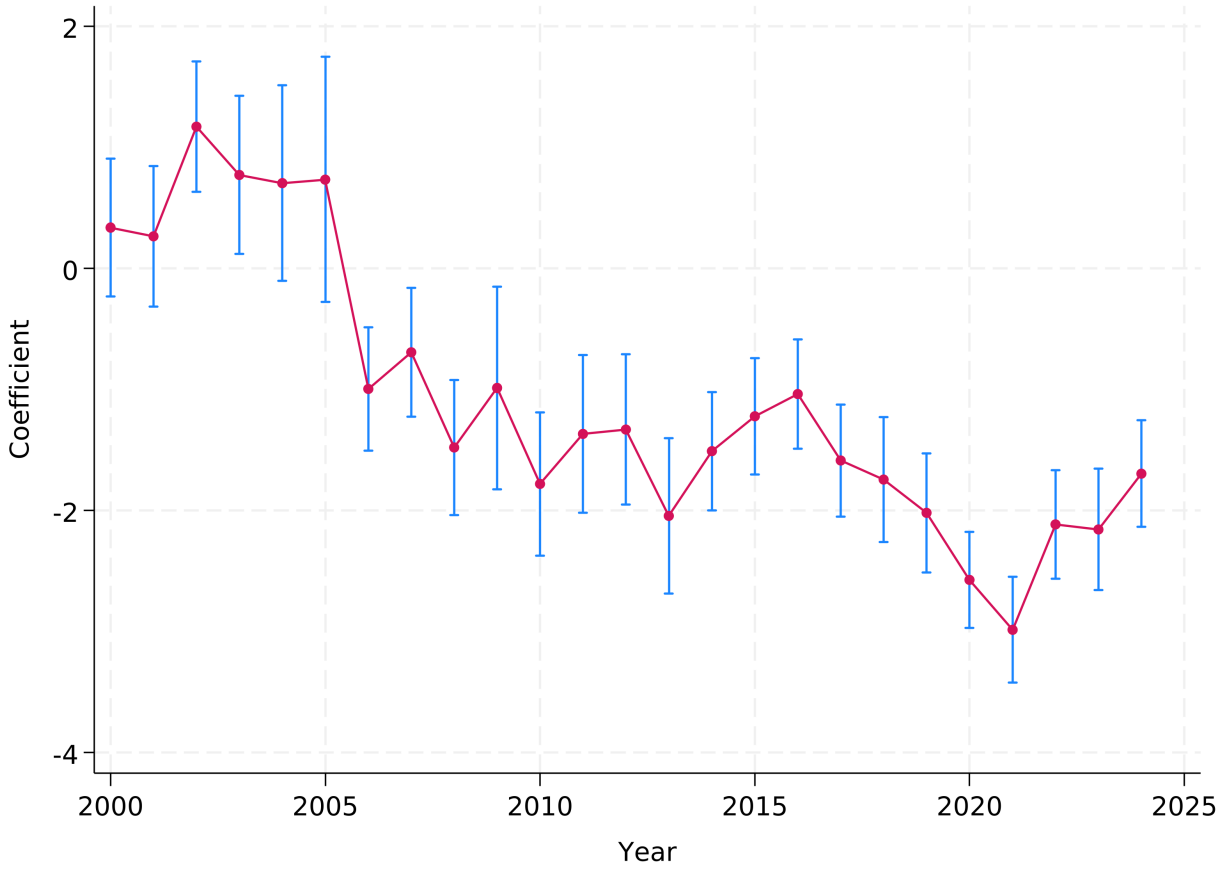


Notes. This figure plots the coefficients $\{\phi_t\}$ from equation (1):

$$\log P_{it} = \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where P_{it} is the transaction price of property i located in Census block b in year t, α_{bt} is a block-by-year fixed effect, A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), and D_{st} is dummy for year t (equals 1 when $s = t$). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the Census block.

FIGURE II
PRICE AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: RAW

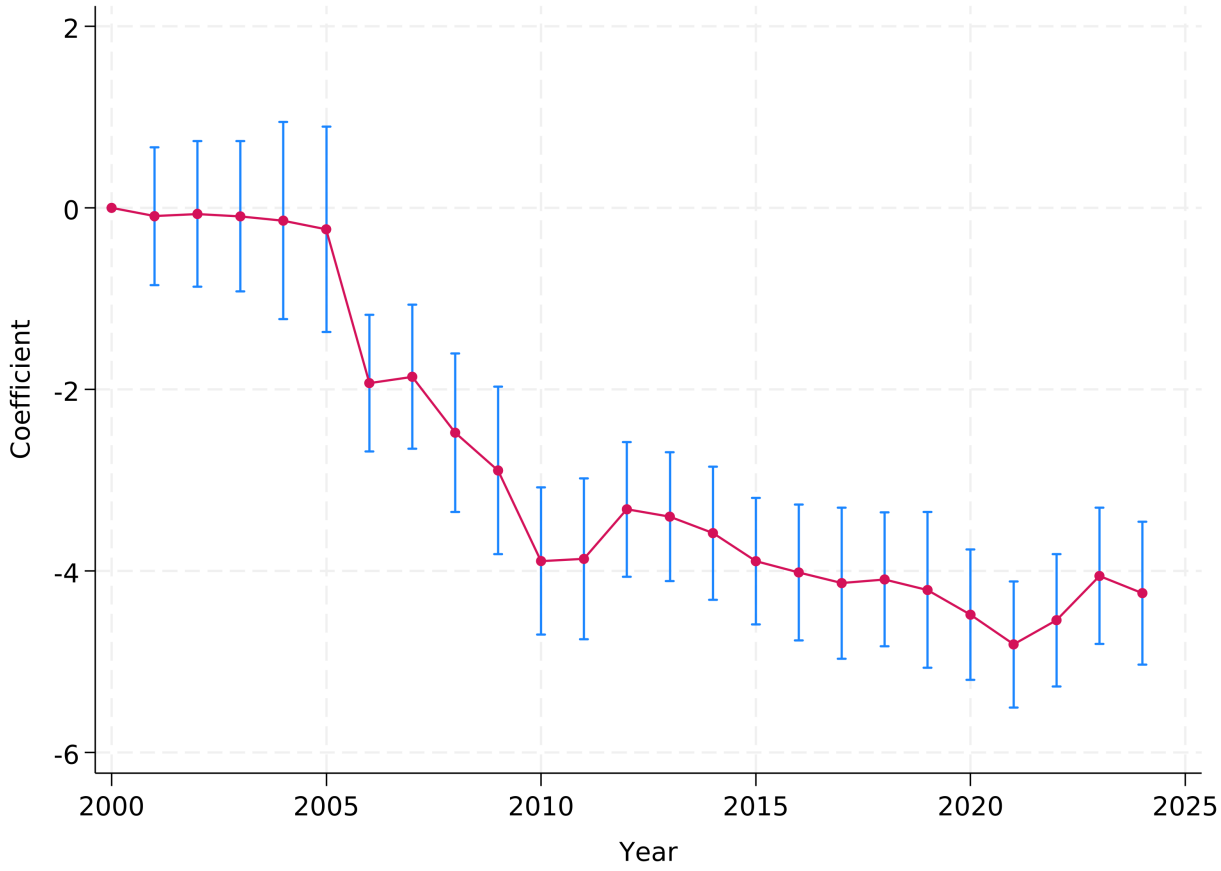


Notes. This figure plots the coefficients $\{\phi_t\}$ from equation (1), augmented with square footage controls:

$$\log P_{it} = \alpha_{bt} + \sum_s \zeta_s D_{st} \times \text{logSqFt}_i + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where P_{it} is the transaction price of property i located in Census block b in year t, α_{bt} is a block-by-year fixed effect, A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), and D_{st} is dummy for year t (equals 1 when $s = t$). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the Census block.

FIGURE III
PRICE AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE

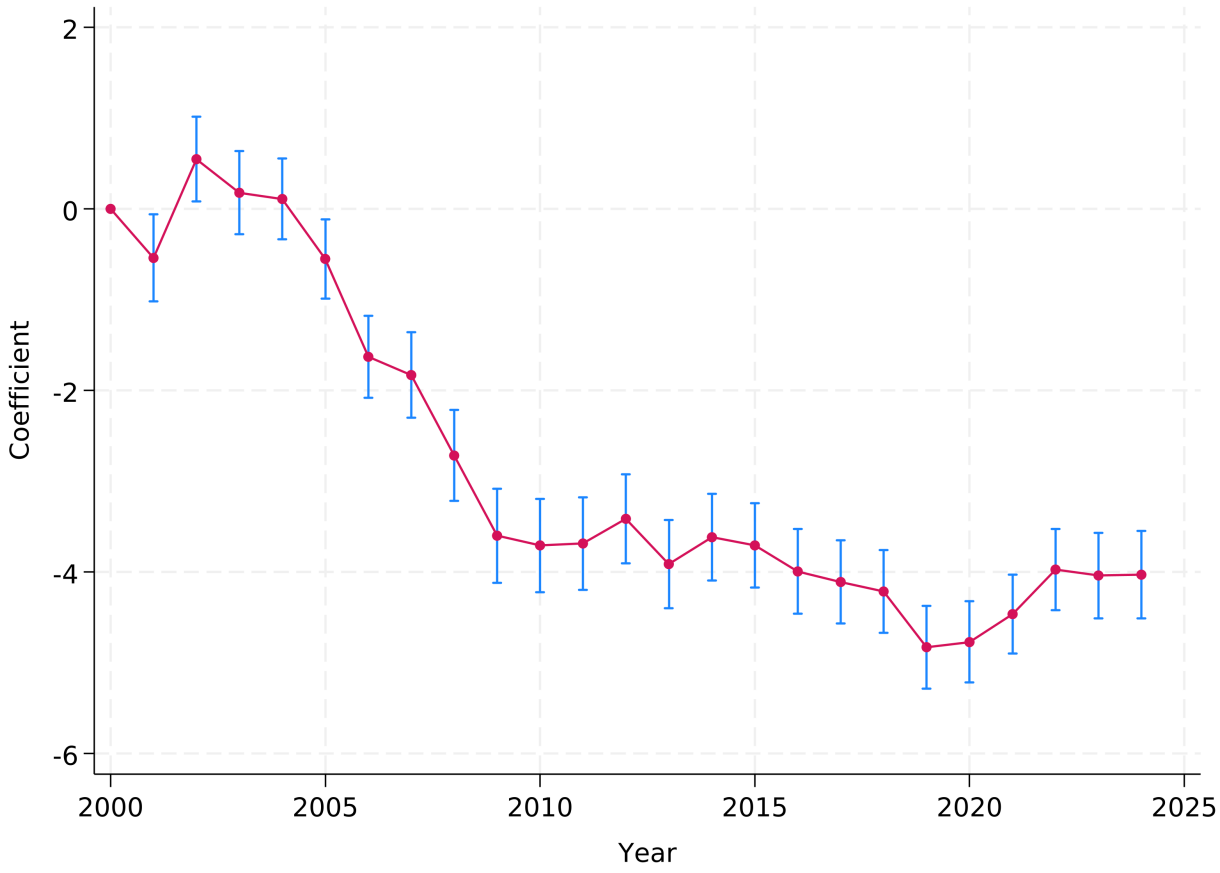


Notes. This figure plots the coefficients $\{\phi_t\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property. There are 45,282,295 observations in this regression.

FIGURE IV
PRICE AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES, TWO-STAGE



Notes. This figure plots the coefficients $\{\phi_t\}$ from equation (6):

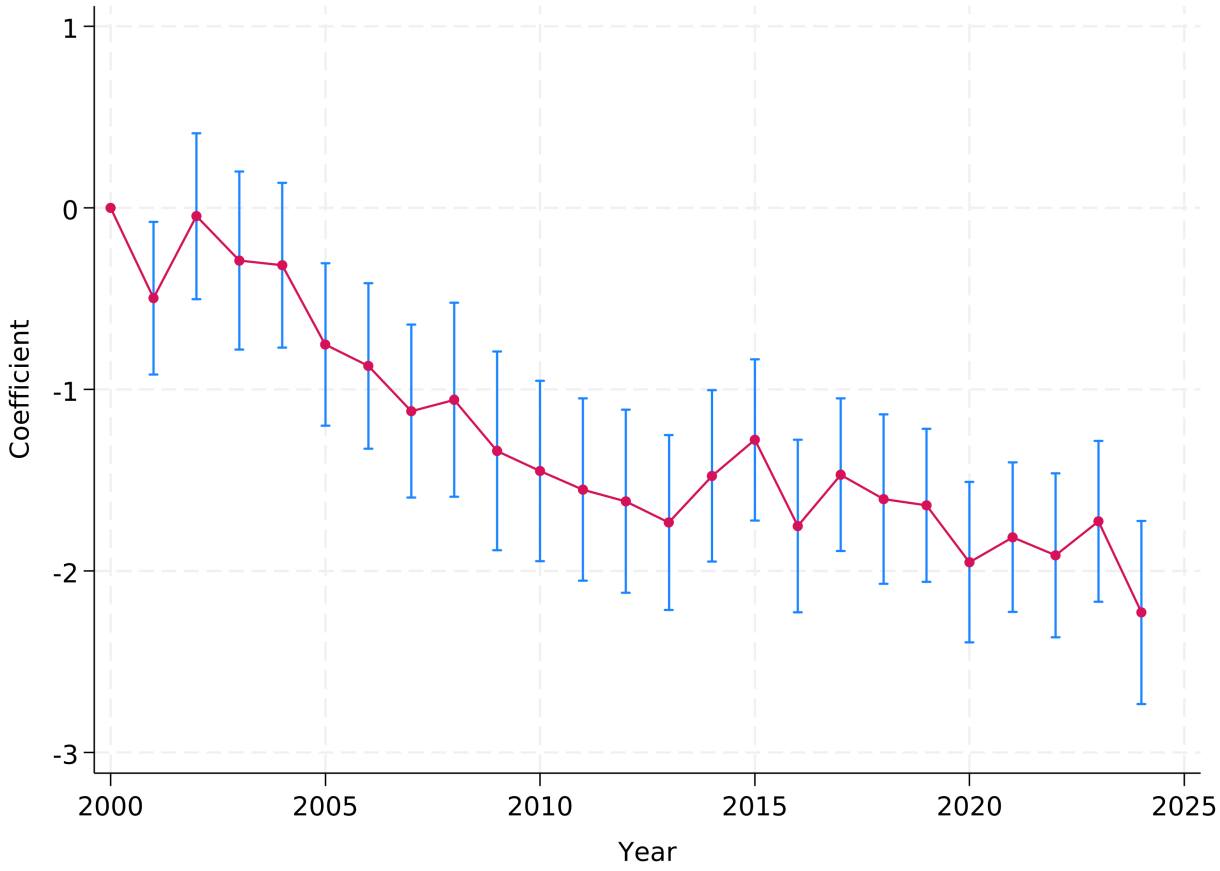
$$\log P_{it} = \gamma_i + \alpha_t + \sum_s \phi_s D_{st} \times \varepsilon_i + \nu_{it}$$

where P_{it} is the transaction price of property i, α_t is a year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and ε_i are the residuals estimated from equation (5):

$$A_i = \alpha_b + \varepsilon_i$$

where A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i located in Census block b. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE V
OWNER OCCUPATION AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES

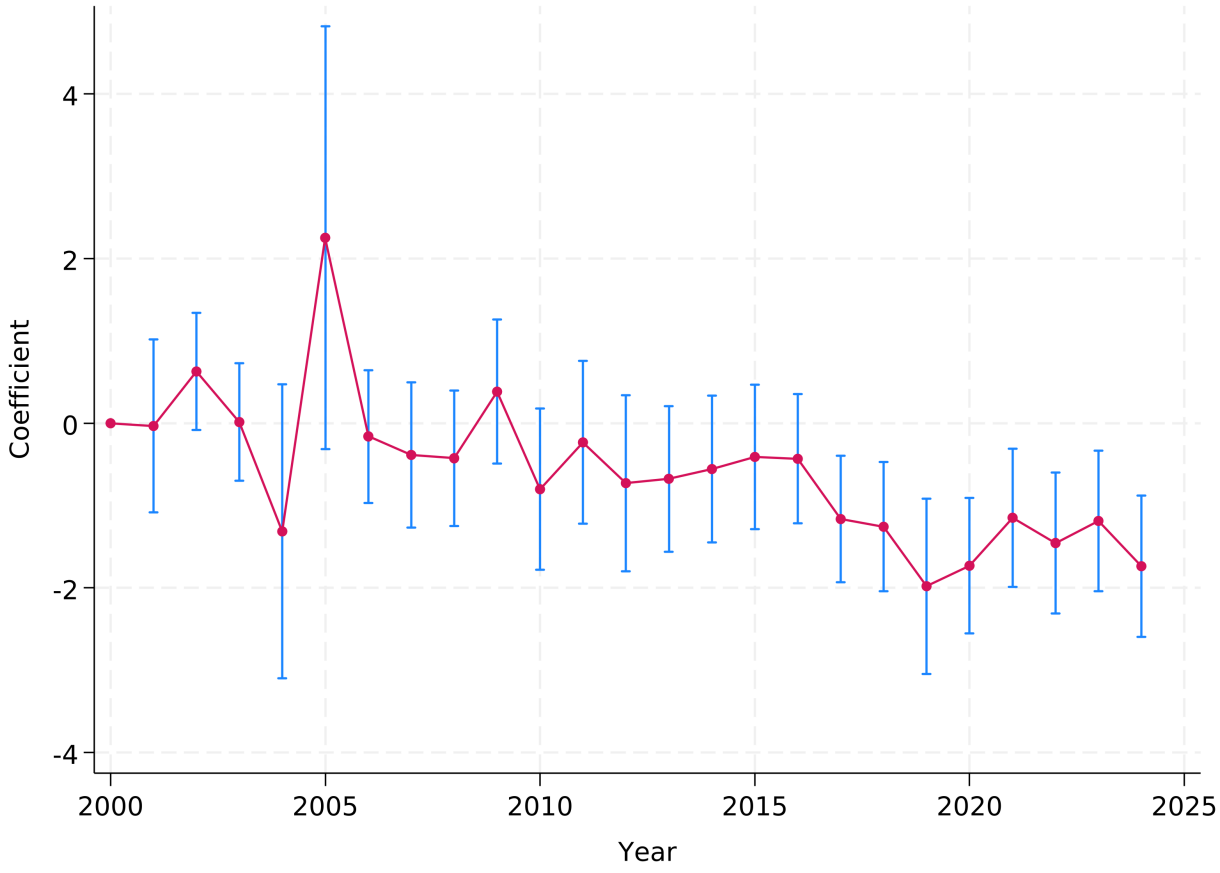


Notes. This figure plots the coefficients $\{\phi_t\}$ from equation (3):

$$H_{it} = \gamma_i + \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where H_{it} is an indicator that equals 1 when transacted property i was bought by a buyer to be owner-occupied, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE VI
COMPOSITE AAL REPEAT SALES (ONE SHOT) WITH PROPERTY CHARACTERISTIC FES

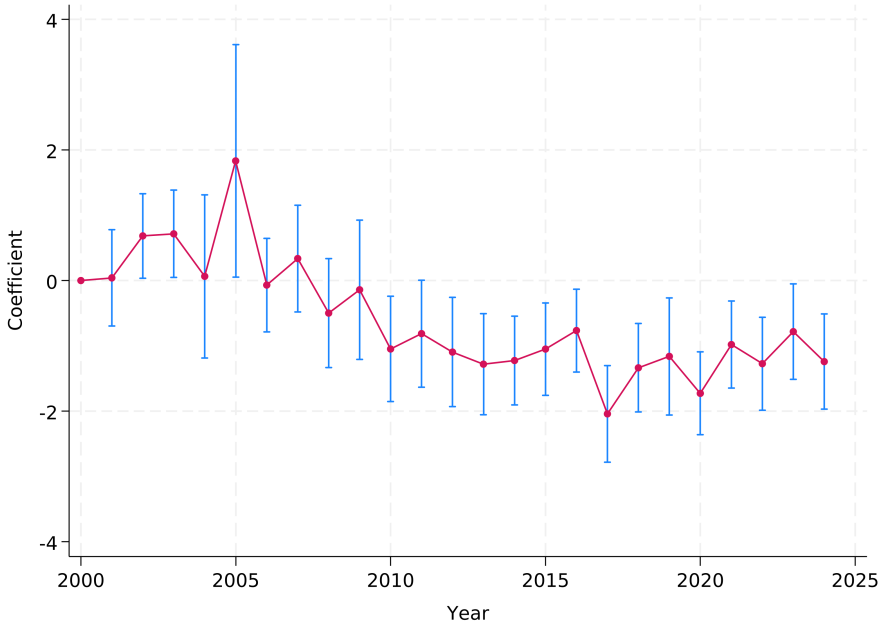


Notes. This figure plots the coefficients $\{\phi_t\}$ from equation (2):

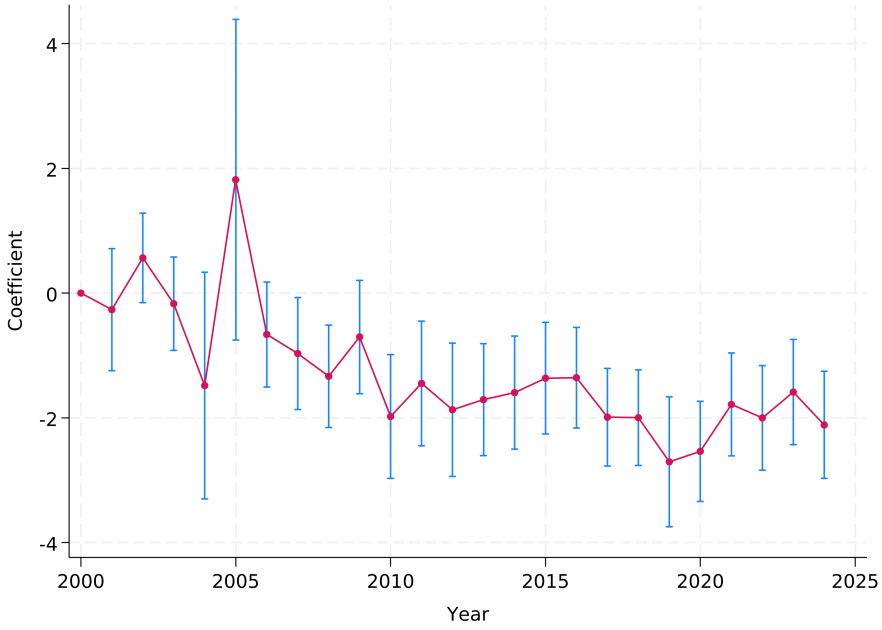
$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s D_{st} \times A_i + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property. There are 28,634,913 observations in this regression.

FIGURE VII
REPEAT SALES WITH ADDING HEDONICS (BLOCK)

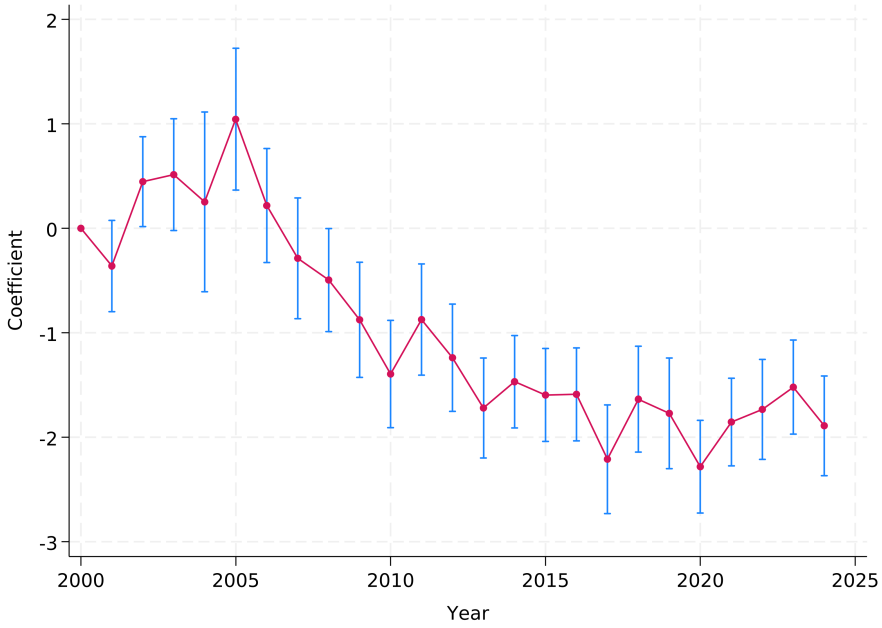


(A) Sqft only

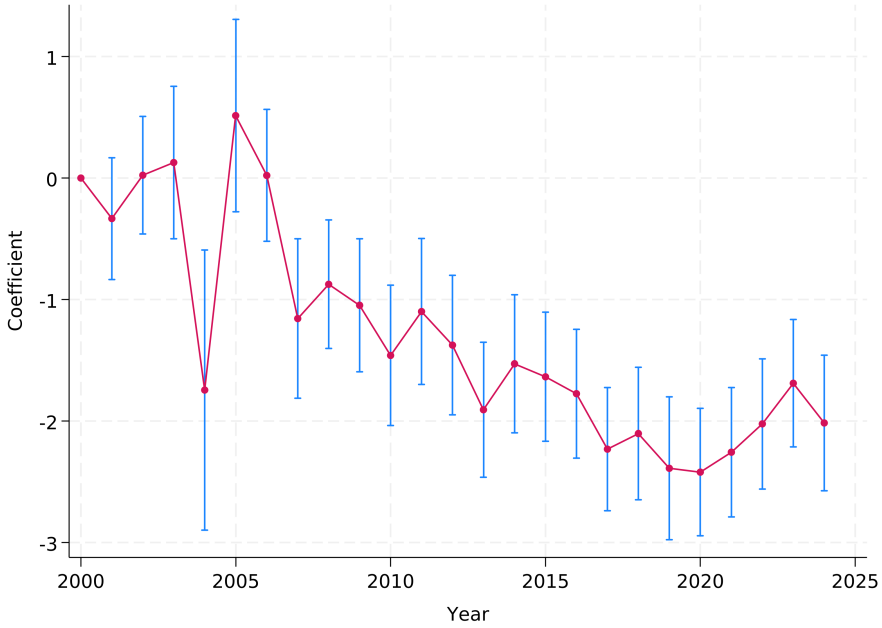


(B) Bedroom Bins and Sqft

FIGURE VIII
REPEAT SALES WITH ADDING HEDONICS (TRACT)

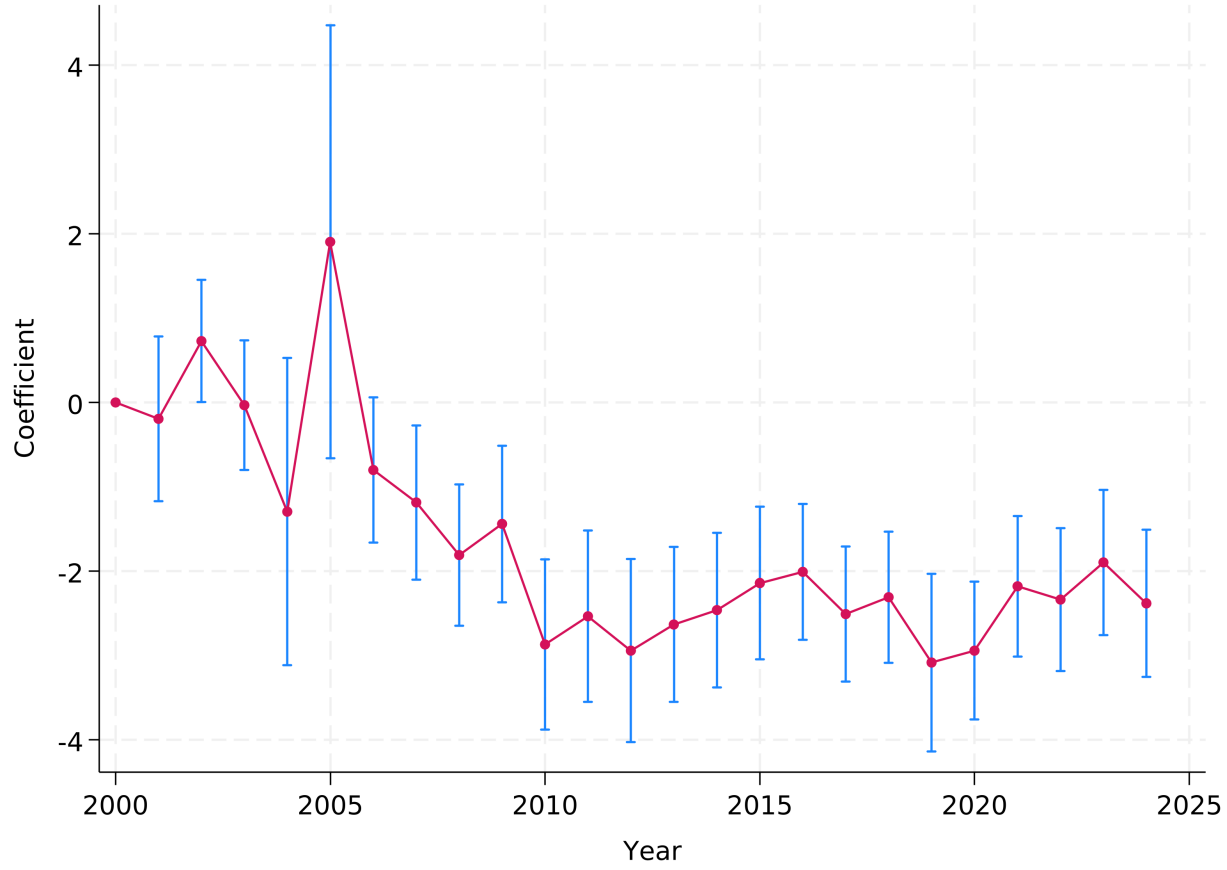


(A) Sqft only



(B) Bedroom Bins and Sqft

FIGURE IX
COMPOSITE AAL REPEAT SALES (ONE SHOT) WITH NON-MISSING PROPERTY CHARACTERISTICS

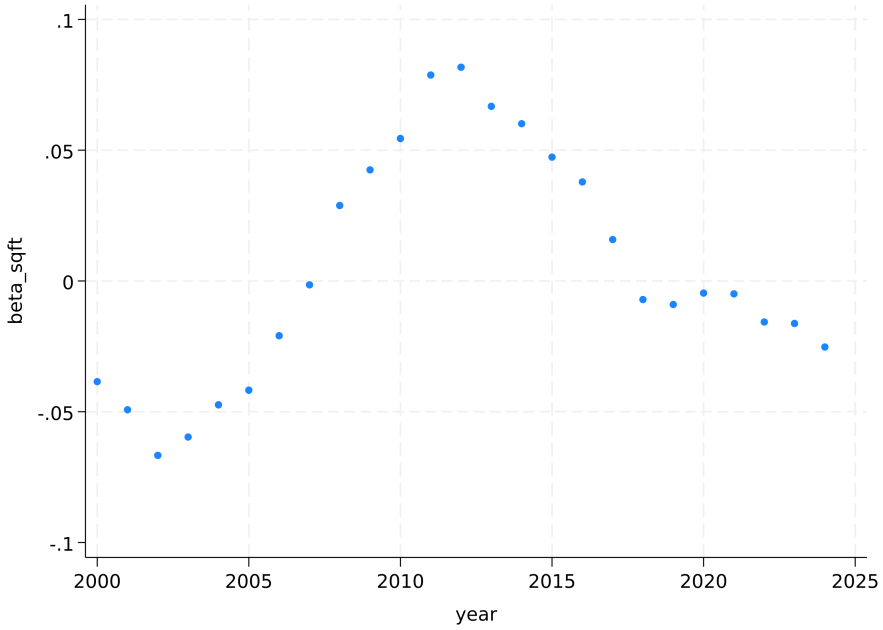


Notes. This figure plots the coefficients $\{\phi_t\}$ from equation (2):

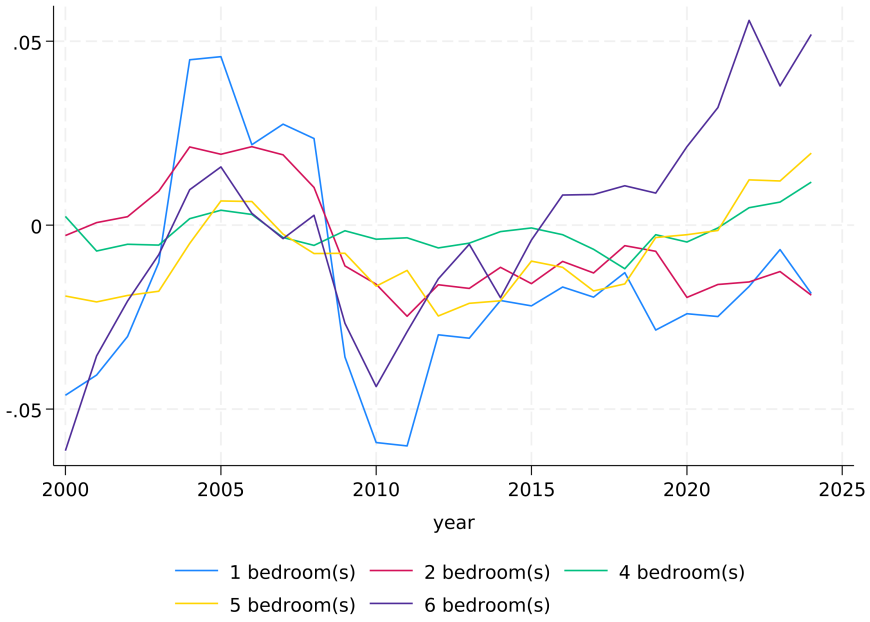
$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s D_{st} \times A_i\right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. This regression is limited to properties with non-missing observations for the number of bedrooms, the year built, and the log square feet that are included in the regression above. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property. There are 28,634,913 observations in this regression (the exact same sample of transactions from Figure VI).

FIGURE X
BLOCK PRICE FIXED EFFECT COEFFICIENTS FOR PROPERTY CHARACTERISTICS



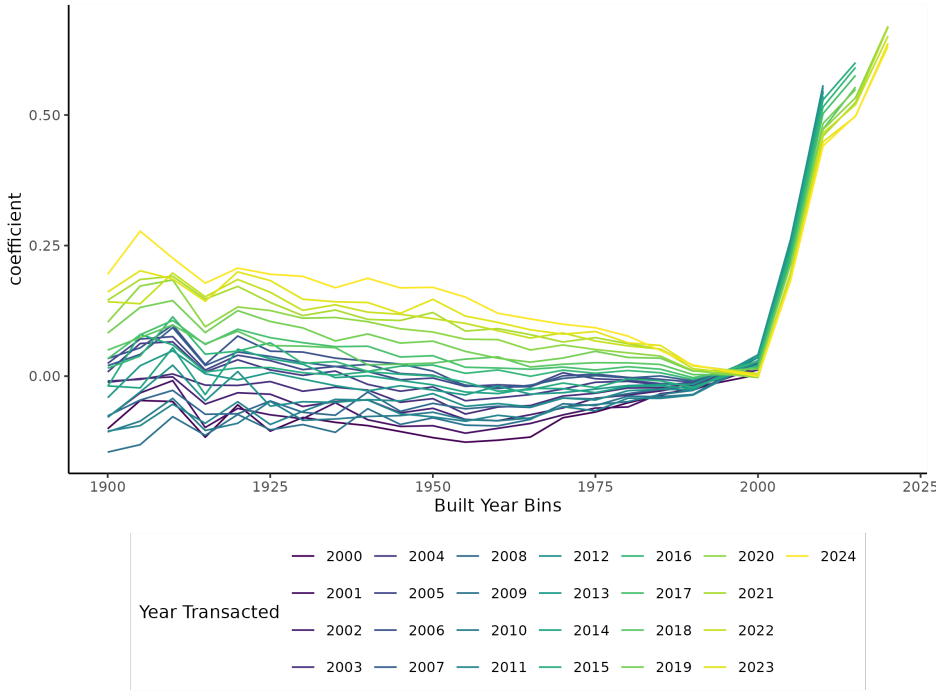
(A) Fixed Effect Coefficient Square Footage by year



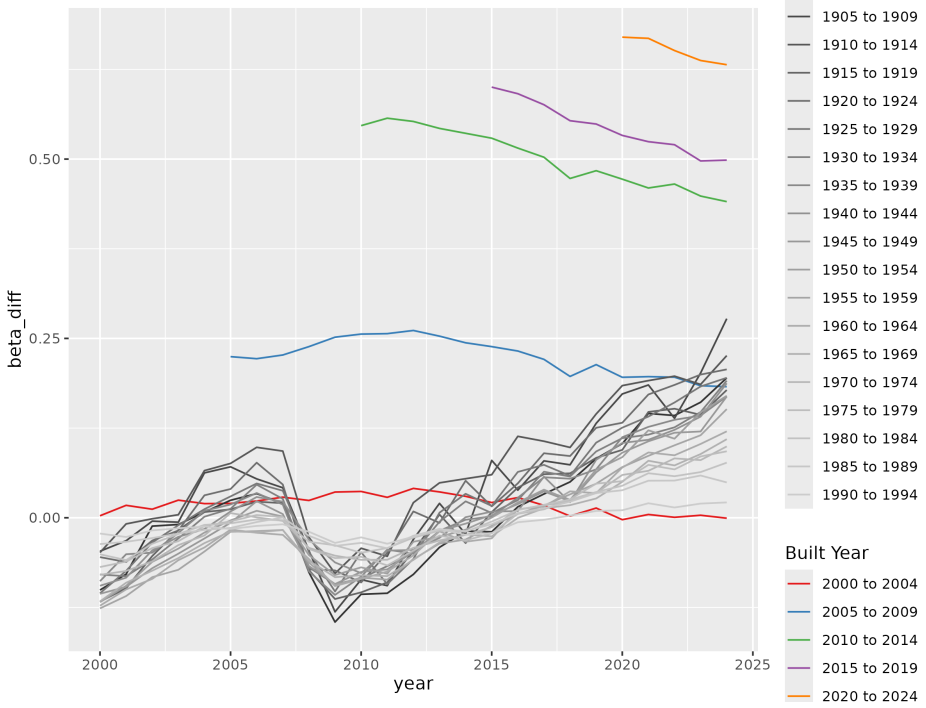
(B) Fixed Effect Coefficient Number of Bedrooms by year

Notes. The figures show the coefficients on the hedonic variables logSqFt_i and the Bedrooms_i fixed effect, both by year, from the regression corresponding to Figure VI.

FIGURE X
BLOCK PRICE FIXED EFFECT COEFFICIENTS FOR PROPERTY CHARACTERISTIC



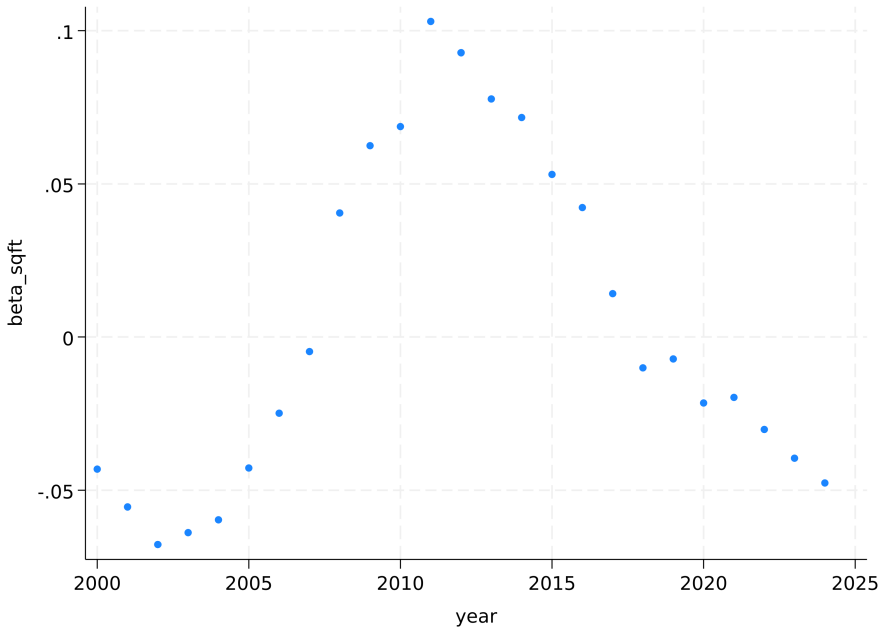
(C) Fixed Effect Coefficient Built Year Bins by transacted year



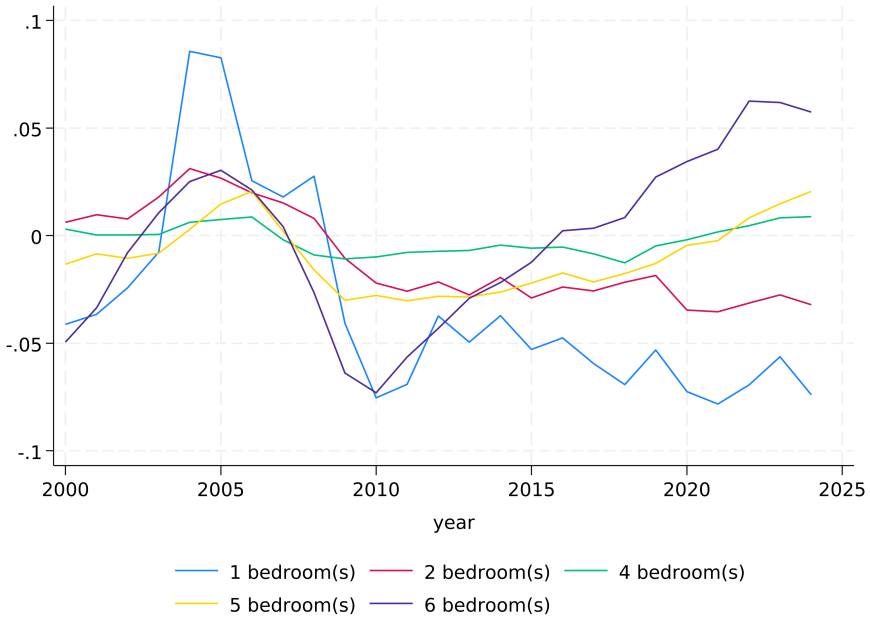
(D) Fixed Effect Coefficient Built Year Bins by year transacted

Notes. The figures show the coefficients on the hedonic variable YearBuiltBin_i, by year, from the regression corresponding to Figure VI.

FIGURE XI
TRACT PRICE FIXED EFFECT COEFFICIENTS FOR PROPERTY CHARACTERISTICS



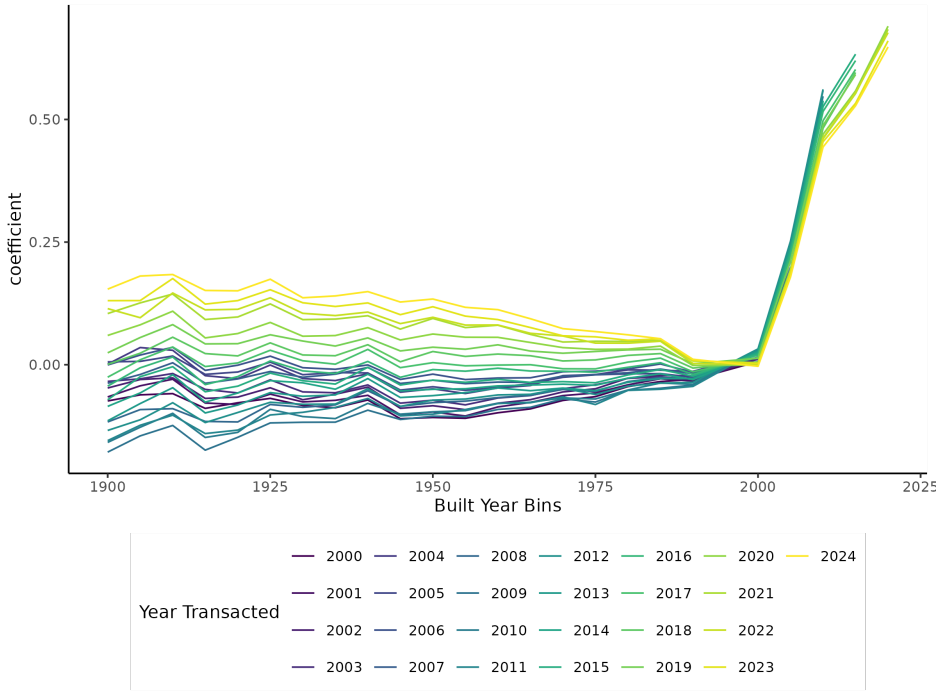
(A) Fixed Effect Coefficient Square Footage by year



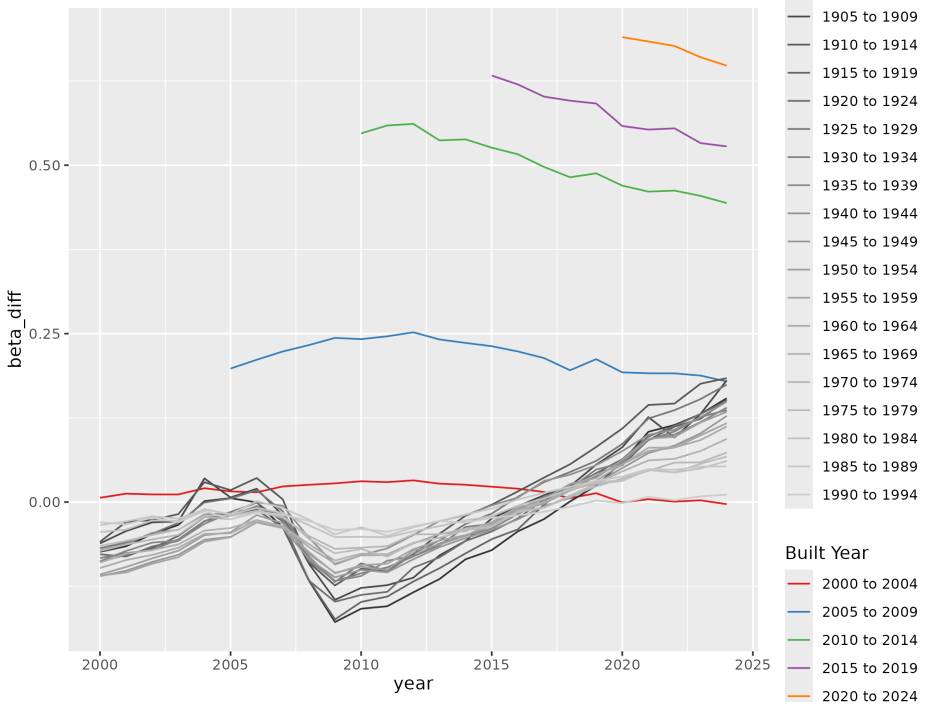
(B) Fixed Effect Coefficient Number of Bedrooms by year

Notes. The figures show the coefficients on the hedonic variables logSqFt_i and the Bedrooms_i fixed effect, both by year, from the regression corresponding to Figure VI.

FIGURE XI
TRACT PRICE FIXED EFFECT COEFFICIENTS FOR PROPERTY CHARACTERISTIC (CONTINUED)



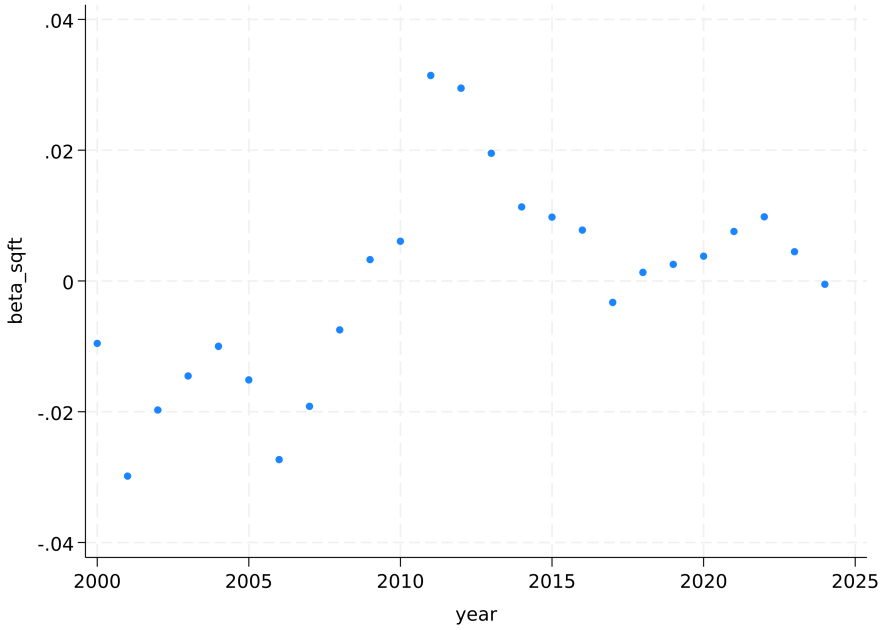
(C) Fixed Effect Coefficient Built Year Bins by transacted year



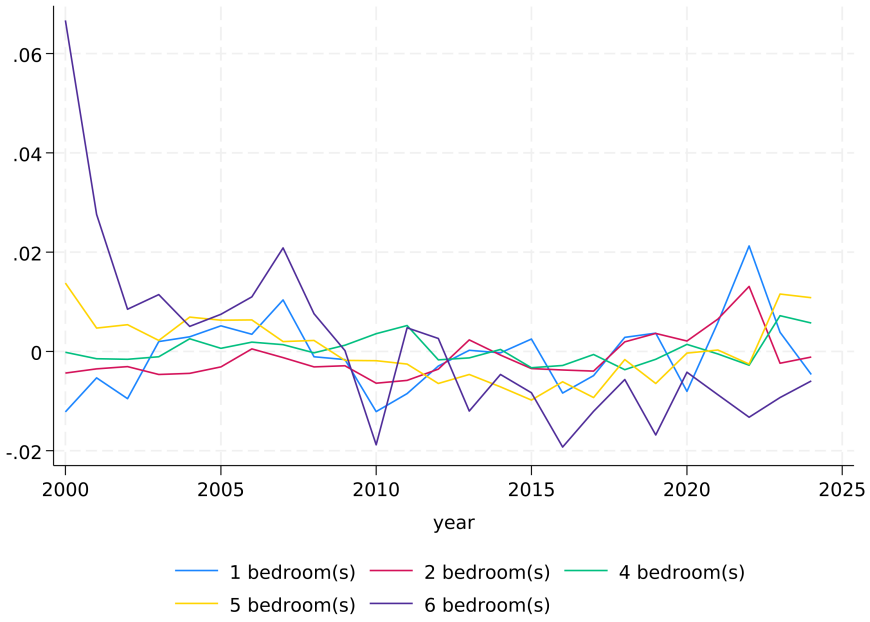
(D) Fixed Effect Coefficient Built Year Bins by year transacted

Notes. The figures show the coefficients on the hedonic variable YearBuiltBin_i, by year, from the regression corresponding to Figure VI.

FIGURE XII
BLOCK OWNER OCCUPANCY FIXED EFFECT COEFFICIENTS FOR PROPERTY CHARACTERISTICS



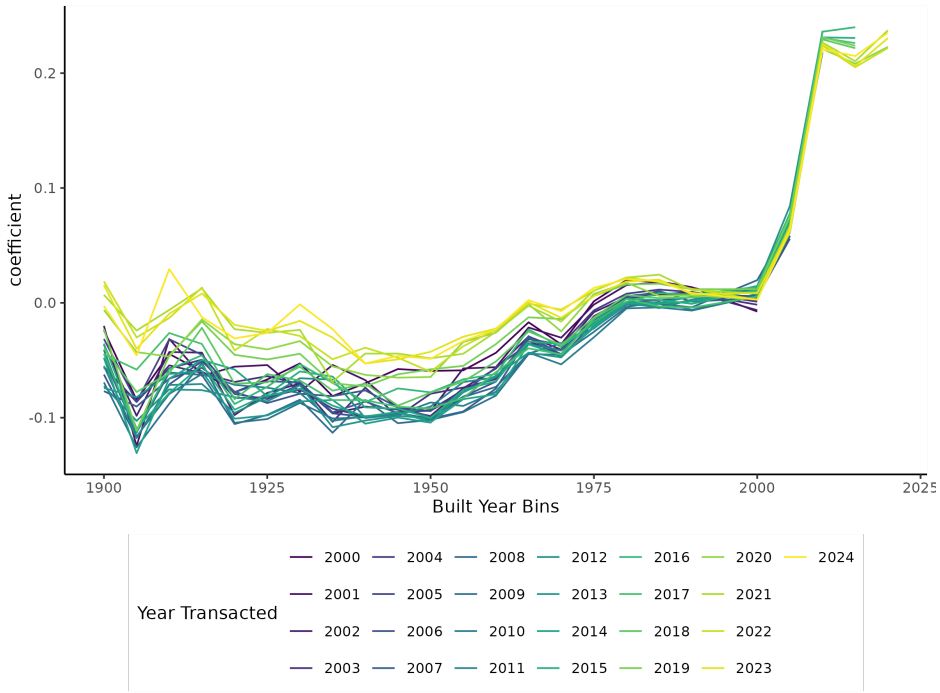
(A) Fixed Effect Coefficient Square Footage by year



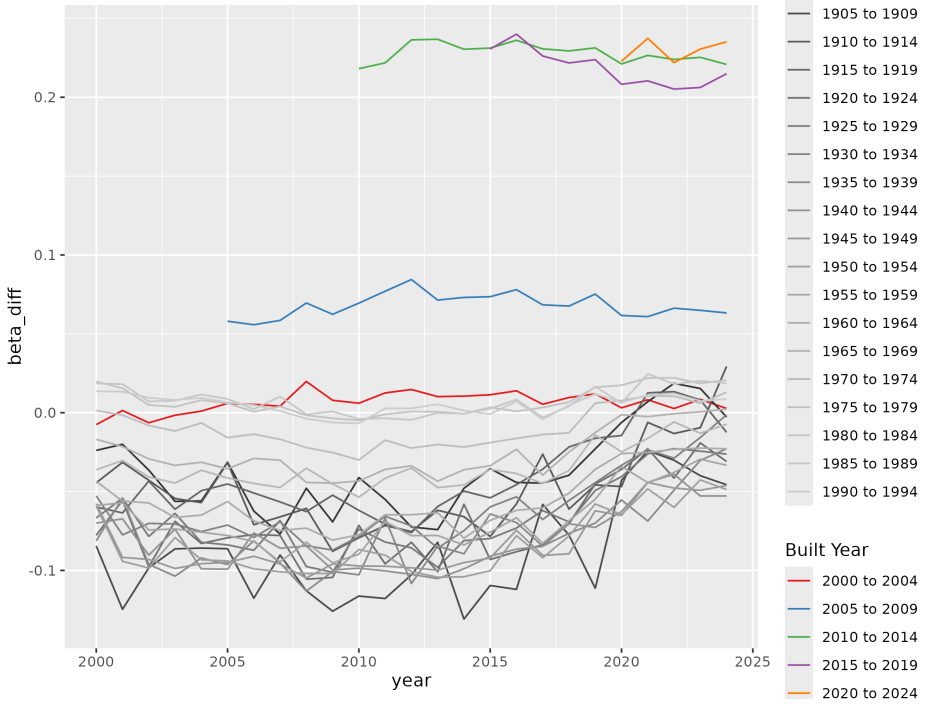
(B) Fixed Effect Coefficient Number of Bedrooms by year

Notes. The figures show the coefficients on the hedonic variables logSqFt_i and the Bedrooms_i fixed effect, both by year, from the regression corresponding to Figure VI.

FIGURE XII
BLOCK OWNER OCCUPANCY FIXED EFFECT COEFFICIENTS FOR PROPERTY CHARACTERISTIC (CONTINUED)



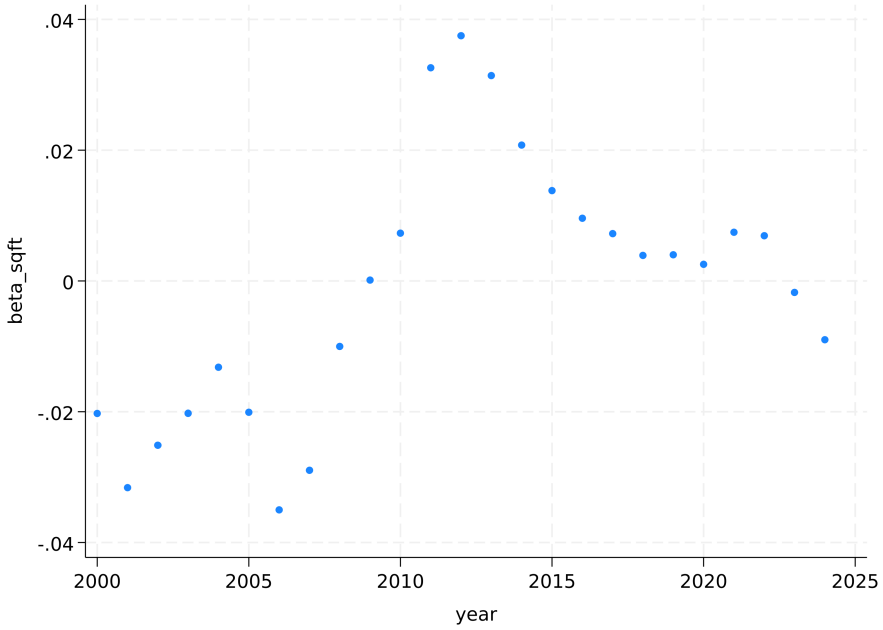
(C) Fixed Effect Coefficient Built Year Bins by transacted year



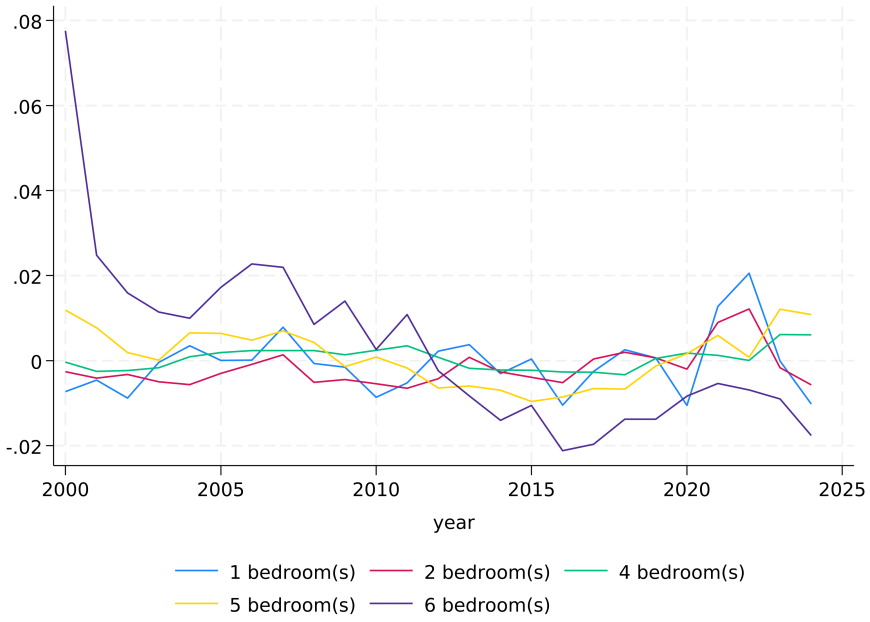
(D) Fixed Effect Coefficient Built Year Bins by year transacted

Notes. The figures show the coefficients on the hedonic variable YearBuiltBin_i, by year, from the regression corresponding to Figure VI.

FIGURE XIII
TRACT OWNER OCCUPANCY FIXED EFFECT COEFFICIENTS FOR PROPERTY CHARACTERISTICS



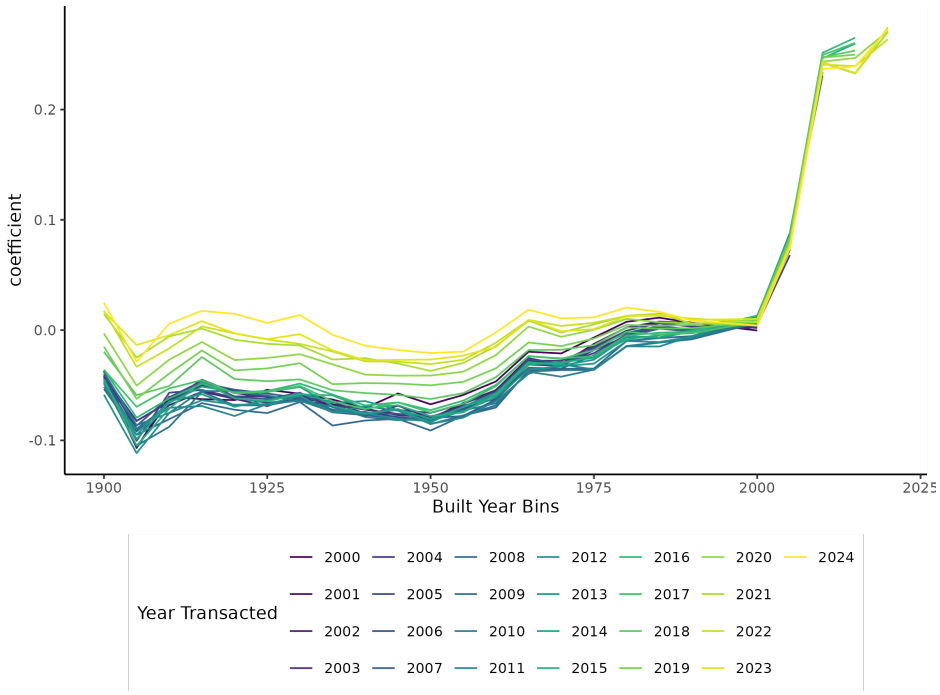
(A) Fixed Effect Coefficient Square Footage by year



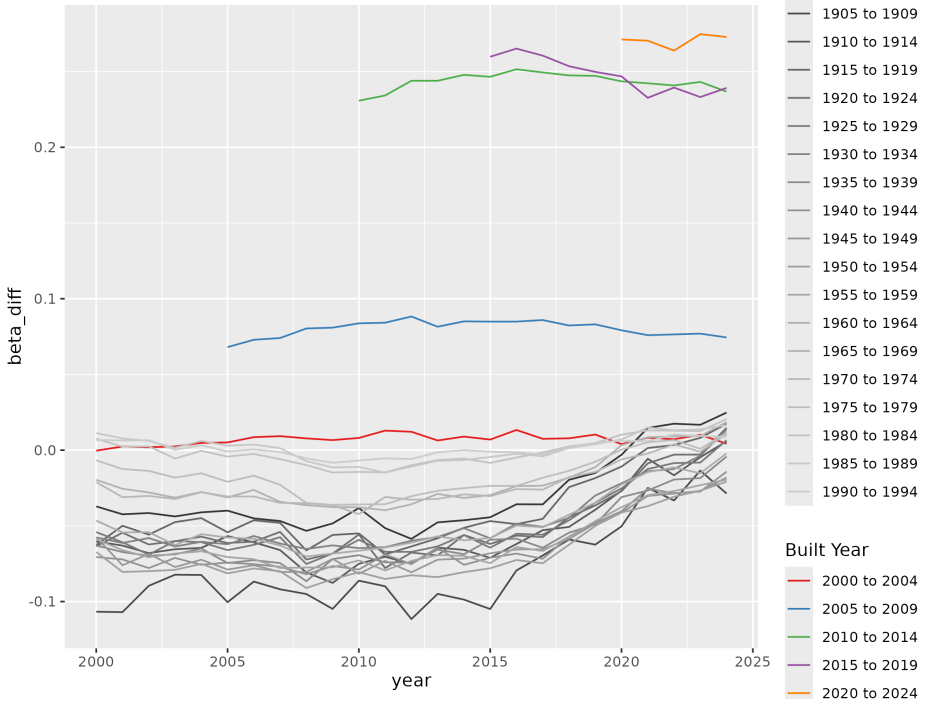
(B) Fixed Effect Coefficient Number of Bedrooms by year

Notes. The figures show the coefficients on the hedonic variables logSqFt_i and the Bedrooms_i fixed effect, both by year, from the regression corresponding to Figure VI.

FIGURE XIII
TRACT OWNER OCCUPANCY FIXED EFFECT COEFFICIENTS FOR PROPERTY CHARACTERISTIC (CONTINUED)



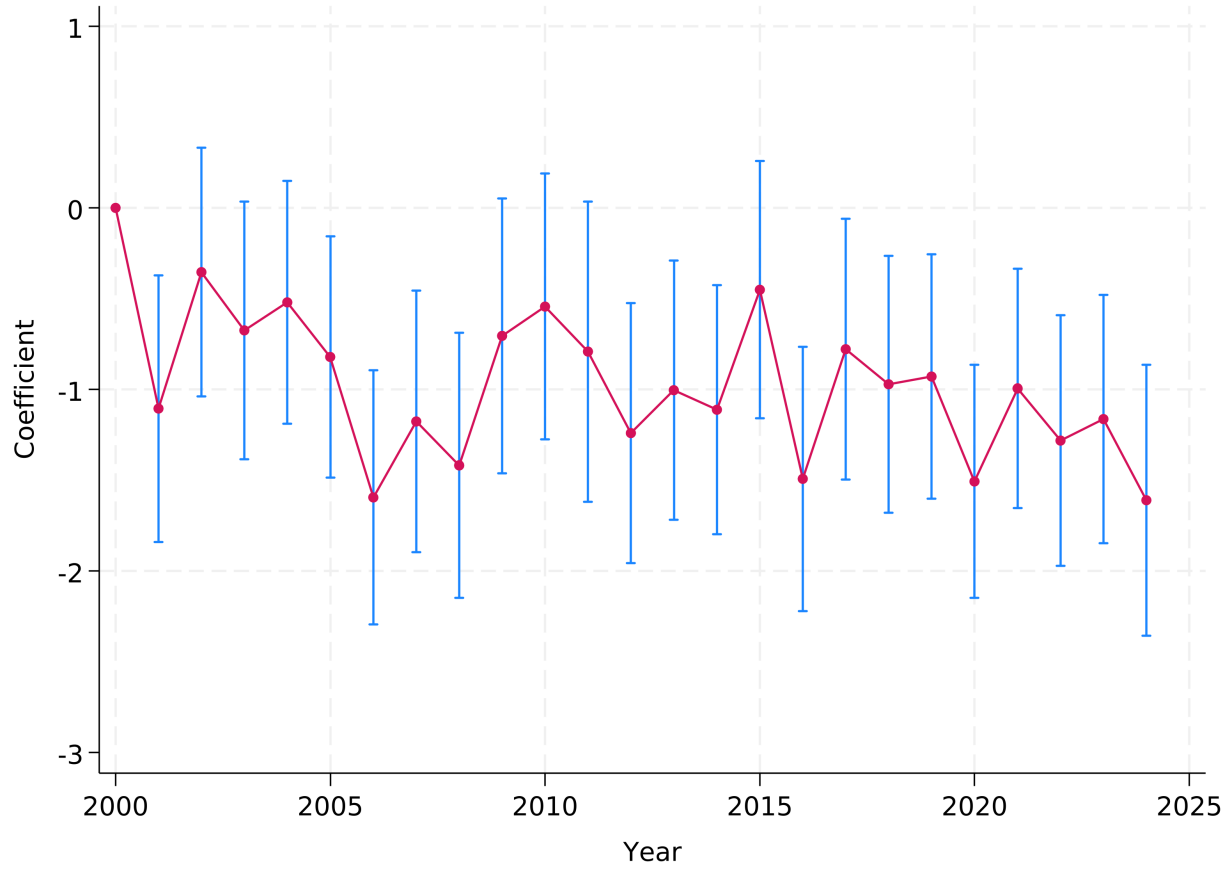
(C) Fixed Effect Coefficient Built Year Bins by transacted year



(D) Fixed Effect Coefficient Built Year Bins by year transacted

Notes. The figures show the coefficients on the hedonic variable YearBuiltBin_i, by year, from the regression corresponding to Figure VI.

FIGURE XIV
OWNER OCCUPATION AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES WITH HEDONIC CONTROLS

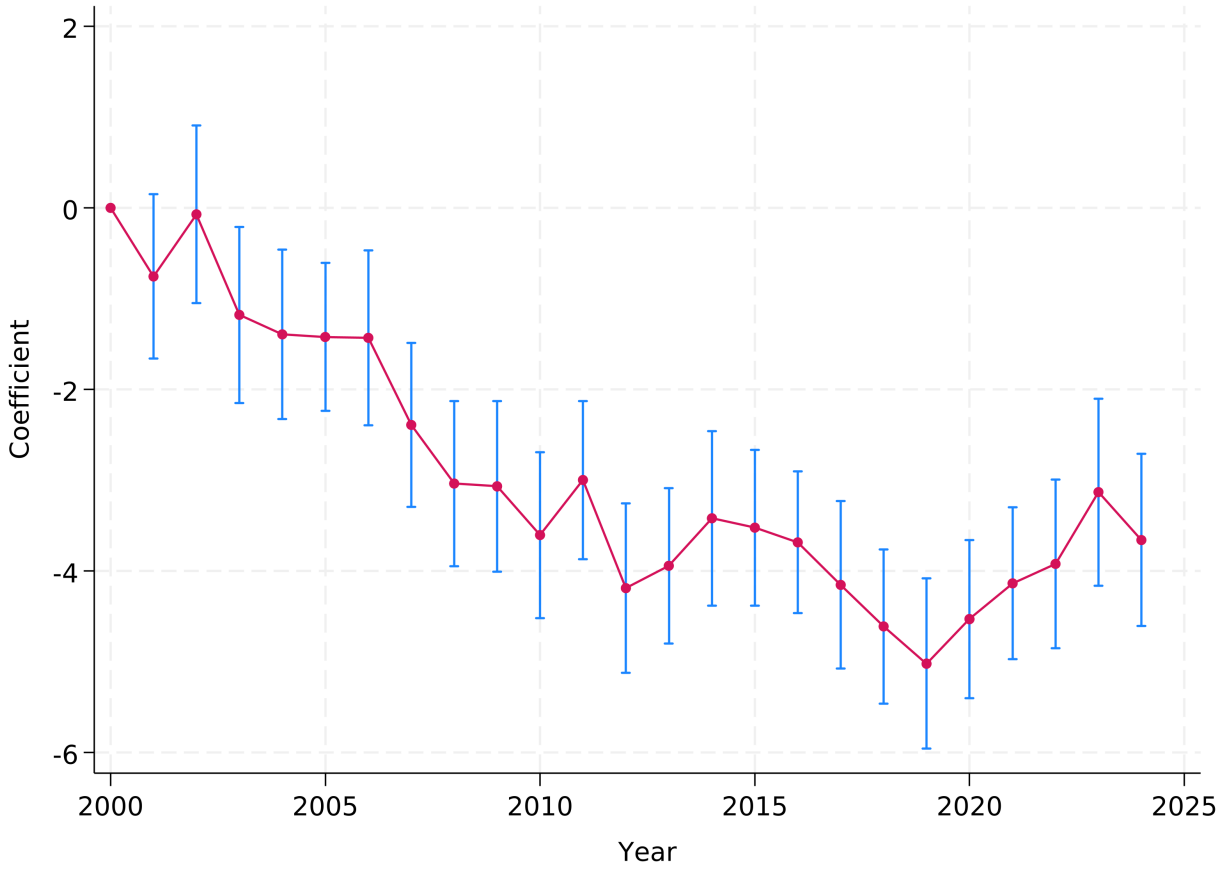


Notes. This figure plots the coefficients $\{\phi_t\}$ from equation (2):

$$H_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s D_{st} \times A_i + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where H_{it} is an indicator that equals 1 when transacted property i was bought by a buyer to be owner-occupied, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+).

FIGURE XV
PRICE AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE (SINGLE FAMILY HOMES)

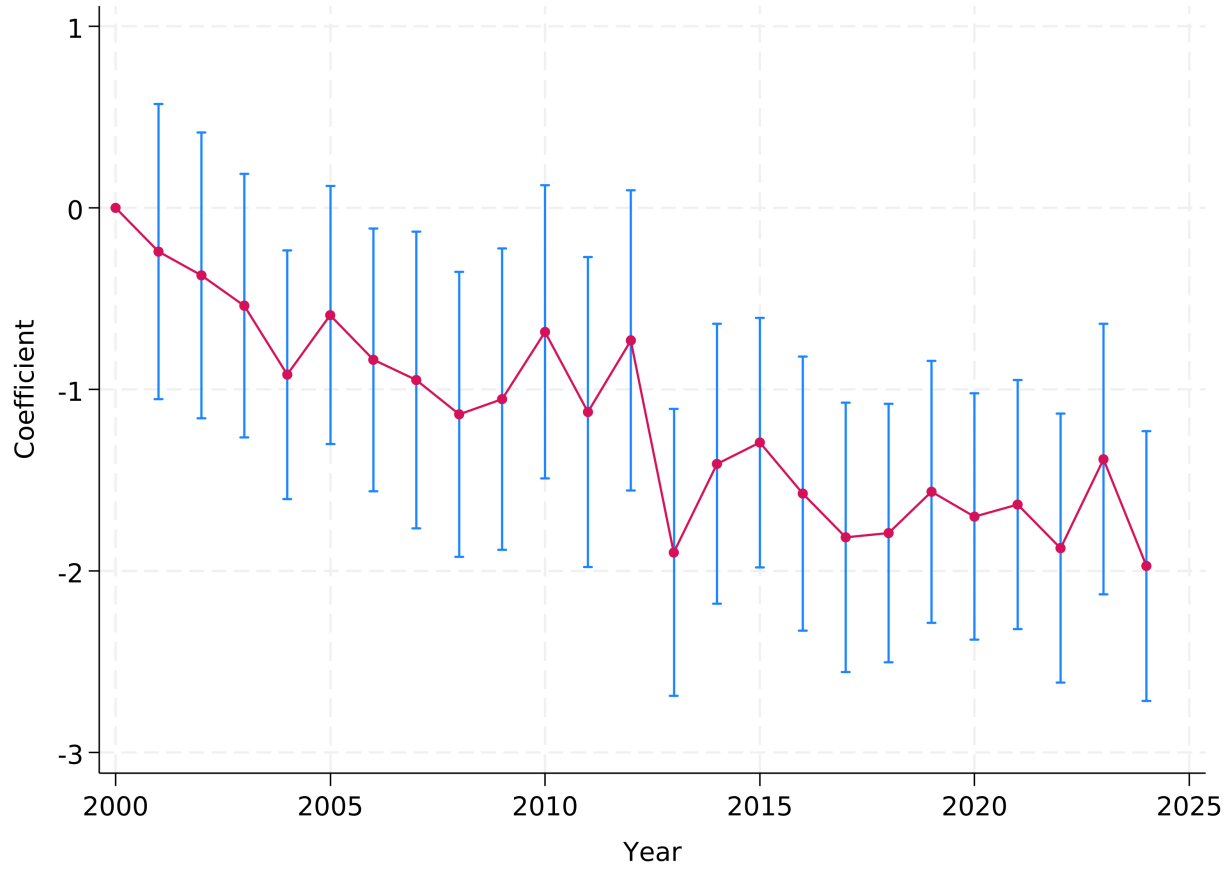


Notes. Restricting the sample to single-family homes, this figure plots the coefficients $\{\phi_t\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XVI
OWNER OCCUPATION AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES (SINGLE FAMILY HOMES)

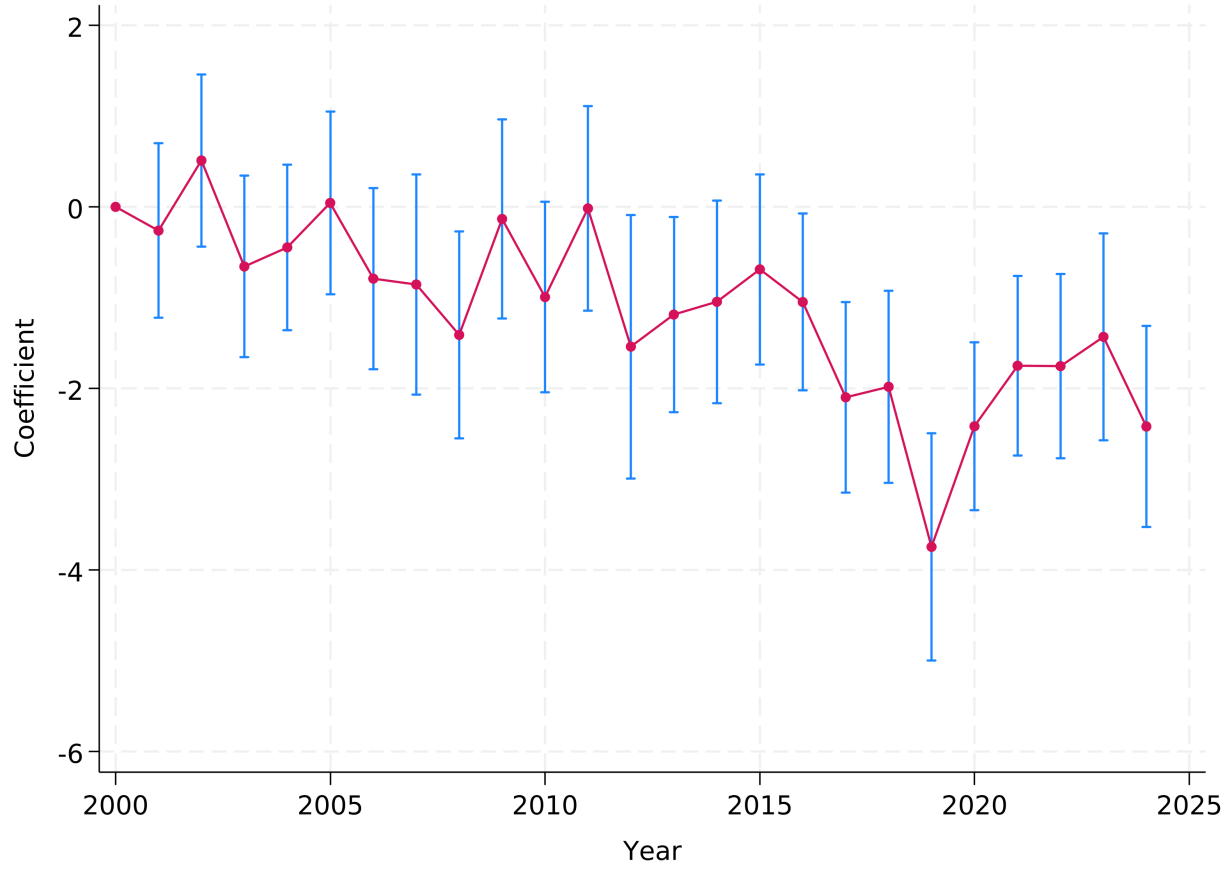


Notes. Restricting the sample to single-family homes, this figure plots the coefficients $\{\phi_t\}$ from equation (3):

$$H_{it} = \gamma_i + \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where H_{it} is an indicator that equals 1 when transacted property i was bought by a buyer to be owner-occupied, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XVII
COMPOSITE AAL REPEAT SALES (ONE SHOT) WITH PROPERTY CHARACTERISTIC FES (SINGLE FAMILY HOMES)

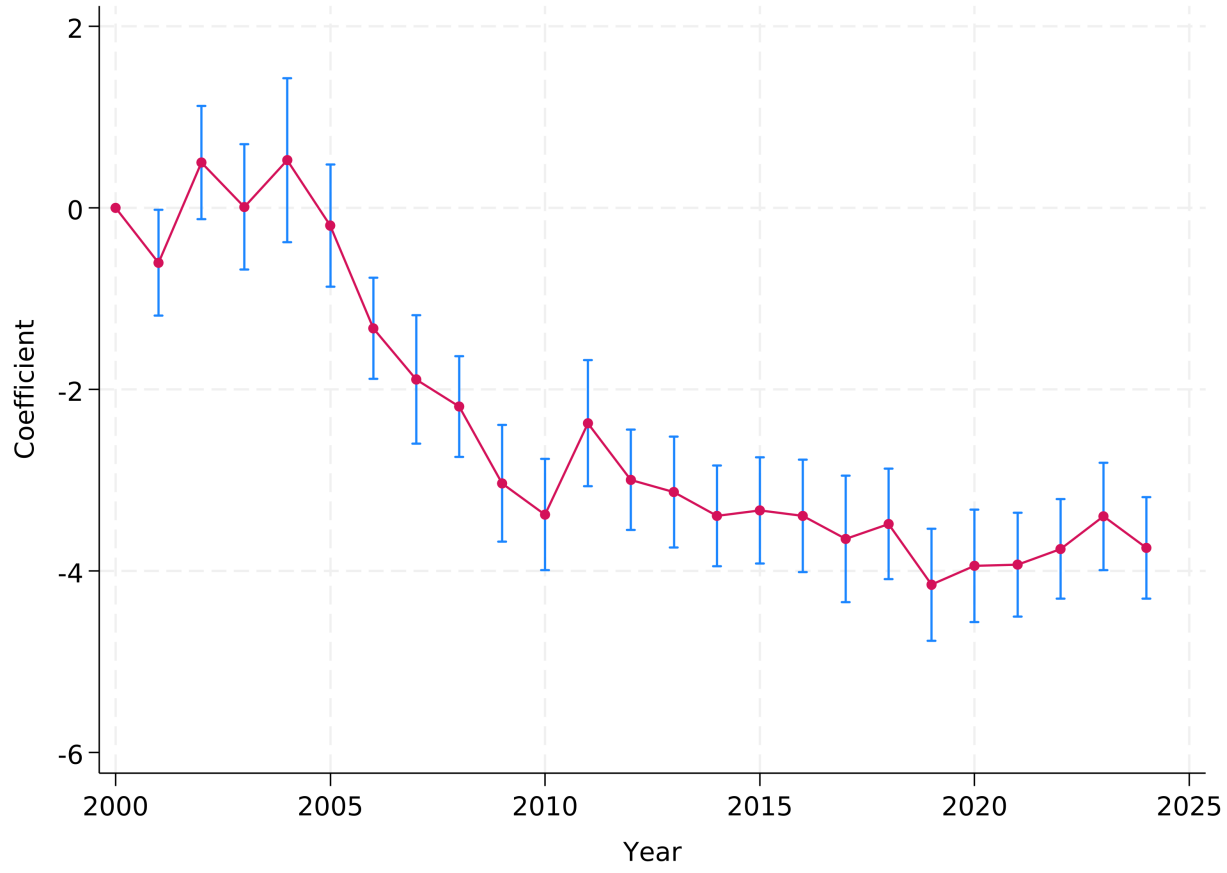


Notes. Restricting the sample to single-family homes, this figure plots the coefficients $\{\phi_t\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s D_{st} \times A_i + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XVIII
PRICE AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE (TRACT LEVEL)

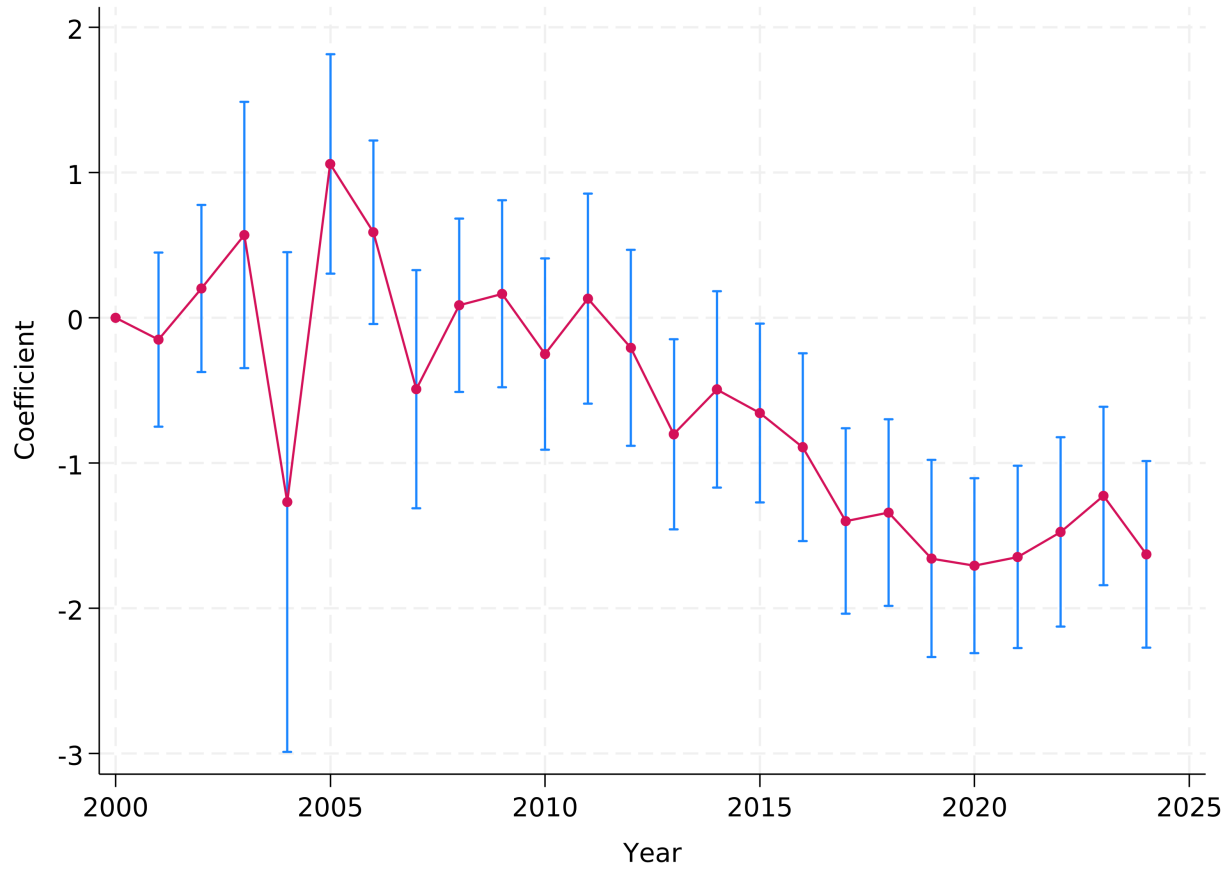


Notes. Using tract level fixed effects, this figure plots the coefficients $\{\phi_t\}$ from equation (**??**):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census tract-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XIX
PRICE AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE WITH HEDONIC CONTROLS (TRACT LEVEL)

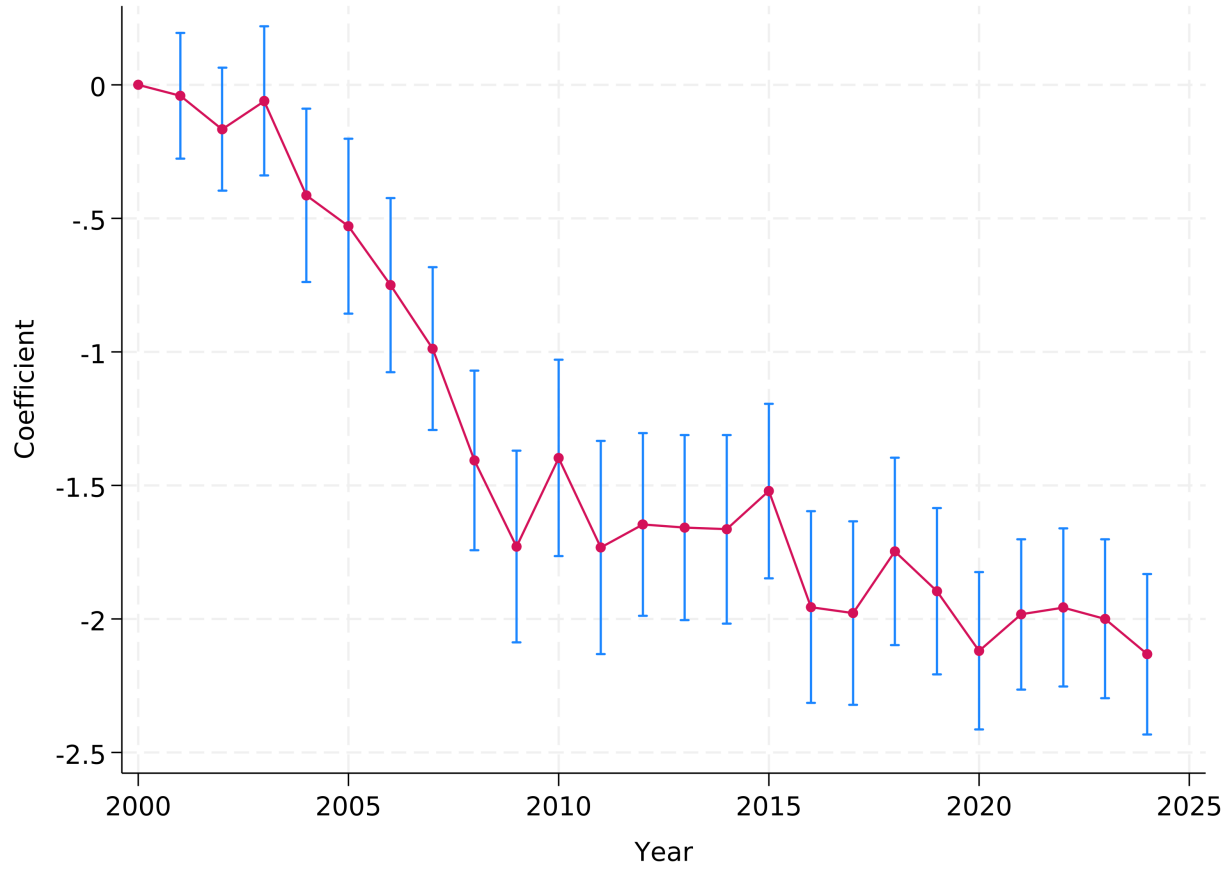


Notes. Using tract level fixed effects, this figure plots the coefficients $\{\phi_t\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s D_{st} \times A_i + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XX
OWNER OCCUPATION AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES (TRACT LEVEL)

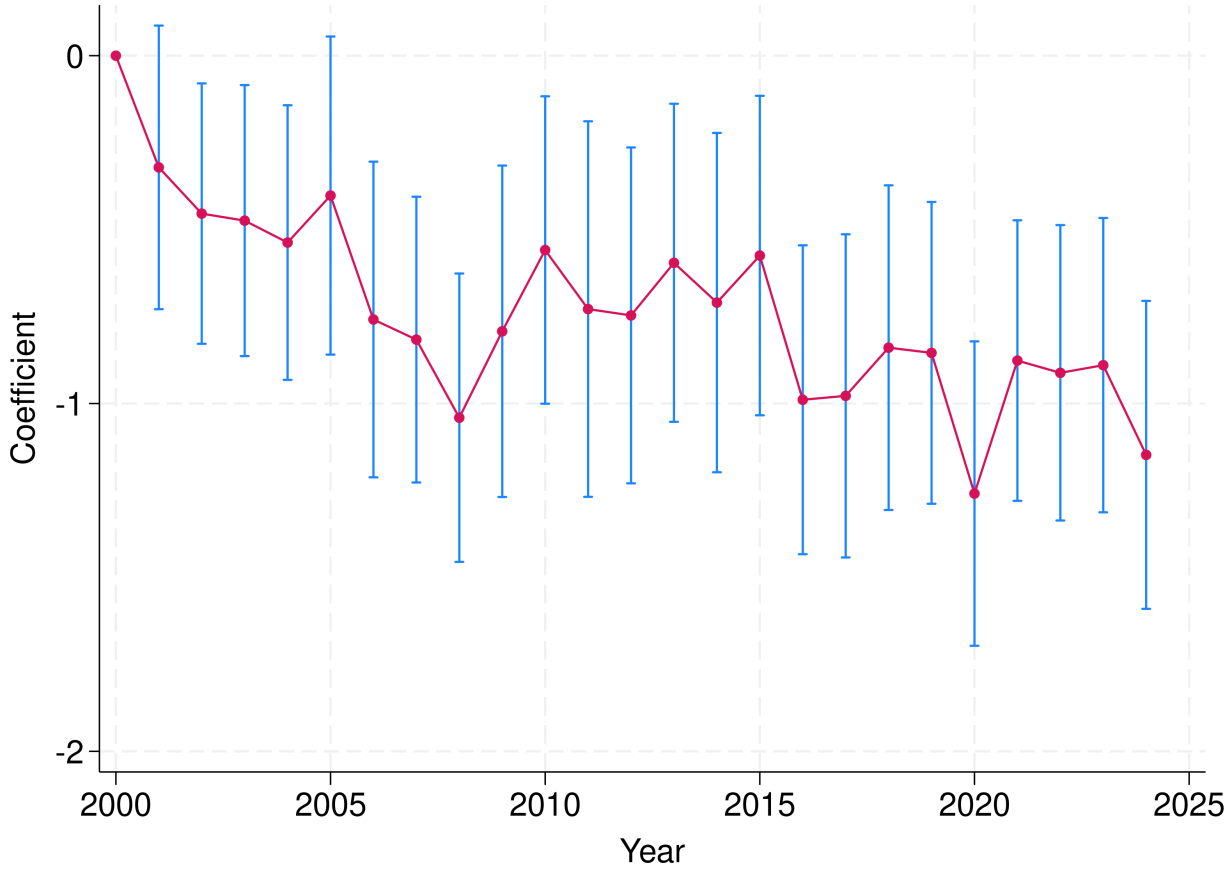


Notes. Using tract level fixed effects, this figure plots the coefficients $\{\phi_t\}$ from equation (3):

$$H_{it} = \gamma_i + \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where H_{it} is an indicator that equals 1 when transacted property i was bought by a buyer to be owner-occupied, α_{bt} is a Census tract-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXI
OWNER OCCUPATION AGAINST WITHIN-BLOCK CLIMATE EXPOSURE, BY YEAR: REPEAT-SALES (TRACT LEVEL) WITH PROPERTY CHARACTERISTICS CONTROLS



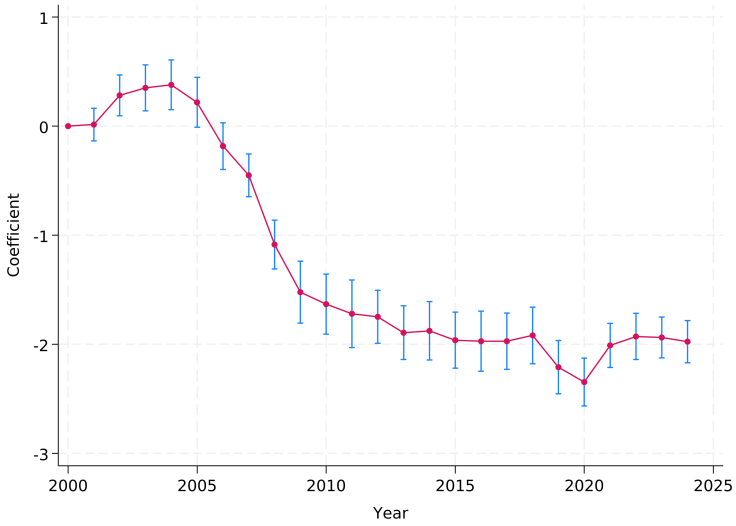
Notes. Using tract level fixed effects, this figure plots the coefficients $\{\phi_t\}$ from equation (2):

$$H_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s D_{st} \times A_i + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where H_{it} is an indicator that equals 1 when transacted property i was bought by a buyer to be owner-occupied, α_{bt} is a Census tract-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXI
LTV RATIO, TRACT LEVEL

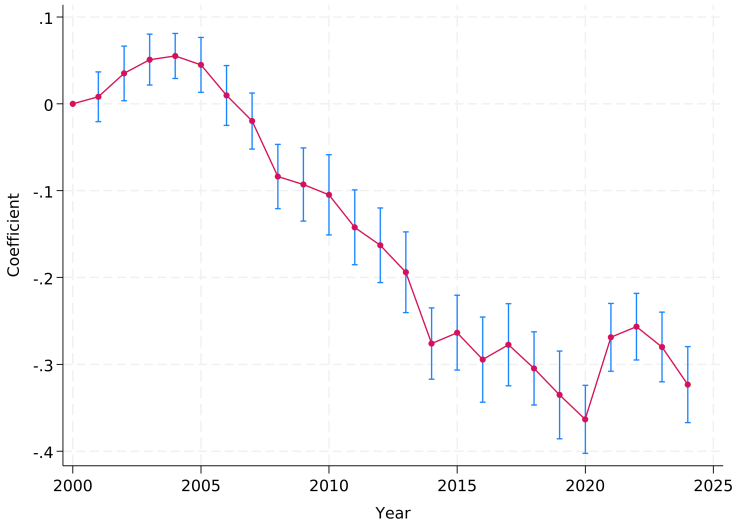
(A) Repeat Sales



(B) Hedonic Controls

FIGURE XXI
VA INDICATOR, TRACT LEVEL

(C) Repeat Sales



(D) Hedonic Controls

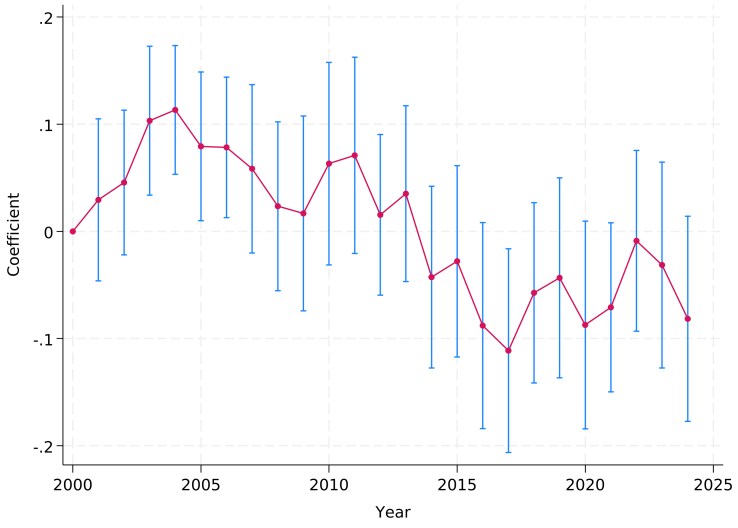
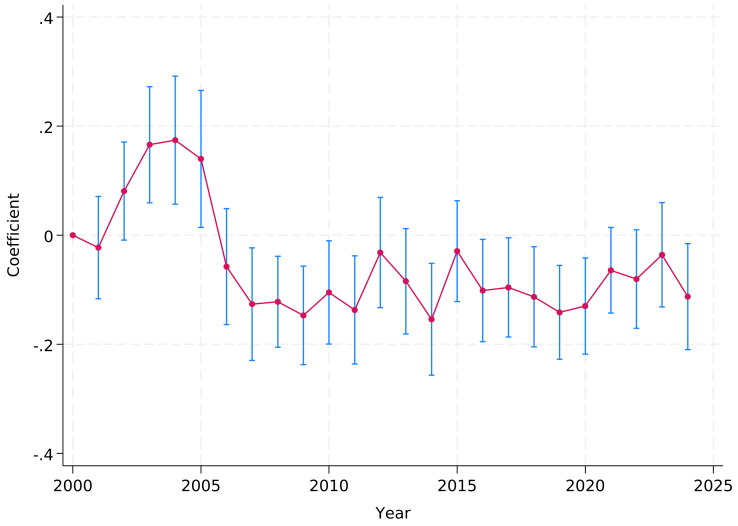


FIGURE XXI
VARIABLE RATE INDICATOR, TRACT LEVEL

(E) Repeat Sales



(F) Hedonic Controls

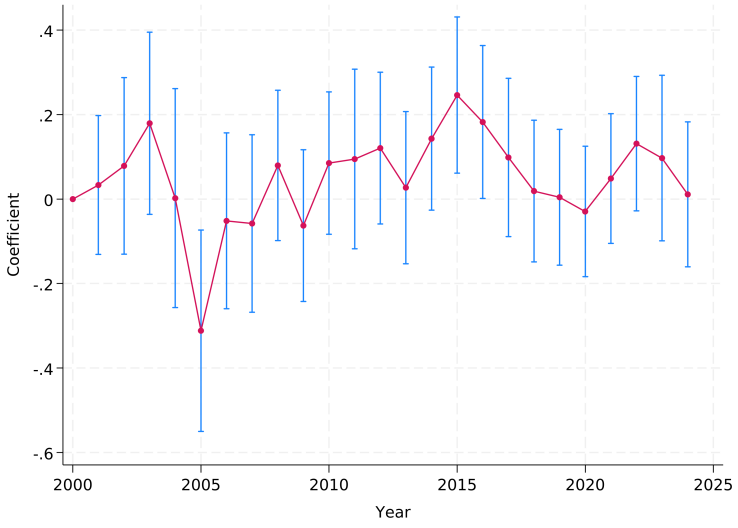
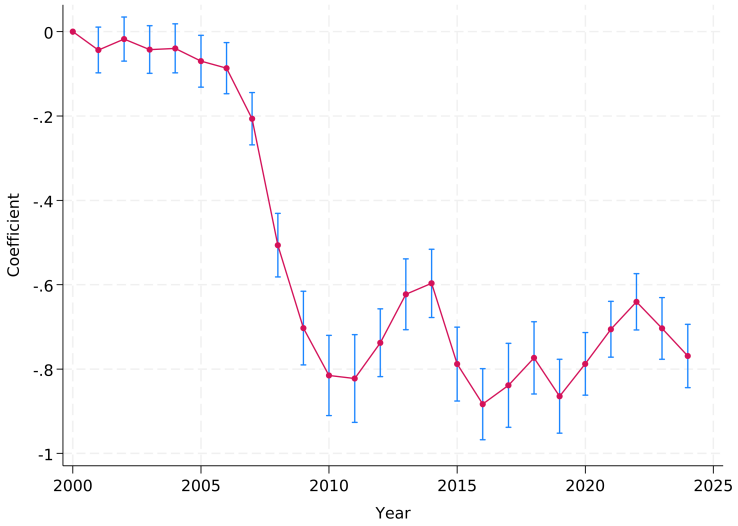


FIGURE XXI
FHA INDICATOR, TRACT LEVEL

(G) Repeat Sales



(H) Hedonic Controls

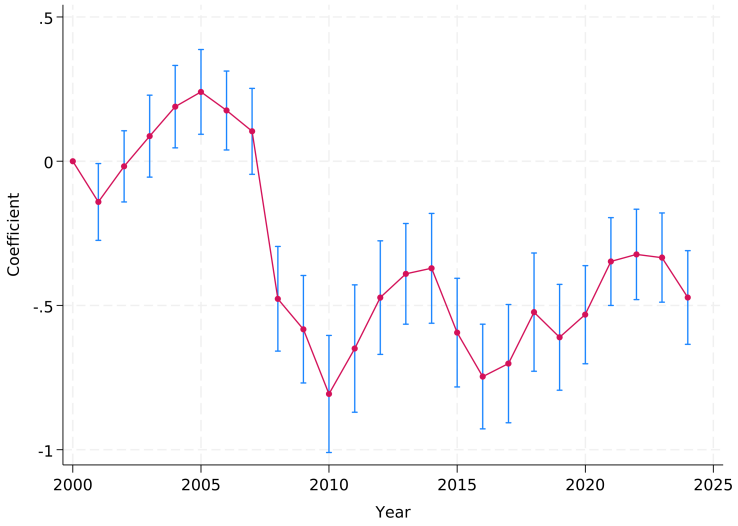
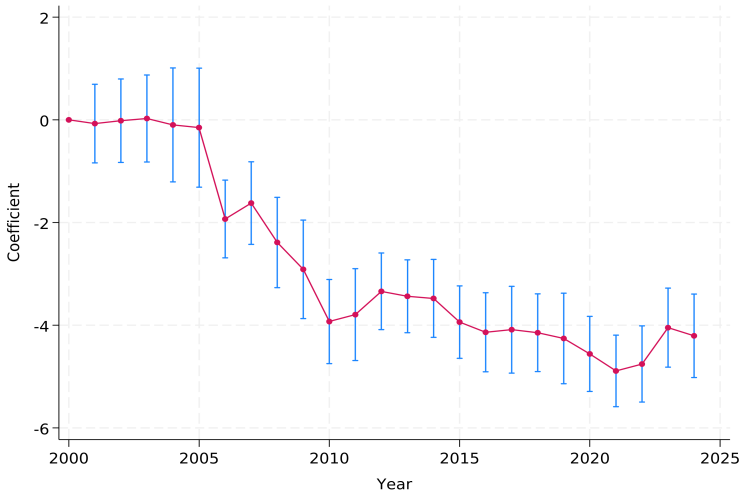
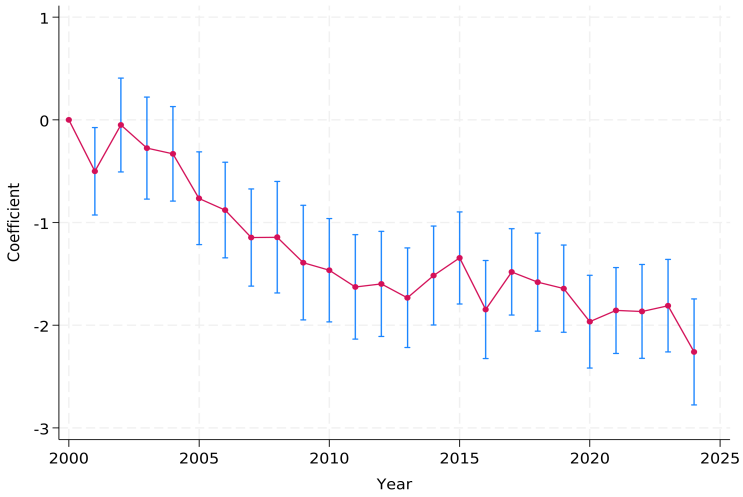


Figure XXII
Excluding states affected by Katrina

(A) Price



(B) Owner occupation



Notes. Using data excluding the three states of Alabama, Louisiana and Mississippi that were directly impacted by Hurricane Katrina, both figures plot the coefficients $\{\phi_t\}$ from equations (2) and (3):

$$Y_{it} = \gamma_i + \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where in Panel (A), $Y_{it} = \log P_{it}$ is the log transaction price of property i, and in Panel (B) $Y_{it} = H_{it}$ is an indicator that equals 1 when transacted property i was bought by a buyer to be owner-occupied, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), and A_i is the Composite AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXIII
FORECLOSURE CRISIS



Notes. Panel (A) plots the number of REO sales by year from the CoreLogic Owner Transfer data. Panel (B) plots the coefficients $\{\phi_t\}$ from:

$$Y_{it} = \alpha_{bt} + \sum_s \phi_s D_{st} \times A_i + \nu_{it}$$

where Y_{it} is an indicator that equals 1 for REO sale, for property i located in Census block b in year t, A_i is the composite AAL for the year 2050 under a moderate scenario (Scenario 4.5), and D_{st} is dummy for year t (equals 1 when $s = t$). Panel (C) plots the coefficients $\{\phi_t\}$ from:

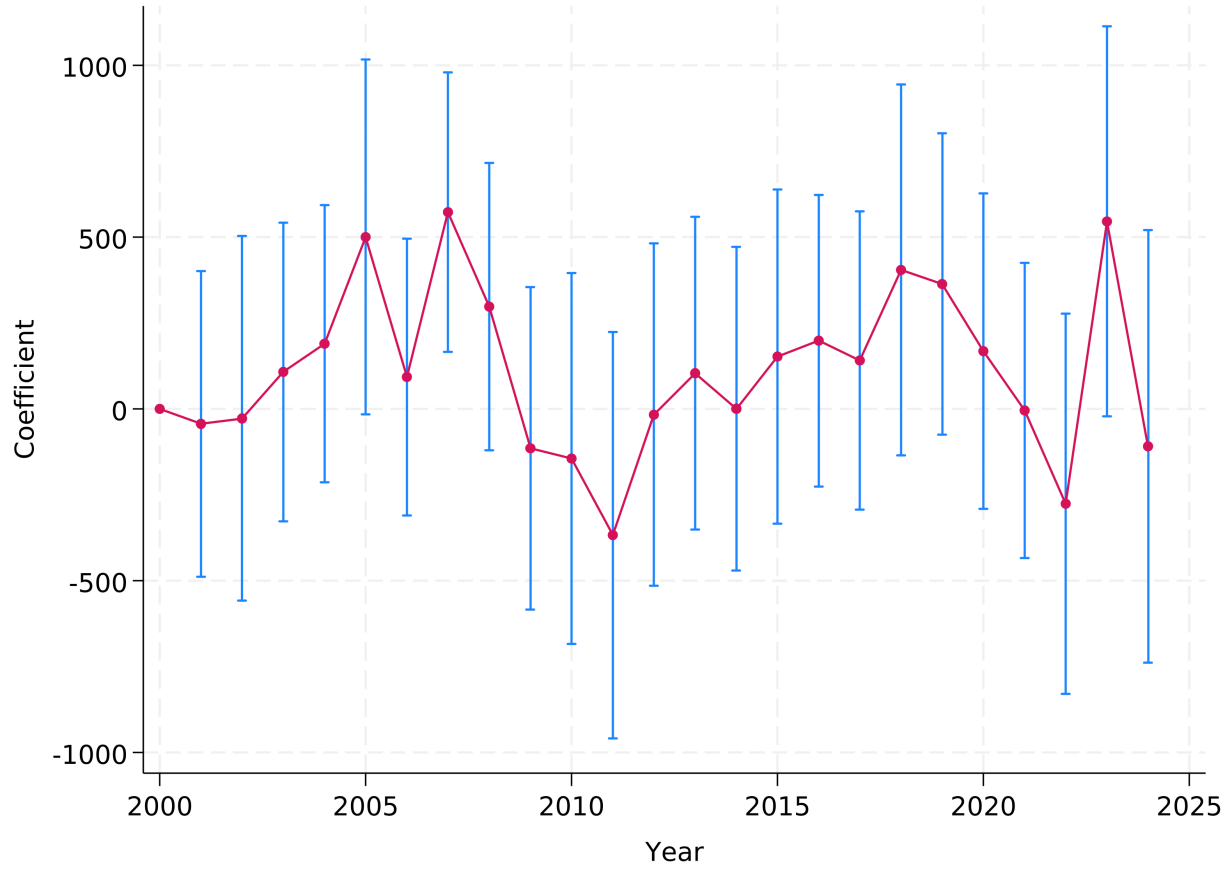
$$Y_{it} = \gamma_i + \alpha_t + \sum_s \phi_s D_{st} \times \varepsilon_i + \nu_{it}$$

where γ_i is a property fixed effect, and ε_i are the residuals estimated from equation (5):

$$A_i = \alpha_b + \varepsilon_i.$$

In Panels (B-C), the blue bars indicate the 95% confidence intervals on the coefficient estimates.

FIGURE XXIV
PRICE AGAINST WITHIN-BLOCK EARTHQUAKE (FIRE-FOLLOWING) EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE, HEDONIC CONTROLS

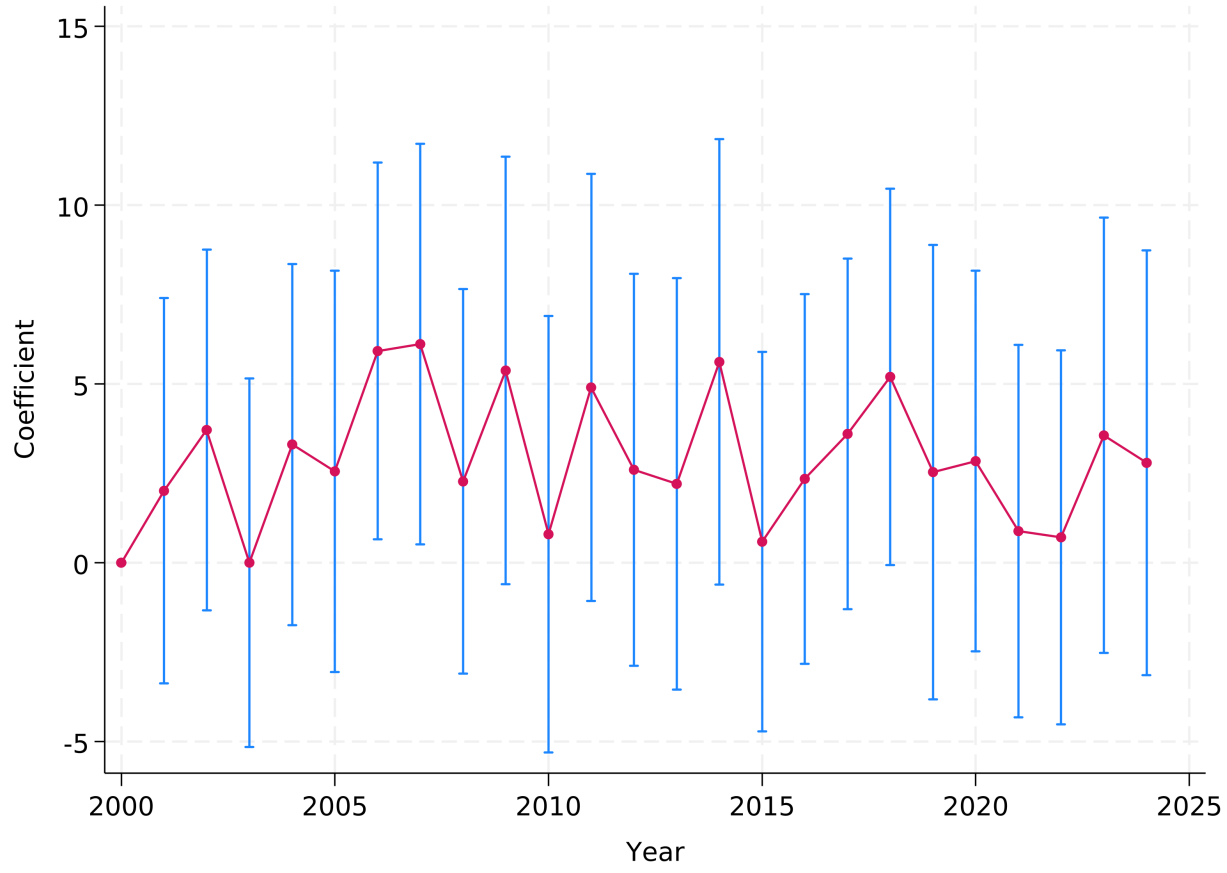


Notes. This figure plots the coefficients $\{\phi_t^p\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s^p D_{st} \times A_i^p + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \log\text{SqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), A_i^p is the peril-specific AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, $\log\text{SqFt}_i$ is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXV
PRICE AGAINST WITHIN-BLOCK WILDFIRE (FIRE + SMOKE) EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE, HEDONIC CONTROLS

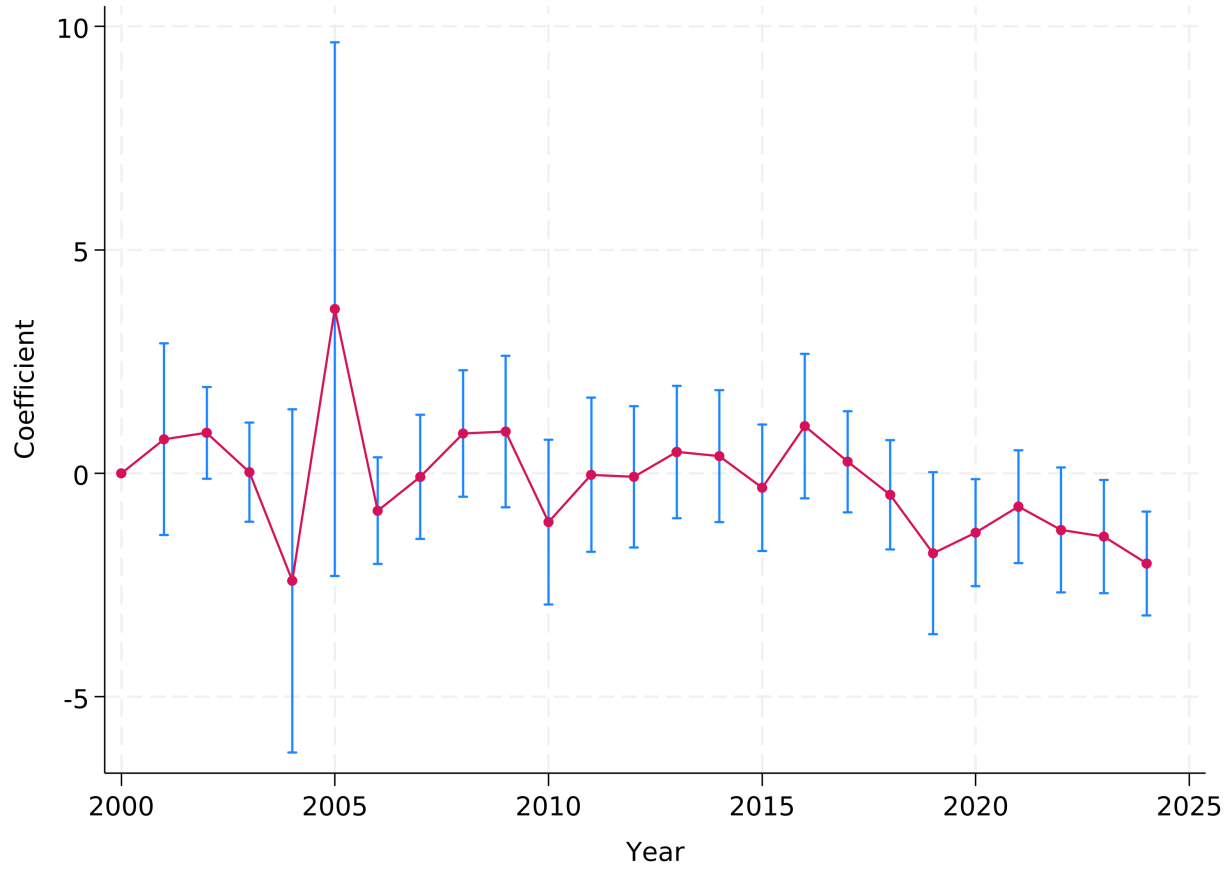


Notes. This figure plots the coefficients $\{\phi_t^p\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s^p D_{st} \times A_i^p + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), A_i^p is the peril-specific AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXVI
PRICE AGAINST WITHIN-BLOCK HURRICANE STORM SURGE EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE, HEDONIC CONTROLS

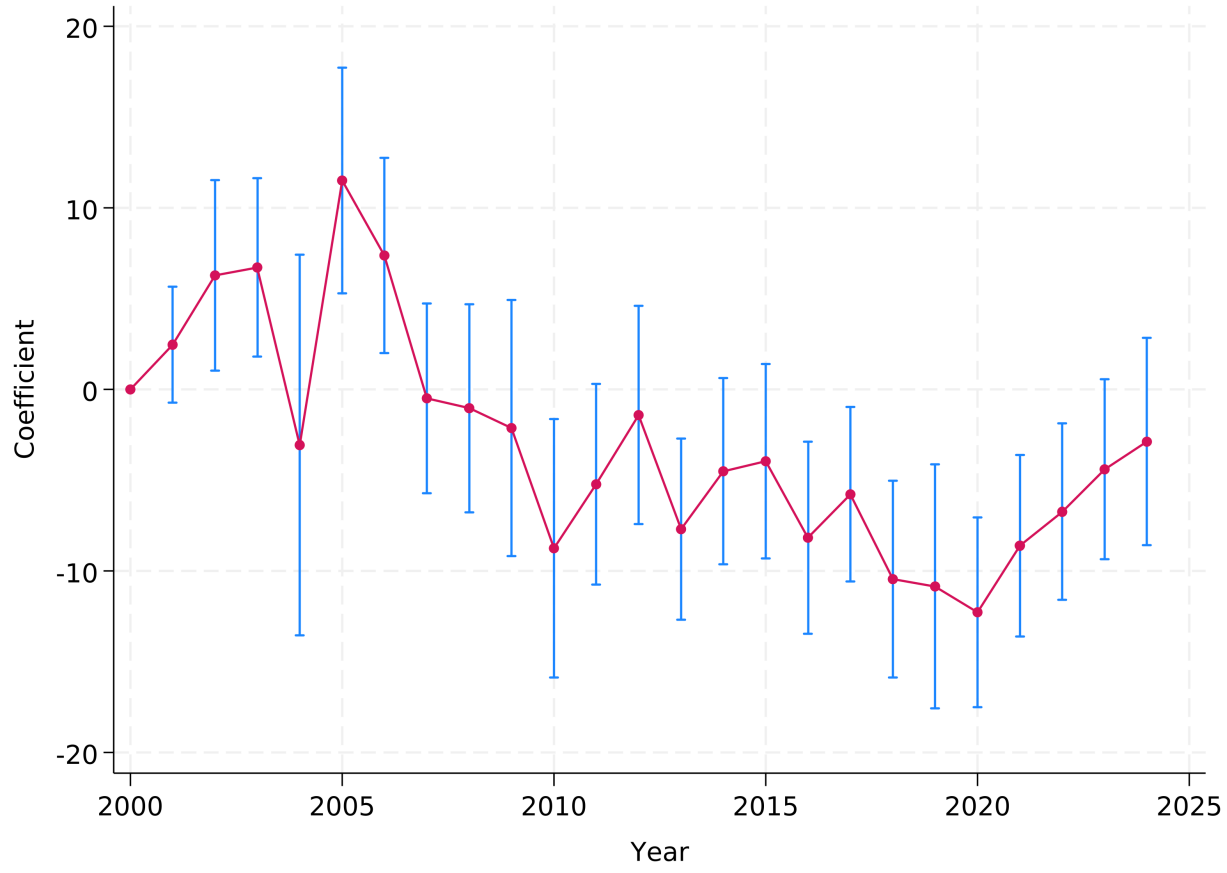


Notes. This figure plots the coefficients $\{\phi_t^p\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s^p D_{st} \times A_i^p + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), A_i^p is the peril-specific AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXVII
PRICE AGAINST WITHIN-BLOCK HURRICANE WIND EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE, HEDONIC CONTROLS

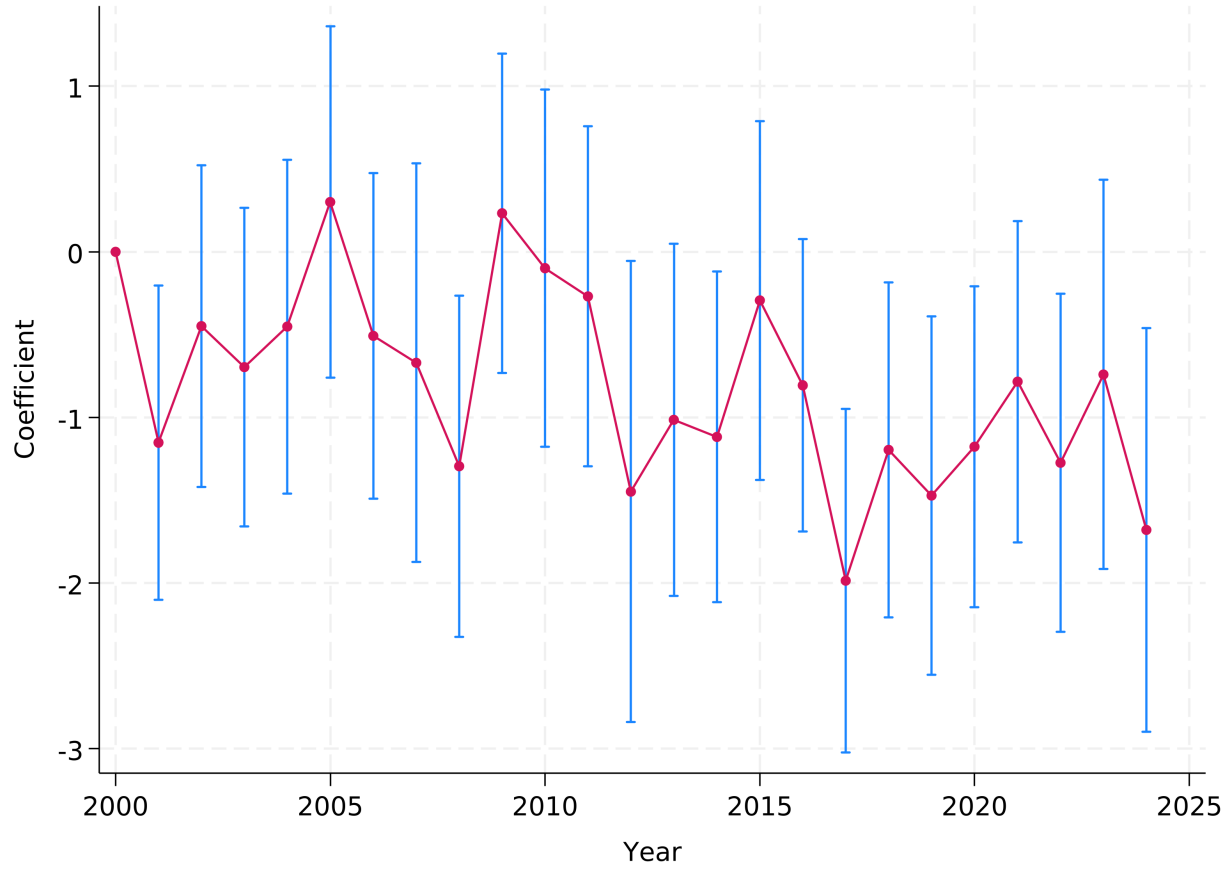


Notes. This figure plots the coefficients $\{\phi_t^p\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s^p D_{st} \times A_i^p + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), A_i^p is the peril-specific AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXVIII
PRICE AGAINST WITHIN-BLOCK INLAND FLOOD EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE, HEDONIC CONTROLS

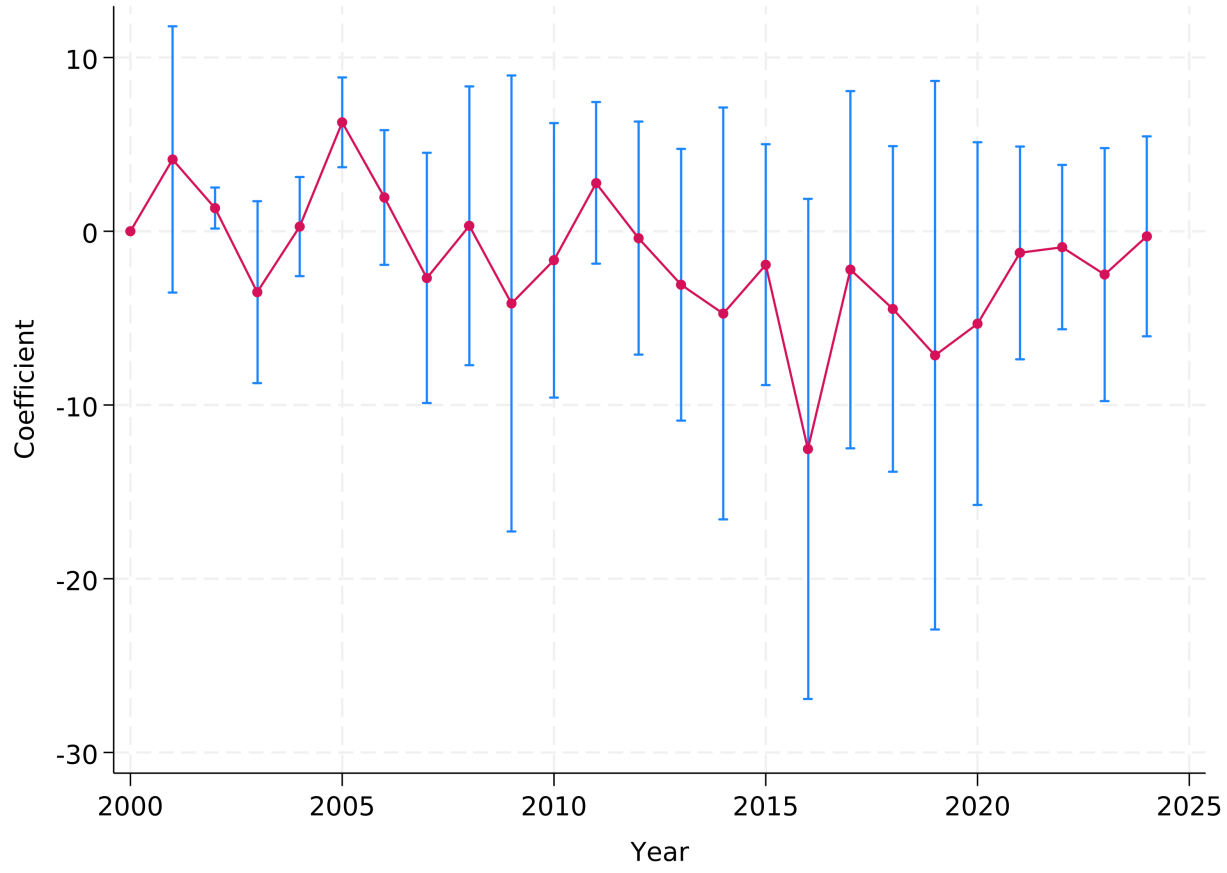


Notes. This figure plots the coefficients $\{\phi_t^p\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s^p D_{st} \times A_i^p + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \log\text{SqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), A_i^p is the peril-specific AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, $\log\text{SqFt}_i$ is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXIX
PRICE AGAINST WITHIN-BLOCK SEVERE CONVECTIVE STORM EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE, HEDONIC CONTROLS

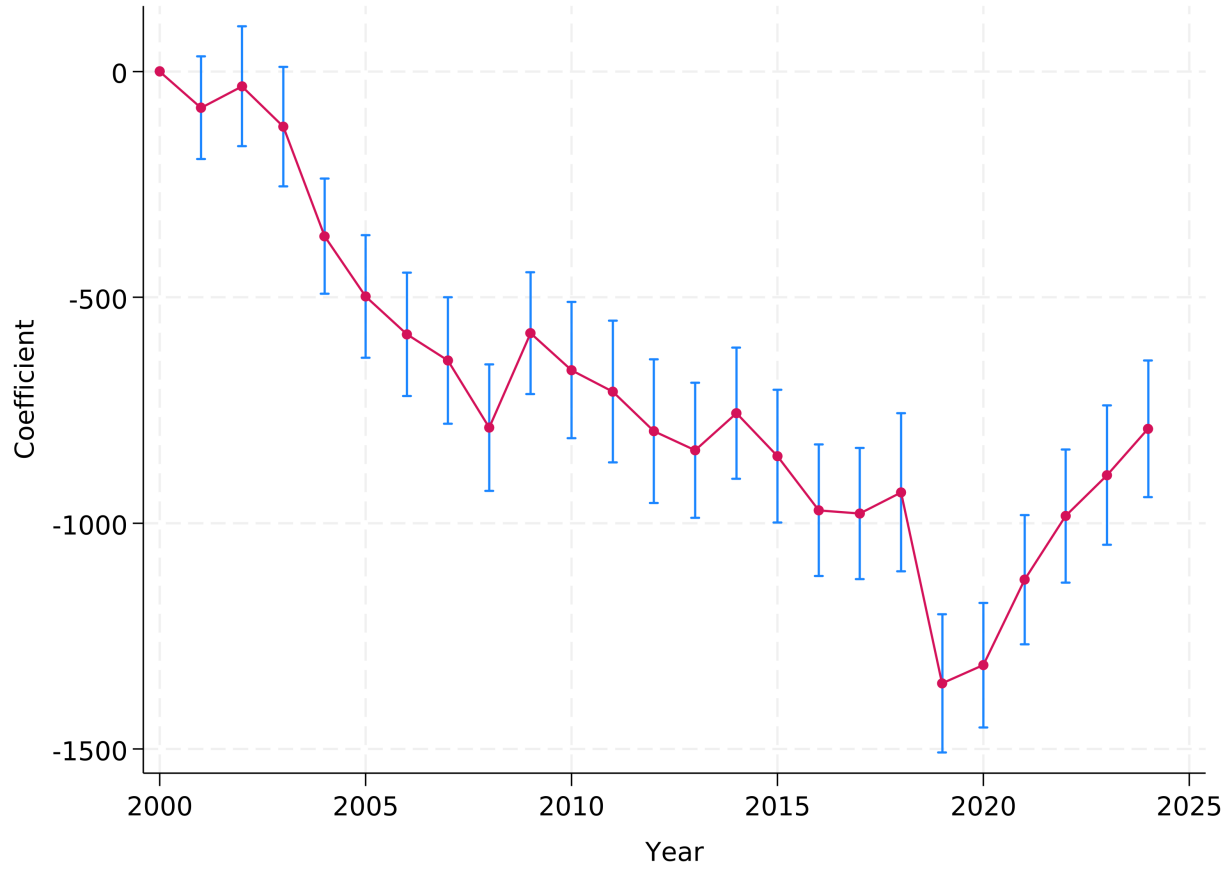


Notes. This figure plots the coefficients $\{\phi_t^p\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s^p D_{st} \times A_i^p + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \text{logSqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), A_i^p is the peril-specific AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, logSqFt_i is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

FIGURE XXX
PRICE AGAINST WITHIN-BLOCK WINTER STORM EXPOSURE, BY YEAR: REPEAT-SALES, ONE-STAGE, HEDONIC CONTROLS



Notes. This figure plots the coefficients $\{\phi_t^p\}$ from equation (2):

$$\log P_{it} = \gamma_i + \alpha_{bt} + \sum_s \left[\phi_s^p D_{st} \times A_i^p + \eta_s D_{st} \times \text{YearBuiltBin}_i + \zeta_s D_{st} \times \log\text{SqFt}_i + \sum_r \delta_s^r D_{st} D_i^{\text{Bedrooms}_i = r} \right] + \nu_{it}$$

where P_{it} is the transaction price of property i, α_{bt} is a Census block-by-year fixed effect, D_{st} is dummy for year t (equals 1 when $s = t$), A_i^p is the peril-specific AAL for the year 2050 under a moderate scenario (RCP 4.5), for property i. The hedonic controls are as follows: YearBuiltBin_i is a dummy for property i being built in a particular 5-year bin, $\log\text{SqFt}_i$ is the log of square-footage, and $D_i^{\text{Bedrooms}_i = r}$ is a dummy for property i having r bedrooms (this is sorted into bins from 1 to 6 bedrooms+). The blue bars indicate the 95% confidence intervals on the coefficient estimates, with standard errors clustered by the property.

Figure XXXI
Owner Occupation against within-Tract Earthquake (Fire Following) Exposure, by Year: Repeat-Sales, One-Stage, Controls for all Perils, Hedonic Controls

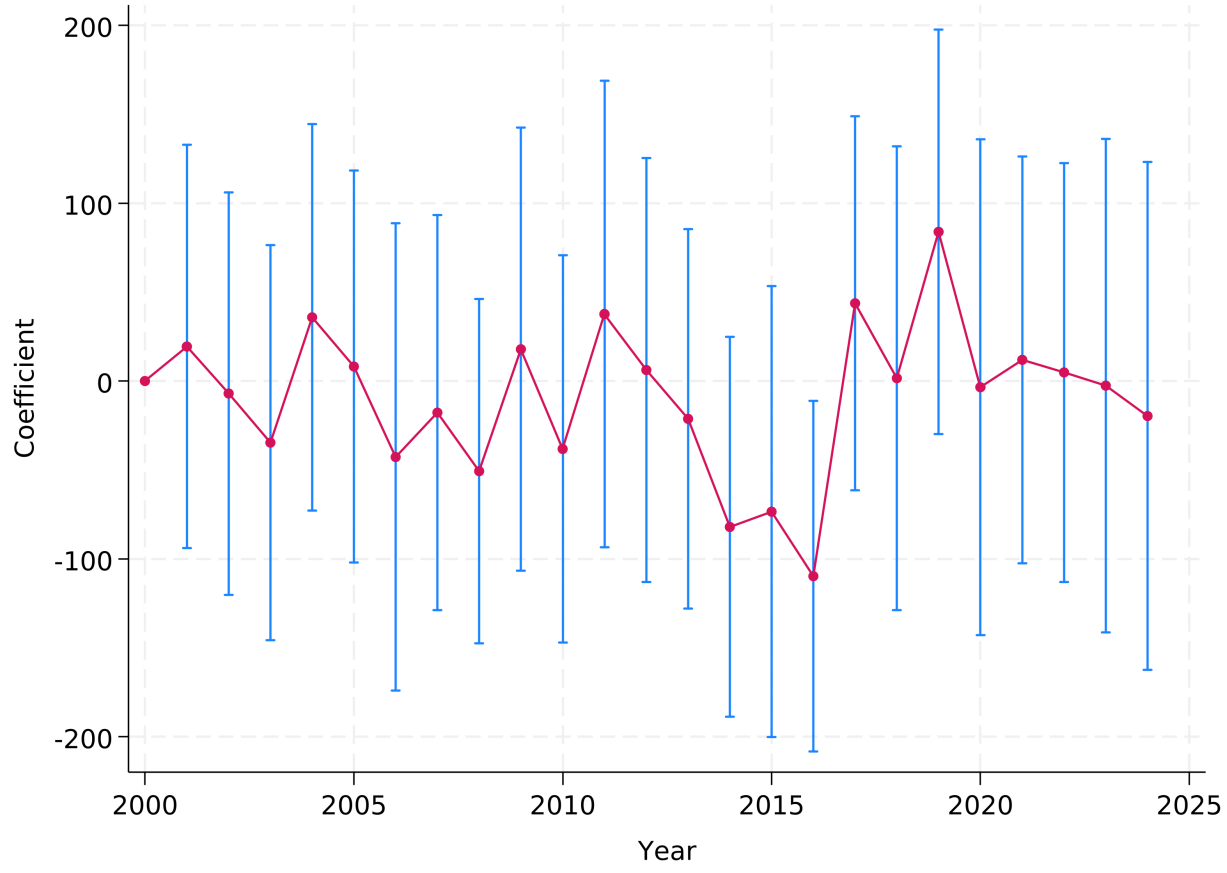


Figure XXXII
Owner Occupation against within-Tract Wildfire (Fire + Smoke) Exposure, by Year: Repeat-Sales, One-Stage, Controls for all Perils, Hedonic Controls

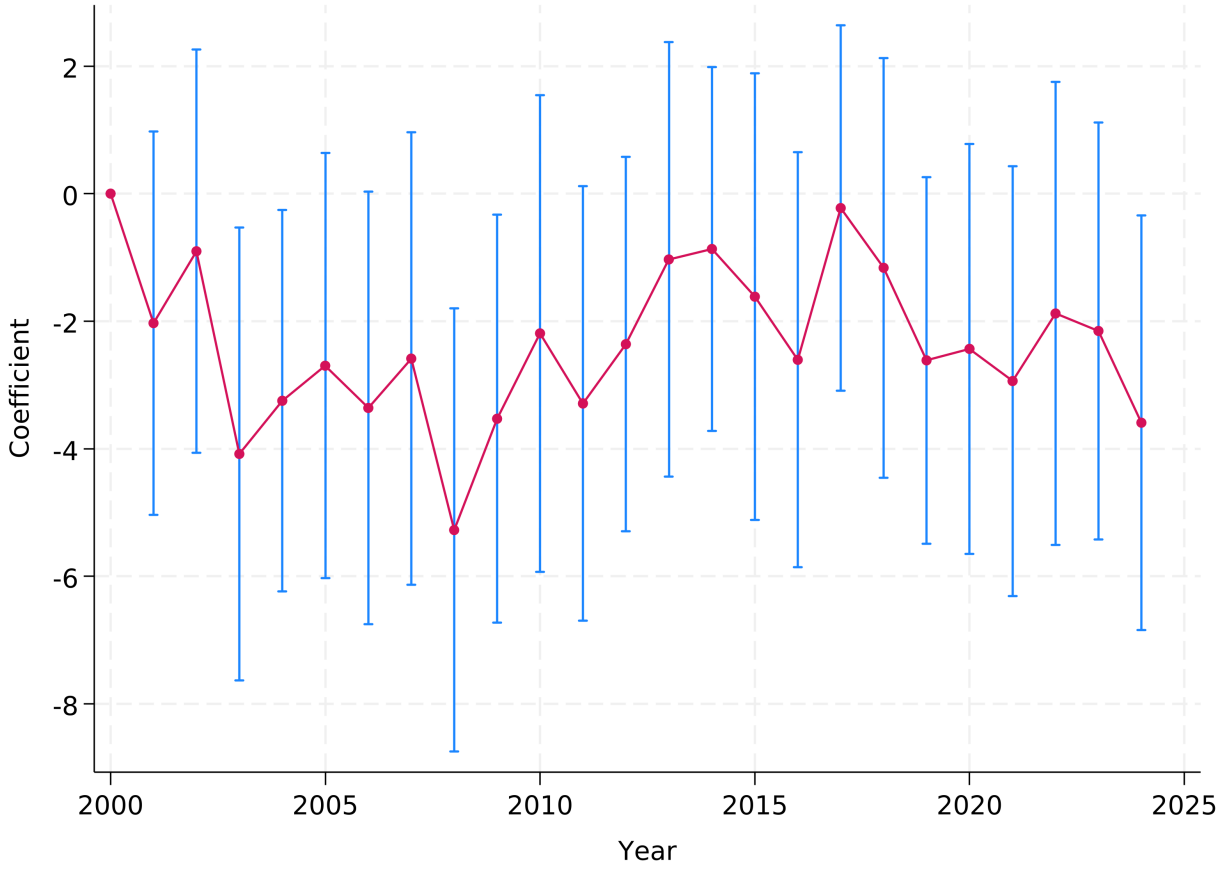


Figure XXXIII
Owner Occupation against within-Tract Inland Flood Exposure, by Year: Repeat-Sales, One-Stage, Controls for all Perils, Hedonic Controls

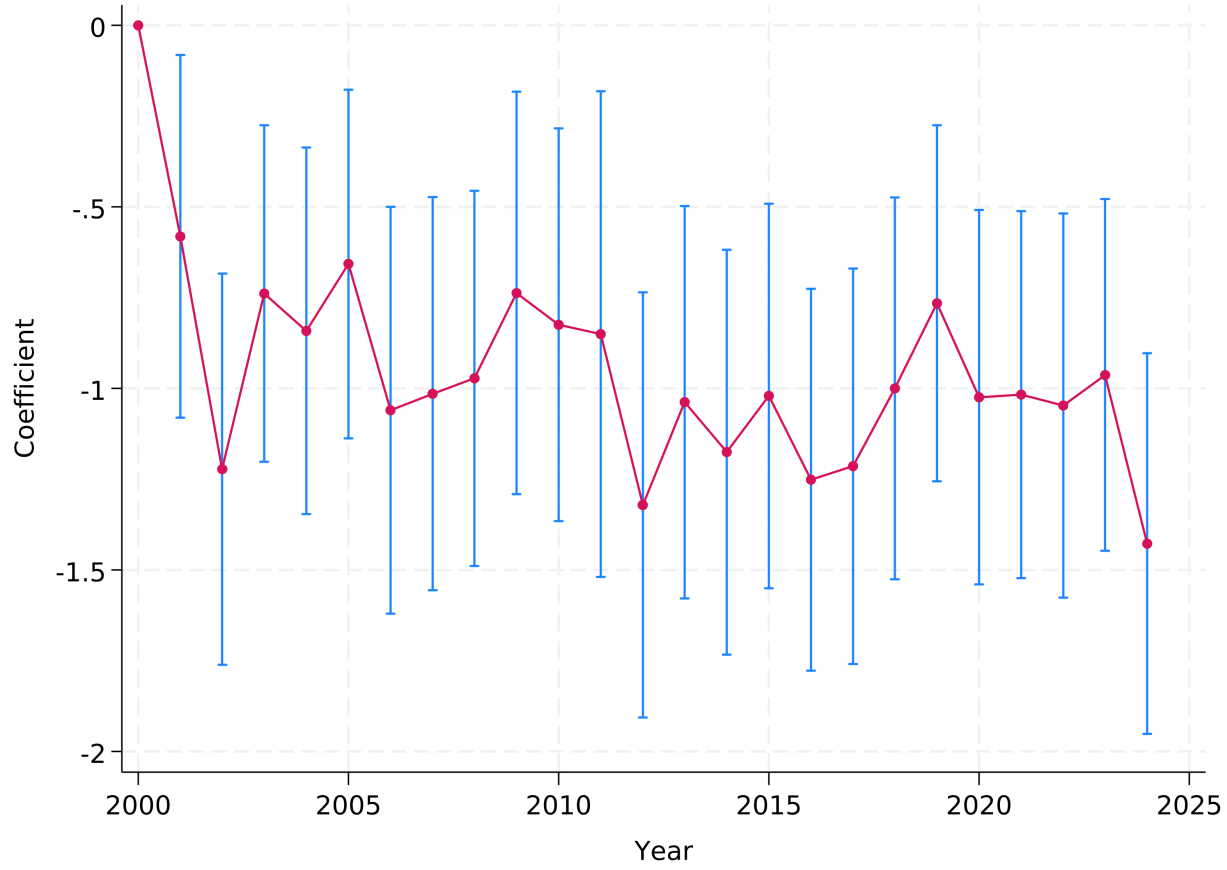


Figure XXXIV
Owner Occupation against within-Tract Convective Storm Exposure, by Year: Repeat-Sales, One-Stage, Controls for all Perils, Hedonic Controls

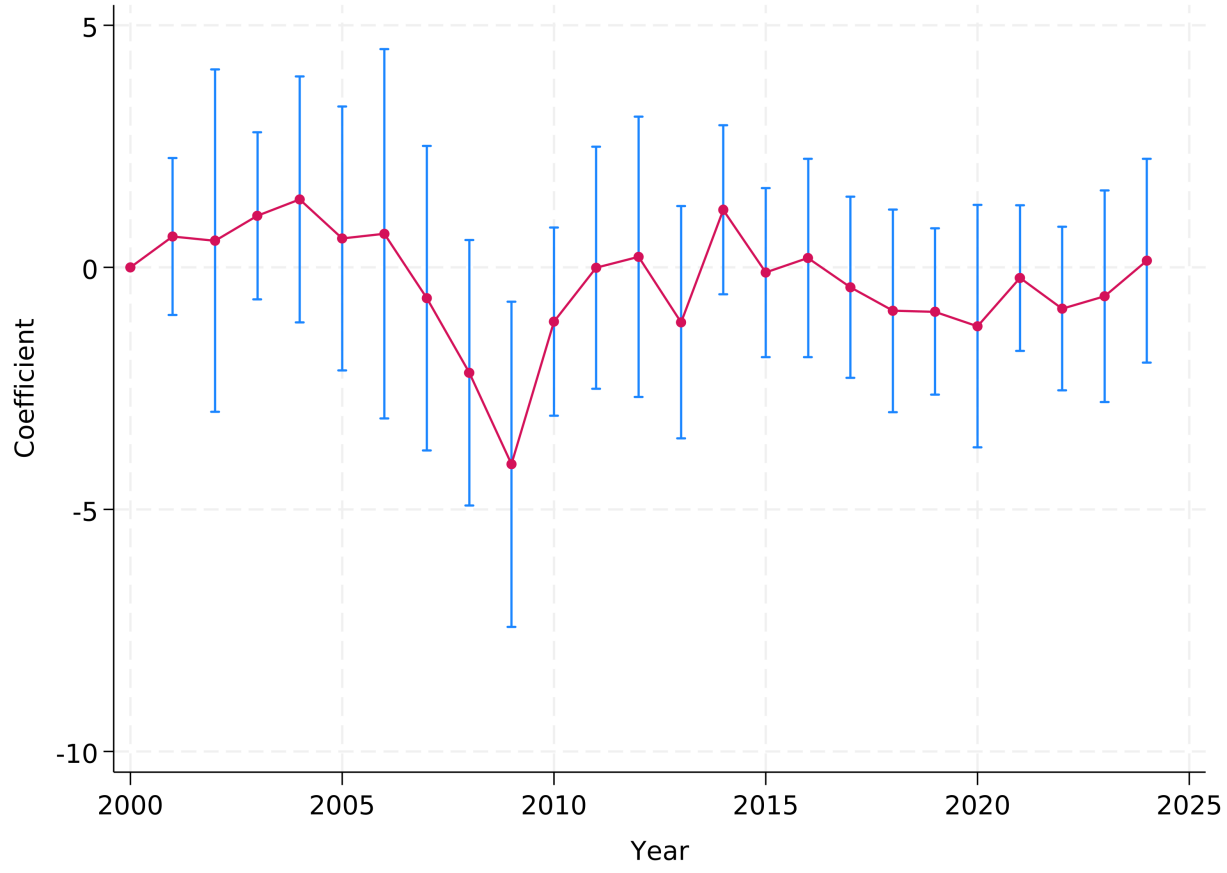


Figure XXXV
Owner Occupation against within-Tract Winter Storm Exposure, by Year: Repeat-Sales, One-Stage, Controls for all Perils, Hedonic Controls

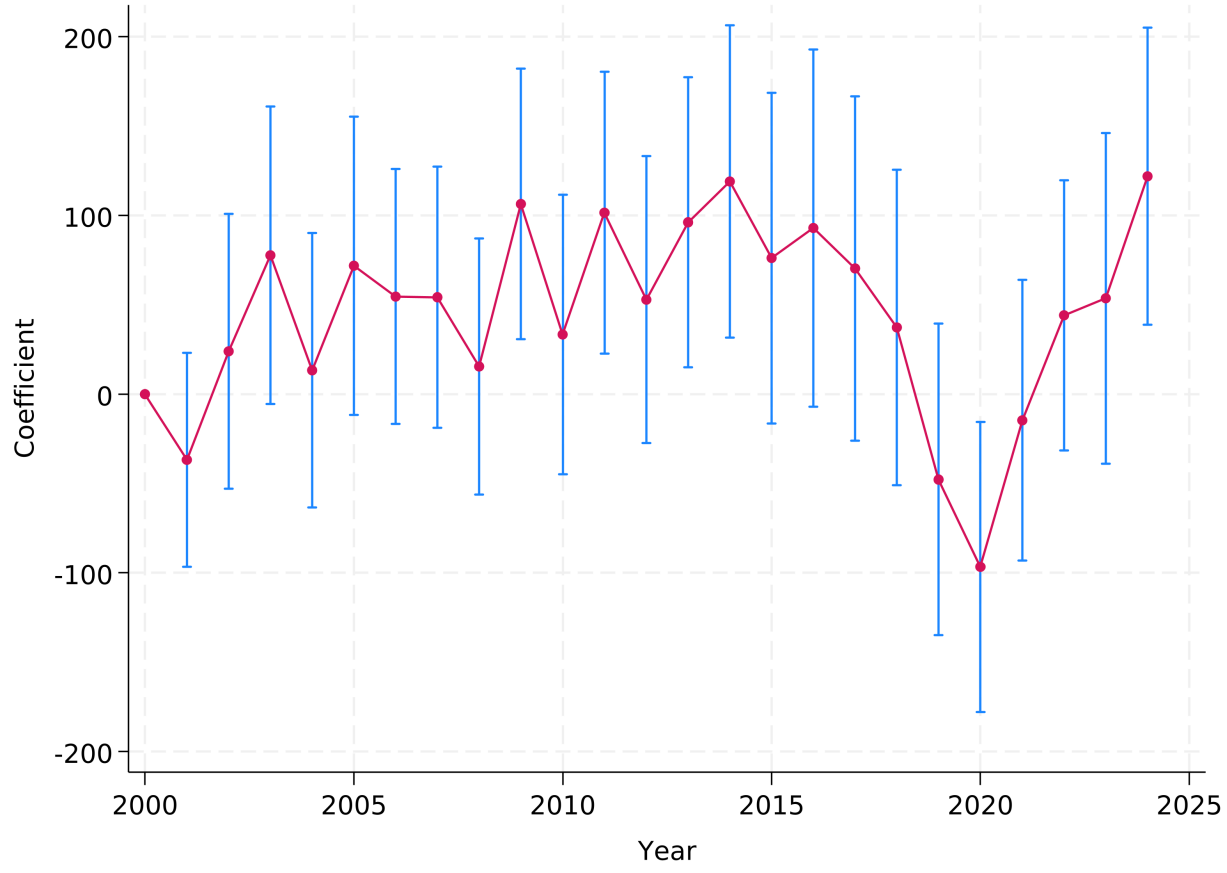


Figure XXXVI
Owner Occupation against within-Tract Hurricane Wind Exposure, by Year: Repeat-Sales, One-Stage, Controls for all Perils, Hedonic Controls

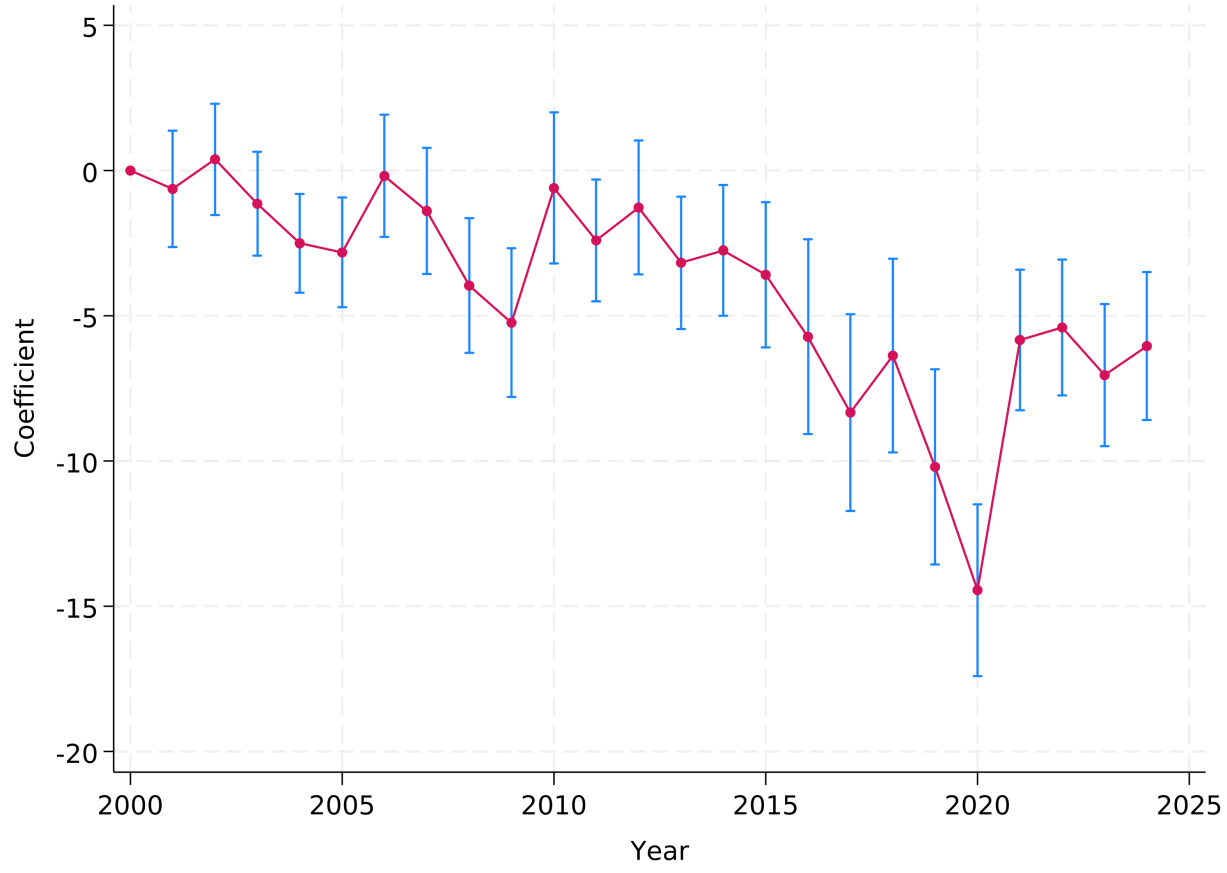


Figure XXXVII
Owner Occupation against within-Tract Hurricane Storm Surge Exposure, by Year: Repeat-Sales, One-Stage, Controls for all Perils, Hedonic Controls

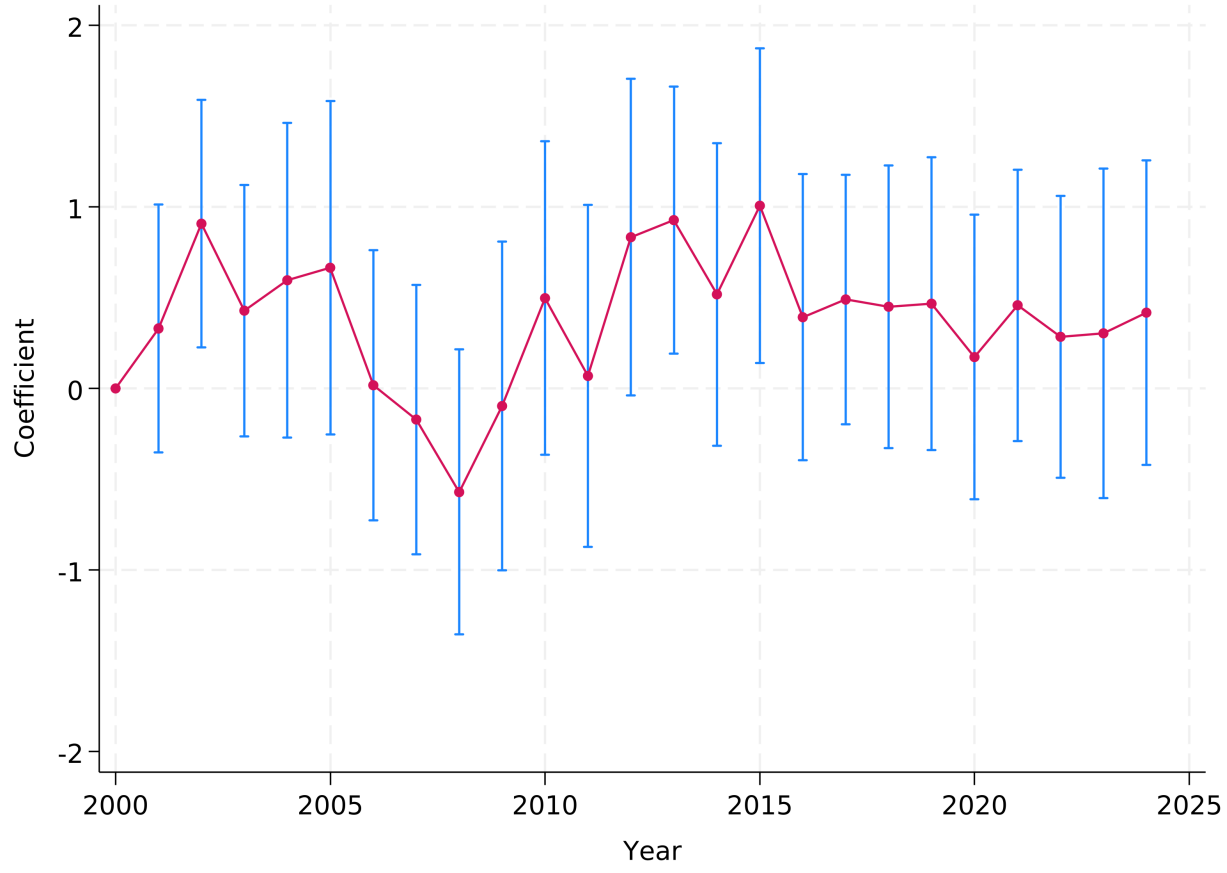
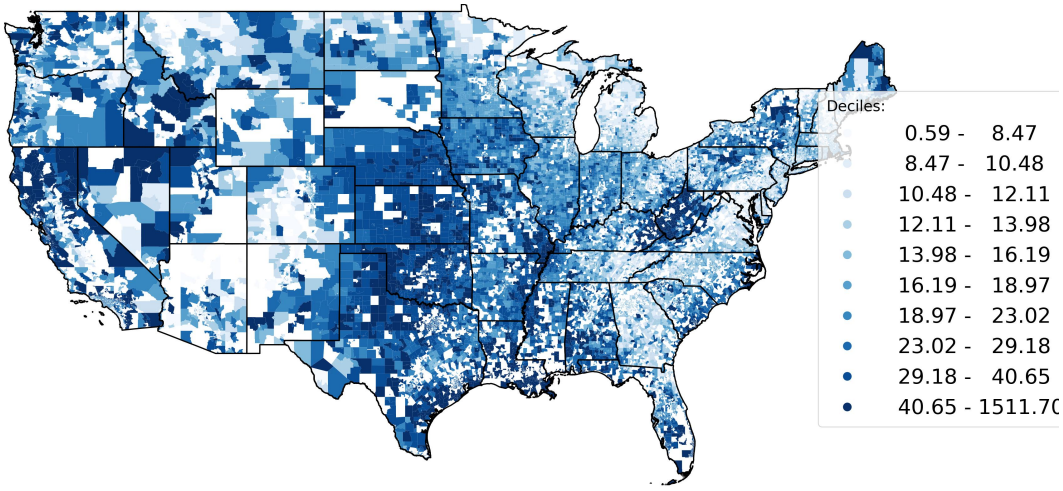
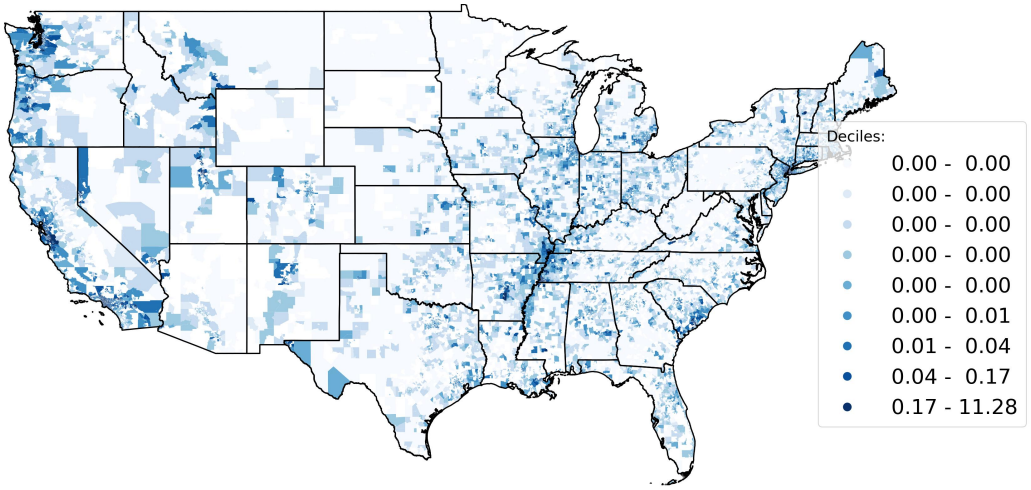


FIGURE XXXVIII
TRACT-LEVEL MAP OF PERIL AAL

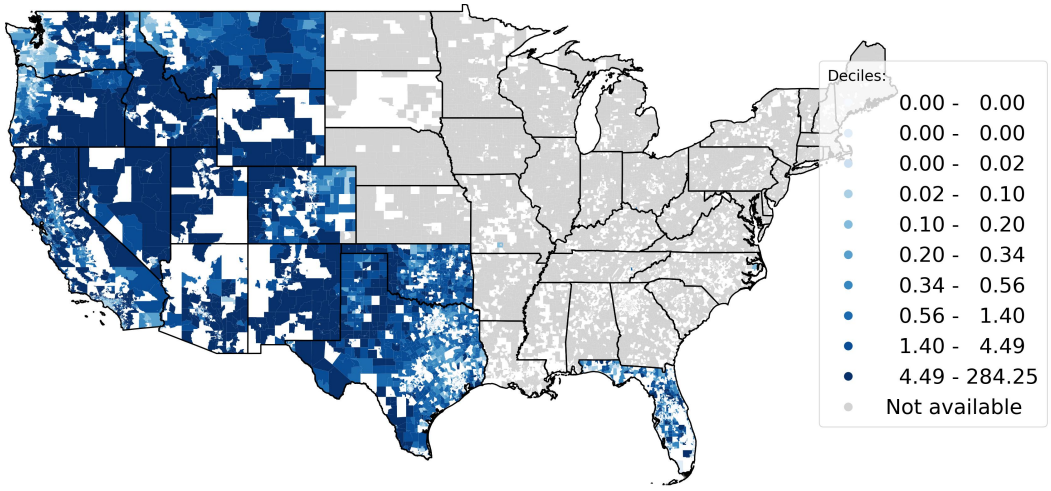


(A) Composite All Perils

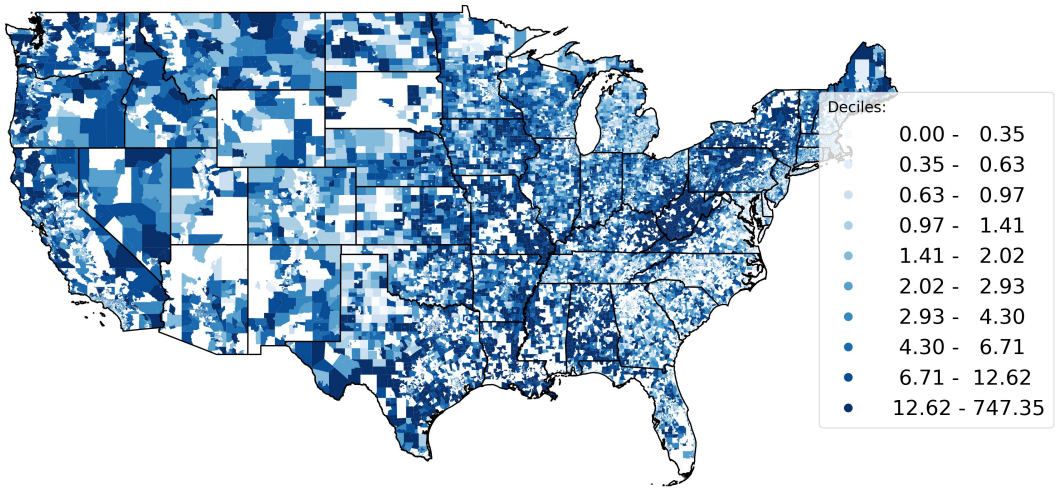


(B) Earthquake (Fire Following)

FIGURE XXXVIII
TRACT-LEVEL MAP OF PERIL AAL (CONTINUED)

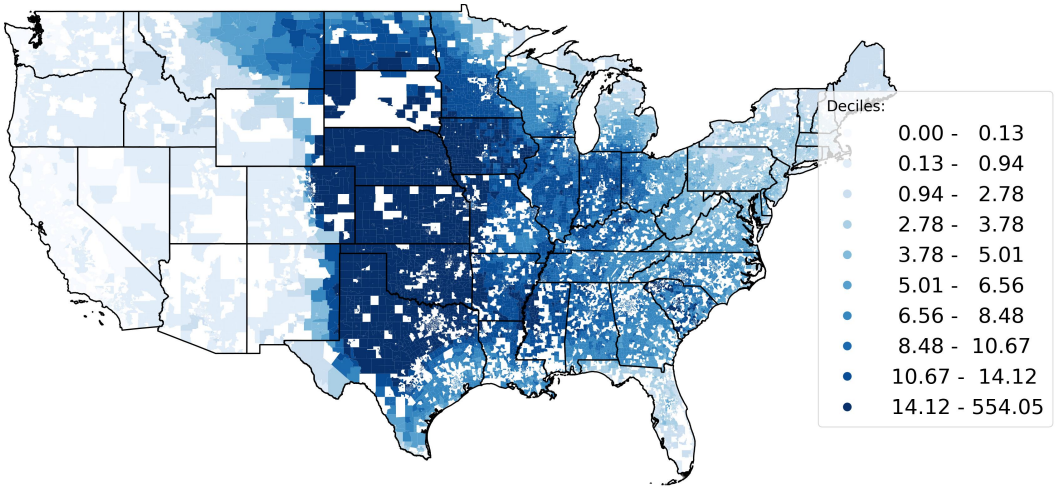


(C) Wildfire (Fire + Smoke)

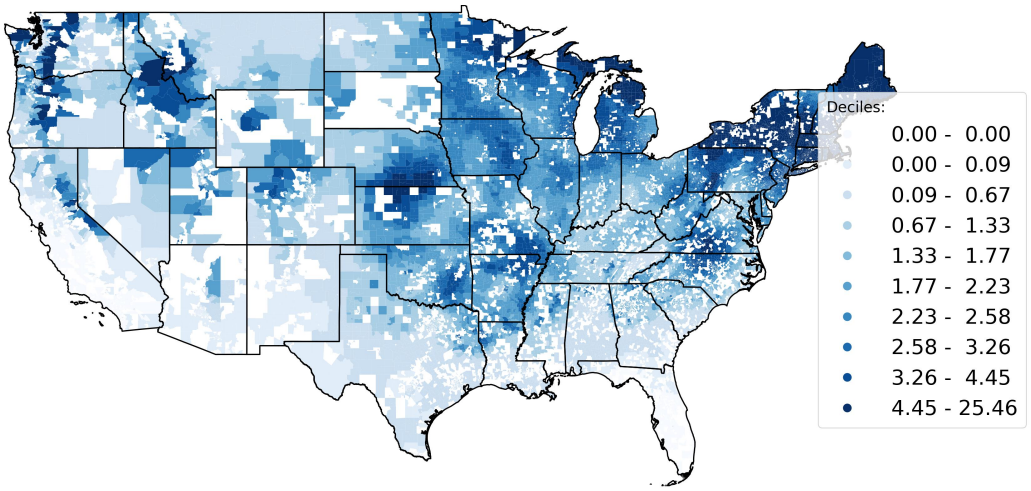


(D) Inland Flood

FIGURE XXXVIII
TRACT-LEVEL MAP OF PERIL AAL (CONTINUED)

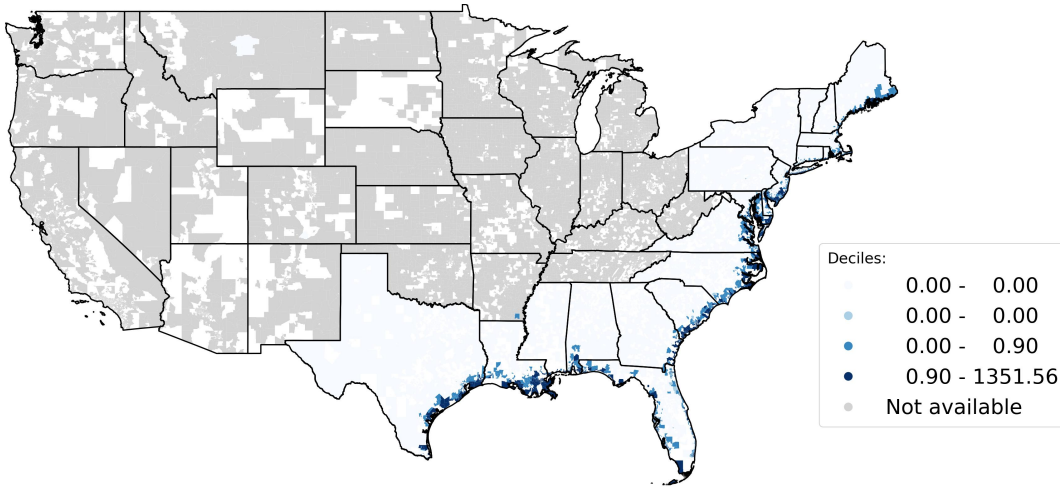


(E) Severe Convective Storm

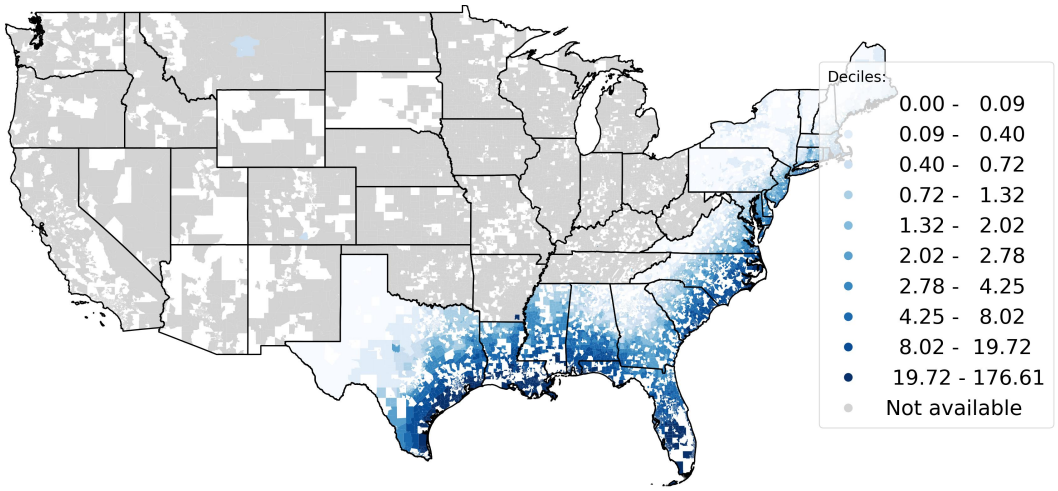


(F) Winter Storm

FIGURE XXXVIII
TRACT-LEVEL MAP OF PERIL AAL (CONTINUED)



(G) Hurricane Storm Surge



(H) Hurricane Wind

Notes. Each map shows the Census tract average AAL in basis points, i.e. AAL × 10,000. Tracts are divided into deciles unless we cannot form distinct deciles because more than 10% of the tracts have 0 or N/A.

TABLE I
SUMMARY STATISTICS

AAL	count	mean	p1	p5	p10	p25	p50	p75	p90	p95	p99
Wildfire	61,712,911	0.0245	0.0000	0.0000	0.0000	0.0000	0.0002	0.0041	0.0375	0.1122	0.5025
Hurricane Storm Surge	69,055,194	0.0578	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0079	0.1500	1.6579
Hurricane Wind	69,055,194	0.1058	0.0000	0.0004	0.0013	0.0055	0.0223	0.1105	0.2842	0.5101	1.0648
Earthquake Fire Following	141,337,976	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0006	0.0018	0.0070
Inland Flood	141,337,976	0.0497	0.0000	0.0000	0.0000	0.0000	0.0000	0.0074	0.0478	0.1357	0.9241
Severe Convective Storm	141,337,976	0.0725	0.0001	0.0008	0.0017	0.0157	0.0523	0.1001	0.1544	0.2406	0.3401
Winter Storm	141,337,976	0.0166	0.0000	0.0000	0.0000	0.0011	0.0134	0.0241	0.0378	0.0501	0.0898
Composite	141,337,976	0.2522	0.0165	0.0400	0.0620	0.0936	0.1404	0.2318	0.3990	0.6840	2.5231

Notes. Summary statistics for the Average Annual Loss (AAL) by peril, with the composite at the end. The AAL is for the year 2050 under a moderate scenario (RCP 4.5), multiplied by 100 (i.e., units are percentage losses per year).

Table II
Climate Risk Exposure (AAL) Variation

(a) By Block, Peril, Scenario, Time Frame

Fixed Effects	R2, Sample 1	R2, Sample 2
block	0.109	0.109
block x scenario	0.111	0.111
block x timeframe	0.111	0.112
block x peril	0.597	0.615
block x timeframe x scenario block x peril	0.599	0.617
block x scenario x peril block x timeframe	0.602	0.620
block x peril x timeframe block x scenario	0.605	0.623
block x peril x scenario x timeframe	0.608	0.626

(b) R^2 for Block and Tract FEs

Dependent variable	Fixed Effect	R^2
AAL	Tract	0.370
AAL	Block	0.613
Log Sale Amount	Tract X Year	0.840
Log Sale Amount	Block X Year	0.912

(c) Variance-Covariance by Peril ($\times 10^{-9}$)

	Earthquake: Fire	Earthquake: Tsunami	Wildfire	Inland Flood	Convective Storm	Winter Storm	Hurricane Storm Surge	Hurricane Wind
Earthquake: Fire	**0.42**	0.02	-0.30	-1.22	-1.34	-0.12	-0.04	-0.79
Earthquake: Tsunami	0.02	**0.72**	-0.09	0.31	-0.54	-0.12	-0.17	-0.33
Wildfire	-0.30	-0.09	**2,410.00**	-14.40	-75.50	-18.20	-17.90	38.20
Inland Flood	-1.22	0.31	-14.40	**27,900.00**	66.20	-3.31	73.20	-6.28
Convective Storm	-1.34	-0.54	-75.50	66.20	**2,370.00**	-0.70	-90.60	-120.00
Winter Storm	-0.12	-0.12	-18.20	-3.31	-0.70	**37.30**	-21.80	-51.30
Hurricane Storm Surge	-0.04	-0.17	-17.90	73.20	-90.60	-21.80	**6,610.00**	1,230.00
Hurricane Wind	-0.79	-0.33	38.20	-6.28	-120.00	-51.30	1,230.00	**1,980.00**

Notes. Panel (A) presents unadjusted R^2 from various fixed-effects regression of AAL at the property × peril × scenario × timeframe level. Samples 1 and 2 are 5% random samples of properties in the CoreLogic Climate Risk data. Panel (B) presents R-squareds from fixed effect specifications of AAL (2050 timeframe, intermediate scenario) and log sale price onto various geographic fixed effects. Panel (C) presents the variance-covariance matrix for property-level AAL for the 8 perils, for the 2050 timeframe under intermediate scenario (RCP 4.5). The actual covariances can be obtained by multiplying the numbers in Table (B) by 10^{-9}. Variances along the diagonal are in bold. For perils with limited geographic coverage (Earthquake: Tsunami, Wildfire, Hurricane Storm Surge, and Hurricane Wind), missing AAL has been assigned a value of 0.

Table III
Earthquake (Fire-following): Projected losses on property characteristics

	aal	aep500	aep500_tvar	oep500	oep500_tvar
ffh_std	0.00476***	0.000504***	0.00507***	0.000459***	0.00554***
	(0.000111)	(0.000150)	(0.000105)	(0.000151)	(0.000116)
gr_el_std	-0.0177***	-0.0104***	-0.0174***	-0.0109***	-0.0217***
	(0.00143)	(0.00119)	(0.00144)	(0.00124)	(0.00175)
light steel	-0.0132***	0.00516***	-0.0148***	0.00525***	-0.0129***
	(0.00152)	(0.00191)	(0.00145)	(0.00200)	(0.00159)
re. concrete	-0.0298***	-0.0352***	-0.0268***	-0.0365***	-0.0321***
	(0.00455)	(0.00808)	(0.00371)	(0.00841)	(0.00456)
re. masonry	-0.00176	0.00779***	-0.00300***	0.00816***	-0.00329***
	(0.00109)	(0.000829)	(0.00112)	(0.000860)	(0.00105)
steel	-0.0193***	-0.0181***	-0.0182***	-0.0189***	-0.0206***
	(0.00312)	(0.00524)	(0.00259)	(0.00547)	(0.00318)
timber	0.0550***	0.0377***	0.0539***	0.0388***	0.0544***
	(0.00119)	(0.00196)	(0.00103)	(0.00204)	(0.00113)
veneer	-0.0240***	-0.0267***	-0.0220***	-0.0279***	-0.0241***
	(0.00125)	(0.00199)	(0.00111)	(0.00207)	(0.00124)
Observations	9825727	9825727	9825727	9825727	9825727
ymean	0.00000258	0.0000560	0.00125	0.0000545	0.00111
ysvd	0.0000173	0.00115	0.00813	0.00110	0.00659
r2	0.982	0.968	0.983	0.969	0.983
r2_a	0.977	0.959	0.978	0.960	0.979
r2_within	0.00379	0.000831	0.00398	0.000901	0.00429
r2_a_within	0.00379	0.000830	0.00398	0.000900	0.00429

Standard errors in parentheses are clustered at the Census block level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. This table displays slope coefficients from regressions of earthquake-related losses on property characteristics and Census block fixed effects. The earthquake-related loss projections are taken from the CoreLogic Climate Risk data for the 2050 timeframe under intermediate scenario (RCP 4.5). Going across columns, the dependent variable represents different moments of the loss distribution, each standardized to have zero mean and unit variance (the mean and standard deviation of the raw independent variables are displayed at the bottom of the table). "aal" is Average Annual Losses; "aep500", or Average Exceedance Probability 500, is the probability that the sum of losses in a year will exceed a loss threshold identified as the the worst 1/500 total loss outcomes; "aep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability; "oep500", or Occurrence Exceedance Probability 500, is the probability that the largest annual loss will exceed a loss threshold identified as the the worst 1/500 events; and "oep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability. The independent variables are different property characteristics. The first two variables are continuous: "ffh_std" is (standardized) first-floor height; "gr_el_std" is (standardized) ground elevation. The remaining variables are dummies for materials in the structure. The R-squared, adjusted R-squared, within-block R-squared, and adjusted within-block R-squared are displayed in the final rows.

Table IV
Inland Flood: Projected losses on property characteristics

	aal	aep50	aep50_tvar	aep500	aep500_tvar	oep50	oep50_tvar	oep500	oep500_tvar
ffh_std	-0.0136***	-0.00844***	-0.0308***	-0.0488***	-0.0667***	-0.00822***	-0.0329***	-0.0522***	-0.0707***
	(0.000364)	(0.000369)	(0.000392)	(0.000438)	(0.000422)	(0.000368)	(0.000399)	(0.000453)	(0.000434)
gr_el_std	-1.172***	-1.161***	-1.378***	-1.435***	-1.556***	-1.156***	-1.400***	-1.443***	-1.557***
	(0.0244)	(0.0238)	(0.0270)	(0.0274)	(0.0293)	(0.0237)	(0.0273)	(0.0274)	(0.0293)
light steel	-0.0311**	-0.0332**	-0.0360***	-0.0329***	-0.0332***	-0.0327**	-0.0362***	-0.0332***	-0.0316***
	(0.0133)	(0.0133)	(0.0128)	(0.0122)	(0.0122)	(0.0134)	(0.0125)	(0.0116)	(0.0119)
re. concrete	-0.0368***	-0.0359***	-0.0546***	-0.0699***	-0.0843***	-0.0362***	-0.0577***	-0.0745***	-0.0909***
	(0.00584)	(0.00570)	(0.00668)	(0.00887)	(0.00855)	(0.00562)	(0.00680)	(0.00929)	(0.00892)
re. masonry	-0.0358***	-0.0338***	-0.0459***	-0.0538***	-0.0606***	-0.0329***	-0.0469***	-0.0550***	-0.0625***
	(0.00513)	(0.00529)	(0.00613)	(0.00739)	(0.00727)	(0.00511)	(0.00631)	(0.00778)	(0.00759)
steel	-0.0518***	-0.0505***	-0.0627***	-0.0689***	-0.0809***	-0.0508***	-0.0638***	-0.0719***	-0.0886***
	(0.00756)	(0.00785)	(0.00758)	(0.00729)	(0.00725)	(0.00788)	(0.00752)	(0.00717)	(0.00713)
timber	-0.0318***	-0.0316***	-0.0292***	-0.0231***	-0.0175***	-0.0319***	-0.0276***	-0.0184***	-0.0122***
	(0.00235)	(0.00232)	(0.00231)	(0.00225)	(0.00226)	(0.00232)	(0.00230)	(0.00226)	(0.00227)
veneer	0.0101***	0.00909**	0.0147***	0.0178***	0.0237***	0.00918**	0.0147***	0.0175***	0.0240***
	(0.00378)	(0.00405)	(0.00416)	(0.00416)	(0.00422)	(0.00403)	(0.00422)	(0.00424)	(0.00424)
Observations	9825727	9825727	9825727	9825727	9825727	9825727	9825727	9825727	9825727
ymean	0.000630	0.00683	0.0152	0.0298	0.0471	0.00663	0.0144	0.0283	0.0450
ysvd	0.00458	0.0531	0.0703	0.105	0.129	0.0517	0.0638	0.0959	0.118
r2	0.430	0.440	0.490	0.558	0.579	0.440	0.497	0.571	0.591
r2_a	0.275	0.287	0.351	0.438	0.465	0.288	0.360	0.455	0.480
r2_within	0.00732	0.00718	0.0118	0.0161	0.0216	0.00713	0.0125	0.0171	0.0229
r2_a_within	0.00732	0.00717	0.0118	0.0161	0.0216	0.00713	0.0125	0.0171	0.0229

Standard errors in parentheses are clustered at the Census block level

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes. This table displays slope coefficients from regressions of flood-related losses on property characteristics and Census block fixed effects. The flood-related loss projections are taken from the CoreLogic Climate Risk data for the 2050 timeframe under intermediate scenario (RCP 4.5). Going across columns, the dependent variable represents different moments of the loss distribution, each standardized to have zero mean and unit variance (the mean and standard deviation of the raw independent variables are displayed at the bottom of the table). "aal" is Average Annual Losses; "aep500", or Average Exceedance Probability 500, is the probability that the sum of losses in a year will exceed a loss threshold identified as the the worst 1/500 total loss outcomes; "aep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability; "oep500", or Occurrence Exceedance Probability 500, is the probability that the largest annual loss will exceed a loss threshold identified as the the worst 1/500 events; and "oep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability. Analogous descriptions hold for "aep50" and "oep50". The independent variables are different property characteristics. The first two variables are continuous: "ffh_std" is (standardized) first-floor height; "gr_el_std" is (standardized) ground elevation. The remaining variables are dummies for materials in the structure. The R-squared, adjusted R-squared, within-block R-squared, and adjusted within-block R-squared are displayed in the final rows.

Table V
Wildfire (Fire+Smoke): Projected losses on property characteristics

	aal	aep50	aep50_tvar	aep500	aep500_tvar	oep50	oep50_tvar	oep500	oep500_tvar
ffh_std	-0.00132	-0.00114	-0.00114	-0.000838	0.000345	-0.00112	-0.00113	-0.000846	0.000350
	(0.000937)	(0.000943)	(0.000980)	(0.00101)	(0.000823)	(0.000942)	(0.000978)	(0.00102)	(0.000822)
gr_el_std	0.501***	0.220***	0.549***	0.480***	0.468***	0.220***	0.550***	0.480***	0.469***
	(0.0379)	(0.0390)	(0.0381)	(0.0362)	(0.0308)	(0.0391)	(0.0382)	(0.0362)	(0.0308)
light steel	-0.0128*	-0.00124	-0.0152*	-0.0119	-0.00378	-0.00124	-0.0152*	-0.0118	-0.00376
	(0.00684)	(0.000994)	(0.00825)	(0.00881)	(0.00865)	(0.000993)	(0.00826)	(0.00882)	(0.00866)
re. concrete	-0.00724	-0.00721	-0.00762	-0.00580	-0.00735	-0.00778*	-0.00758	-0.00586	-0.00735
	(0.00945)	(0.00450)	(0.0112)	(0.0109)	(0.00886)	(0.00468)	(0.0112)	(0.0109)	(0.00882)
re. masonry	-0.00831	-0.0123	-0.00610	-0.00793	-0.0119	-0.0124	-0.00603	-0.00793	-0.0120
	(0.00883)	(0.00825)	(0.00859)	(0.00726)	(0.00772)	(0.00829)	(0.00855)	(0.00727)	(0.00771)
steel	-0.0239***	-0.00788	-0.0276***	-0.0356***	-0.0328***	-0.00784	-0.0276***	-0.0357***	-0.0327***
	(0.00734)	(0.00607)	(0.00856)	(0.0109)	(0.00950)	(0.00607)	(0.00856)	(0.0109)	(0.00950)
timber	-0.00240	-0.00162	-0.00236	-0.00621*	-0.00151	-0.00162	-0.00234	-0.00619*	-0.00149
	(0.00259)	(0.00219)	(0.00282)	(0.00361)	(0.00290)	(0.00218)	(0.00283)	(0.00361)	(0.00290)
veneer	-0.0121**	-0.00772	-0.0132**	-0.00737	-0.0126**	-0.00771	-0.0132**	-0.00732	-0.0126**
	(0.00537)	(0.00529)	(0.00585)	(0.00600)	(0.00501)	(0.00529)	(0.00584)	(0.00600)	(0.00500)
Observations	2941647	2941647	2941647	2941647	2941647	2941647	2941647	2941647	2941647
ymean	0.000199	0.000709	0.00954	0.0241	0.0543	0.000705	0.00949	0.0240	0.0541
ysvd	0.00119	0.0205	0.0494	0.128	0.172	0.0204	0.0489	0.128	0.171
r2	0.751	0.675	0.746	0.721	0.773	0.675	0.746	0.721	0.774
r2_a	0.689	0.594	0.682	0.652	0.717	0.594	0.683	0.652	0.717
r2_within	0.00543	0.000806	0.00629	0.00441	0.00515	0.000808	0.00634	0.00442	0.00518
r2_a_within	0.00542	0.000803	0.00629	0.00440	0.00515	0.000805	0.00634	0.00441	0.00518

Standard errors in parentheses are clustered at the Census block level

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes. This table displays slope coefficients from regressions of wildfire-related losses on property characteristics and Census block fixed effects. The wildfire-related loss projections are taken from the CoreLogic Climate Risk data for the 2050 timeframe under intermediate scenario (RCP 4.5). Going across columns, the dependent variable represents different moments of the loss distribution, each standardized to have zero mean and unit variance (the mean and standard deviation of the raw independent variables are displayed at the bottom of the table). "aal" is Average Annual Losses; "aep500", or Average Exceedance Probability 500, is the probability that the sum of losses in a year will exceed a loss threshold identified as the the worst 1/500 total loss outcomes; "aep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability; "oep500", or Occurrence Exceedance Probability 500, is the probability that the largest annual loss will exceed a loss threshold identified as the the worst 1/500 events; and "oep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability. Analogous descriptions hold for "aep50" and "oep50". The independent variables are different property characteristics. The first two variables are continuous: "ffh_std" is (standardized) first-floor height; "gr_el_std" is (standardized) ground elevation. The remaining variables are dummies for materials in the structure. The R-squared, adjusted R-squared, within-block R-squared, and adjusted within-block R-squared are displayed in the final rows.

Table VI
Severe Convective Storm: Projected losses on property characteristics

	aal	aep50	aep50_tvar	aep500	aep500_tvar	oep50	oep50_tvar	oep500	oep500_tvar
ffh_std	0.00731***	0.00338***	0.0270***	0.0298***	0.0443***	0.00224***	0.0267***	0.0298***	0.0443***
	(0.000457)	(0.000554)	(0.000374)	(0.000244)	(0.000221)	(0.000560)	(0.000380)	(0.000246)	(0.000221)
gr_el_std	0.00535*	0.00504*	0.00945***	0.0118***	0.00765***	0.00457*	0.00925***	0.0116***	0.00755***
	(0.00302)	(0.00262)	(0.00207)	(0.00177)	(0.00177)	(0.00264)	(0.00210)	(0.00178)	(0.00177)
light steel	0.351***	0.393***	0.727***	0.827***	0.693***	0.370***	0.720***	0.824***	0.690***
	(0.00439)	(0.00724)	(0.00804)	(0.00867)	(0.00654)	(0.00709)	(0.00791)	(0.00857)	(0.00651)
re. concrete	-0.195***	-0.184***	-0.523***	-0.541***	-0.828***	-0.179***	-0.525***	-0.544***	-0.831***
	(0.00315)	(0.00352)	(0.00661)	(0.00793)	(0.00785)	(0.00344)	(0.00660)	(0.00795)	(0.00786)
re. masonry	-0.0474***	-0.0203***	-0.197***	-0.259***	-0.297***	-0.0200***	-0.200***	-0.262***	-0.299***
	(0.00101)	(0.000787)	(0.00281)	(0.00337)	(0.00364)	(0.000731)	(0.00283)	(0.00339)	(0.00366)
steel	-0.380***	-0.386***	-0.940***	-1.000***	-1.298***	-0.372***	-0.941***	-1.001***	-1.301***
	(0.00433)	(0.00532)	(0.00877)	(0.0101)	(0.0102)	(0.00521)	(0.00875)	(0.0101)	(0.0102)
timber	0.174***	0.133***	0.408***	0.381***	0.634***	0.122***	0.408***	0.381***	0.636***
	(0.000614)	(0.000637)	(0.00125)	(0.00127)	(0.00169)	(0.000607)	(0.00124)	(0.00127)	(0.00169)
veneer	-0.0719***	-0.0361***	-0.181***	-0.0688***	-0.408***	-0.0316***	-0.182***	-0.0678***	-0.410***
	(0.000783)	(0.000806)	(0.00174)	(0.00189)	(0.00219)	(0.000769)	(0.00174)	(0.00190)	(0.00219)
Observations	9825727	9825727	9825727	9825727	9825727	9825727	9825727	9825727	9825727
ymean	0.000789	0.00560	0.0240	0.0423	0.121	0.00524	0.0236	0.0416	0.120
ysvd	0.00169	0.0137	0.0213	0.0370	0.0726	0.0136	0.0209	0.0364	0.0720
r2	0.499	0.536	0.797	0.910	0.934	0.525	0.790	0.908	0.934
r2_a	0.363	0.410	0.742	0.886	0.916	0.396	0.733	0.883	0.915
r2_within	0.00187	0.00140	0.0251	0.0547	0.147	0.00119	0.0243	0.0537	0.147
r2_a_within	0.00186	0.00140	0.0251	0.0547	0.147	0.00119	0.0243	0.0537	0.147

Standard errors in parentheses are clustered at the Census block level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. This table displays slope coefficients from regressions of convective storm-related losses on property characteristics and Census block fixed effects. The convective storm-related loss projections are taken from the CoreLogic Climate Risk data for the 2050 timeframe under intermediate scenario (RCP 4.5). Going across columns, the dependent variable represents different moments of the loss distribution, each standardized to have zero mean and unit variance (the mean and standard deviation of the raw independent variables are displayed at the bottom of the table). "aal" is Average Annual Losses; "aep500", or Average Exceedance Probability 500, is the probability that the sum of losses in a year will exceed a loss threshold identified as the the worst 1/500 total loss outcomes; "aep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability; "oep500", or Occurrence Exceedance Probability 500, is the probability that the largest annual loss will exceed a loss threshold identified as the the worst 1/500 events; and "oep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability. Analogous descriptions hold for "aep50" and "oep50". The independent variables are different property characteristics. The first two variables are continuous: "ffh_std" is (standardized) first-floor height; "gr_el_std" is (standardized) ground elevation. The remaining variables are dummies for materials in the structure. The R-squared, adjusted R-squared, within-block R-squared, and adjusted within-block R-squared are displayed in the final rows.

Table VII
Winter Storm: Projected losses on property characteristics

	aal	aep50	aep50_tvar	aep500	aep500_tvar	oep50	oep50_tvar	oep500	oep500_tvar
ffh_std	0.0198***	0.0253***	0.0300***	0.0312***	0.0283***	0.0256***	0.0308***	0.0314***	0.0270***
	(0.000111)	(0.000127)	(0.000148)	(0.000159)	(0.000148)	(0.000128)	(0.000151)	(0.000160)	(0.000144)
gr_el_std	0.0171***	-0.000434	0.0152***	0.0284***	0.0367***	-0.00221	0.0144***	0.0300***	0.0386***
	(0.00399)	(0.00387)	(0.00424)	(0.00566)	(0.00792)	(0.00387)	(0.00425)	(0.00599)	(0.00833)
light steel	-0.229***	-0.333***	-0.426***	-0.463***	-0.407***	-0.346***	-0.448***	-0.481***	-0.381***
	(0.00318)	(0.00553)	(0.00497)	(0.00493)	(0.00432)	(0.00573)	(0.00518)	(0.00515)	(0.00406)
re. concrete	-0.365***	-0.286***	-0.355***	-0.377***	-0.358***	-0.257***	-0.330***	-0.368***	-0.345***
	(0.00713)	(0.00489)	(0.00609)	(0.00654)	(0.00644)	(0.00432)	(0.00565)	(0.00643)	(0.00637)
re. masonry	0.0276***	0.0433***	0.0488***	0.0470***	0.0416***	0.0447***	0.0512***	0.0490***	0.0383***
	(0.00106)	(0.00149)	(0.00161)	(0.00154)	(0.00142)	(0.00152)	(0.00167)	(0.00161)	(0.00133)
steel	-0.205***	-0.274***	-0.350***	-0.374***	-0.359***	-0.276***	-0.363***	-0.393***	-0.355***
	(0.00277)	(0.00304)	(0.00353)	(0.00387)	(0.00426)	(0.00305)	(0.00361)	(0.00401)	(0.00437)
timber	0.0382***	0.0457***	0.0554***	0.0594***	0.0526***	0.0457***	0.0563***	0.0595***	0.0499***
	(0.000660)	(0.000626)	(0.000718)	(0.000767)	(0.000814)	(0.000610)	(0.000711)	(0.000766)	(0.000811)
veneer	-0.0255***	-0.0278***	-0.0314***	-0.0320***	-0.0299***	-0.0273***	-0.0309***	-0.0304***	-0.0280***
	(0.000705)	(0.000833)	(0.000958)	(0.00106)	(0.00101)	(0.000838)	(0.000983)	(0.00111)	(0.000997)
Observations	9825727	9825727	9825727	9825727	9825727	9825727	9825727	9825727	9825727
ymean	0.000205	0.00306	0.00447	0.00633	0.00828	0.00296	0.00420	0.00573	0.00747
ysvd	0.000194	0.00230	0.00265	0.00346	0.00497	0.00220	0.00242	0.00307	0.00464
r2	0.985	0.980	0.976	0.972	0.970	0.980	0.975	0.970	0.970
r2_a	0.980	0.975	0.969	0.964	0.962	0.974	0.968	0.962	0.962
r2_within	0.0300	0.0289	0.0347	0.0331	0.0270	0.0281	0.0342	0.0323	0.0252
r2_a_within	0.0300	0.0289	0.0347	0.0331	0.0270	0.0281	0.0342	0.0323	0.0252

Standard errors in parentheses are clustered at the Census block level

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes. This table displays slope coefficients from regressions of winter storm-related losses on property characteristics and Census block fixed effects. The winter storm-related loss projections are taken from the CoreLogic Climate Risk data for the 2050 timeframe under intermediate scenario (RCP 4.5). Going across columns, the dependent variable represents different moments of the loss distribution, each standardized to have zero mean and unit variance (the mean and standard deviation of the raw independent variables are displayed at the bottom of the table). "aal" is Average Annual Losses; "aep500", or Average Exceedance Probability 500, is the probability that the sum of losses in a year will exceed a loss threshold identified as the the worst 1/500 total loss outcomes; "aep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability; "oep500", or Occurrence Exceedance Probability 500, is the probability that the largest annual loss will exceed a loss threshold identified as the the worst 1/500 events; and "oep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability. Analogous descriptions hold for "aep50" and "oep50". The independent variables are different property characteristics. The first two variables are continuous: "ffh_std" is (standardized) first-floor height; "gr_el_std" is (standardized) ground elevation. The remaining variables are dummies for materials in the structure. The R-squared, adjusted R-squared, within-block R-squared, and adjusted within-block R-squared are displayed in the final rows.

Table VIII
Hurricane Storm Surge: Projected losses on property characteristics

	aal	aep50	aep50_tvar	aep500	aep500_tvar	oep50	oep50_tvar	oep500	oep500_tvar
ffh_std	-0.0628***	-0.0694***	-0.0621***	-0.0501***	-0.0400***	-0.0692***	-0.0614***	-0.0491***	-0.0388***
	(0.00167)	(0.00169)	(0.00139)	(0.00116)	(0.000964)	(0.00168)	(0.00138)	(0.00115)	(0.000953)
gr_el_std	-0.0938***	-0.0908***	-0.107***	-0.110***	-0.116***	-0.0908***	-0.107***	-0.110***	-0.116***
	(0.00331)	(0.00314)	(0.00317)	(0.00310)	(0.00311)	(0.00314)	(0.00318)	(0.00310)	(0.00311)
light steel	0.0315***	0.0425***	0.0427***	0.0373***	0.0342***	0.0433***	0.0433***	0.0379***	0.0345***
	(0.00808)	(0.0129)	(0.00965)	(0.00820)	(0.00796)	(0.0132)	(0.00969)	(0.00828)	(0.00797)
re. concrete	-0.0105	-0.0250	-0.0305**	-0.0302**	-0.0264***	-0.0268	-0.0322**	-0.0311**	-0.0250***
	(0.0151)	(0.0167)	(0.0143)	(0.0122)	(0.00973)	(0.0166)	(0.0141)	(0.0122)	(0.00971)
re. masonry	-0.0225***	-0.0246**	-0.0326***	-0.0354***	-0.0468***	-0.0250**	-0.0329***	-0.0352***	-0.0469***
	(0.00796)	(0.0103)	(0.00931)	(0.00823)	(0.00760)	(0.0104)	(0.00933)	(0.00825)	(0.00760)
steel	-0.0527***	-0.0433***	-0.0532***	-0.0544***	-0.0521***	-0.0417***	-0.0519***	-0.0546***	-0.0529***
	(0.0153)	(0.0145)	(0.0119)	(0.00999)	(0.00905)	(0.0142)	(0.0116)	(0.00994)	(0.00901)
timber	0.0196***	0.0218***	0.0281***	0.0309***	0.0281***	0.0220***	0.0288***	0.0328***	0.0303***
	(0.00330)	(0.00310)	(0.00282)	(0.00262)	(0.00234)	(0.00306)	(0.00277)	(0.00264)	(0.00236)
veneer	0.0270***	0.0268***	0.0529***	0.0649***	0.0796***	0.0279***	0.0561***	0.0677***	0.0835***
	(0.0101)	(0.00930)	(0.00780)	(0.00674)	(0.00584)	(0.00908)	(0.00767)	(0.00681)	(0.00592)
Observations	5593723	5593723	5593723	5593723	5593723	5593723	5593723	5593723	5593723
ymean	0.000498	0.00671	0.0148	0.0267	0.0369	0.00652	0.0144	0.0262	0.0363
ysvd	0.00369	0.0500	0.0789	0.123	0.149	0.0481	0.0758	0.121	0.145
r2	0.772	0.808	0.873	0.907	0.928	0.811	0.876	0.907	0.928
r2_a	0.715	0.760	0.841	0.883	0.910	0.764	0.845	0.884	0.911
r2_within	0.00917	0.0129	0.0159	0.0146	0.0127	0.0131	0.0160	0.0141	0.0122
r2_a_within	0.00917	0.0129	0.0159	0.0146	0.0127	0.0131	0.0160	0.0141	0.0122

Standard errors in parentheses are clustered at the Census block level

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes. This table displays slope coefficients from regressions of hurricane storm surge-related losses on property characteristics and Census block fixed effects. The hurricane storm surge-related loss projections are taken from the CoreLogic Climate Risk data for the 2050 timeframe under intermediate scenario (RCP 4.5). Going across columns, the dependent variable represents different moments of the loss distribution, each standardized to have zero mean and unit variance (the mean and standard deviation of the raw independent variables are displayed at the bottom of the table). "aal" is Average Annual Losses; "aep500", or Average Exceedance Probability 500, is the probability that the sum of losses in a year will exceed a loss threshold identified as the the worst 1/500 total loss outcomes; "aep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability; "oep500", or Occurrence Exceedance Probability 500, is the probability that the largest annual loss will exceed a loss threshold identified as the the worst 1/500 events; and "oep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability. Analogous descriptions hold for "aep50" and "oep50". The independent variables are different property characteristics. The first two variables are continuous: "ffh_std" is (standardized) first-floor height; "gr_el_std" is (standardized) ground elevation. The remaining variables are dummies for materials in the structure. The R-squared, adjusted R-squared, within-block R-squared, and adjusted within-block R-squared are displayed in the final rows.

Table IX
Hurricane Wind: Projected losses on property characteristics

	aal	aep50	aep50_tvar	aep500	aep500_tvar	oep50	oep50_tvar	oep500	oep500_tvar
ffh_std	0.00138***	0.00144***	0.00237***	0.00271***	0.00331***	0.00149***	0.00242***	0.00275***	0.00335***
	(0.000339)	(0.000344)	(0.000314)	(0.000305)	(0.000284)	(0.000343)	(0.000313)	(0.000305)	(0.000284)
gr_el_std	-0.00654***	-0.00437***	-0.00933***	-0.0115***	-0.0159***	-0.00444***	-0.00949***	-0.0117***	-0.0162***
	(0.000839)	(0.000825)	(0.000902)	(0.000955)	(0.00105)	(0.000828)	(0.000906)	(0.000960)	(0.00106)
light steel	0.184***	0.100***	0.242***	0.329***	0.431***	0.0997***	0.245***	0.333***	0.437***
	(0.00916)	(0.00566)	(0.0123)	(0.0169)	(0.0201)	(0.00568)	(0.0124)	(0.0172)	(0.0204)
re. concrete	-1.148***	-1.052***	-0.962***	-0.923***	-0.942***	-1.036***	-0.950***	-0.913***	-0.931***
	(0.0246)	(0.0230)	(0.0205)	(0.0198)	(0.0185)	(0.0227)	(0.0203)	(0.0195)	(0.0183)
re. masonry	-0.253***	-0.242***	-0.253***	-0.262***	-0.226***	-0.242***	-0.253***	-0.260***	-0.229***
	(0.0161)	(0.0155)	(0.0144)	(0.0139)	(0.0127)	(0.0154)	(0.0143)	(0.0139)	(0.0127)
steel	-0.583***	-0.567***	-0.595***	-0.597***	-0.626***	-0.567***	-0.596***	-0.597***	-0.627***
	(0.0273)	(0.0273)	(0.0257)	(0.0249)	(0.0218)	(0.0273)	(0.0256)	(0.0249)	(0.0217)
timber	0.0933***	0.0909***	0.0841***	0.0791***	0.0855***	0.0904***	0.0835***	0.0783***	0.0849***
	(0.00215)	(0.00209)	(0.00186)	(0.00177)	(0.00162)	(0.00206)	(0.00185)	(0.00176)	(0.00162)
veneer	-0.0373***	-0.00420	-0.0686***	-0.107***	-0.154***	-0.00466	-0.0704***	-0.109***	-0.157***
	(0.00316)	(0.00318)	(0.00324)	(0.00347)	(0.00353)	(0.00318)	(0.00325)	(0.00349)	(0.00354)
Observations	5593723	5593723	5593723	5593723	5593723	5593723	5593723	5593723	5593723
ymean	0.000939	0.0124	0.0330	0.0630	0.0965	0.0121	0.0323	0.0619	0.0951
ysvd	0.00198	0.0284	0.0596	0.106	0.138	0.0275	0.0580	0.104	0.135
r2	0.958	0.956	0.962	0.964	0.966	0.956	0.963	0.964	0.966
r2_a	0.947	0.945	0.953	0.955	0.957	0.946	0.953	0.955	0.957
r2_within	0.0694	0.0584	0.0589	0.0584	0.0650	0.0573	0.0581	0.0575	0.0643
r2_a_within	0.0694	0.0584	0.0589	0.0584	0.0650	0.0573	0.0581	0.0575	0.0643

Standard errors in parentheses are clustered at the Census block level

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes. This table displays slope coefficients from regressions of hurricane wind-related losses on property characteristics and Census block fixed effects. The hurricane wind-related loss projections are taken from the CoreLogic Climate Risk data for the 2050 timeframe under intermediate scenario (RCP 4.5). Going across columns, the dependent variable represents different moments of the loss distribution, each standardized to have zero mean and unit variance (the mean and standard deviation of the raw independent variables are displayed at the bottom of the table). "aal" is Average Annual Losses; "aep500", or Average Exceedance Probability 500, is the probability that the sum of losses in a year will exceed a loss threshold identified as the the worst 1/500 total loss outcomes; "aep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability; "oep500", or Occurrence Exceedance Probability 500, is the probability that the largest annual loss will exceed a loss threshold identified as the the worst 1/500 events; and "oep500_tvar" is the average annual losses conditional on exceeding that loss threshold, times the exceedance probability. Analogous descriptions hold for "aep50" and "oep50". The independent variables are different property characteristics. The first two variables are continuous: "ffh_std" is (standardized) first-floor height; "gr_el_std" is (standardized) ground elevation. The remaining variables are dummies for materials in the structure. The R-squared, adjusted R-squared, within-block R-squared, and adjusted within-block R-squared are displayed in the final rows.

Table X
Property Characteristics AAL Composite

	aal_2050	aal_2050	aal_2050	aal_2050
log_sqft	-0.000234***			-0.000226***
	(-314.05)			(-221.05)
bedrooms_all_bldgs		-0.00000577***		-0.00000117***
		(-66.71)		(-13.27)
Coefficients for pre-1945 builds not shown				
Built 1945-1949			0.0000285***	0.00000416
			(9.43)	(1.35)
Built 1950-1954			0.0000451***	0.0000135***
			(16.38)	(4.80)
Built 1955-1959			0.0000247***	0.00000605*
			(8.83)	(2.13)
Built 1960-1964			0.0000926***	0.000103***
			(33.19)	(35.96)
Built 1965-1969			0.000145***	0.000169***
			(50.83)	(57.66)
Built 1970-1974			0.000145***	0.000164***
			(52.82)	(57.92)
Built 1975-1979			-0.0000456***	-0.0000127***
			(-16.72)	(-4.54)
Built 1980-1984			-0.000120***	-0.0000956***
			(-43.32)	(-33.71)
Built 1985-1989			-0.000215***	-0.000185***
			(-79.56)	(-66.71)
Built 1990-1994			-0.000270***	-0.000233***
			(-97.88)	(-82.70)
Built 1995-1999			-0.000386***	-0.000360***
			(-143.05)	(-129.82)
Built 2000-2004			-0.000486***	-0.000445***
			(-182.02)	(-162.51)
Built 2005-2009			-0.000541***	-0.000484***
			(-194.53)	(-168.55)
Built 2010-2014			-0.000599***	-0.000548***
			(-168.84)	(-148.28)
Built 2015-2019			-0.000652***	-0.000603***
			(-170.68)	(-150.20)
Built 2020-2024			-0.000462***	-0.000383***
			(-66.89)	(-50.95)
N	96391001	71301046	98332538	71144802
r2	0.708	0.731	0.699	0.732
r2_within	0.00107	0.0000650	0.00224	0.00370

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. This table displays results from regressions of Composite AAL (for the 2050 timeframe under intermediate scenario RCP 4.5) on Census block fixed effects and either logSqFt_i, Bedrooms_i, or bins YearBuilt_i (as well as all three hedonic variables in the final column). Standard errors are computed by clustering at the Census block level.

Table XI
Property Characteristics AAL Composite Correlations

	aal_2050	logSqFt	Bedrooms	YearBuilt
aal_2050	1			
logSqFt	-0.0737***	1		
Bedrooms	-0.113***	0.650***	1	
YearBuilt	0.00284***	0.177***	0.0546***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. This table displays the correlations between Composite AAL (for the 2050 timeframe under intermediate scenario RCP 4.5), logSqFt_i, Bedrooms_i, and YearBuilt_i.

Table XII
Sample Size for Price, Owner Occupancy, Block and Tract combinations

Dep Variable	Geographic	Hedonic Controls?	Sample Size
Log Sale Amount	Block	N	57,847,086
Log Sale Amount	Tract	N	87,775,926
Owner Occ	Block	N	47,484,397
Owner Occ	Tract	N	72,815,743
Log Sale Amount	Block	Y	28,637,105
Log Sale Amount	Tract	Y	46,109,146
Owner Occ	Block	Y	26,090,778
Owner Occ	Tract	Y	41,432,355