Political Orientation and Household Climate Adaptation: Evidence from Building Permits

Tania Diaz-Bazan*
Yale School of Management

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Abstract

I study how political orientation affects households' decisions to invest in climate adaptation, focusing on hurricane-related wind risk in Florida. Using a novel dataset of 13 million building permits, I apply textual analysis to identify more than half a million wind-adaptation permits (like impact-resistant windows, storm shutters, structural reinforcements) and link them to voter registration records. I show that the probability that registered Republicans invest in wind-adaptation measures is 4.5–6.5% lower than that of registered Democrats, controlling for income and a rich set of demographic controls and property characteristics – including comparing households that purchase the same property at different points in time. These effects are economically meaningful, equivalent to two to three income deciles, and robust across specifications. Four pieces of evidence suggest that the different behavior of Democrats and Republicans reflects different beliefs about climate risks tied to political identity: the partisan gap in adaptation doubles among FEC campaign donors, consistent with stronger partisan identity amplifying the effect; the gap is larger in areas where building codes are less stringent, so household decisions are less constrained; the gap widens sharply at the start of the first Trump administration before narrowing after the relaunch of Florida's *My Safe Florida Home* subsidy program (which was meant to reframe the issue in a less politicized way); and first-hand experience of hurricanes passing nearby induce both Democrats and Republicans to adapt more, but Republicans adjust less strongly, suggesting that political views act as an anchor to updating. I calculate the welfare losses due to partisan views to be around $200 million in aggregate, equivalent to the entire budget of the first *My Safe Florida Home* program.

*tania.diaz-bazan@yale.edu. I am extremely grateful to my advisors Kelly Shue, Paul Goldsmith-Pinkham, Menaka Hampole,and Nick Barberis, for their guidance and support, to Stefano Giglio and Cameron LaPoint for their helpful comments, as well as seminar participants at Yale SOM and at the Baruch-JFQA Climate Finance and Sustainability Conference for their many comments and suggestions.

1 Introduction

Climate change poses large and growing economic risks worldwide. While the global policy response has focused primarily on mitigation, it is increasingly clear that mitigation alone will not prevent substantial damages, making *adaptation* – protecting the economic system from the consequences of climate change – a crucial component of society's response. Along the Atlantic and Gulf coasts of the United States, one of the most consequential hazards that climate change is expected to intensify is severe wind from hurricanes. Hurricanes can (and already do) cause significant economic damages to properties, but property-level adaptation measures have been shown to be highly effective at reducing these losses (Simmons et al., 2018).

Unlike flood risk, for which government infrastructure plays a dominant role, wind resilience falls largely on individual homeowners, who retain significant discretion over whether and how much to invest. These decisions are forward-looking, costly, and depend on subjective assessments of risk – assessments that survey evidence shows are sharply polarized along partisan lines: 78 percent of Democrats view climate change as a serious threat, compared with only 23 percent of Republicans.[1] A large literature has shown that political beliefs bias decisions in many domains; for example, the recent finance literature has documented that credit analysts' ratings (Kempf and Tsoutsoura, 2021) and investor portfolio choice (Meeuwis et al., 2022) are both affected by them. Whether these political belief differences also translate into differences in real, costly investment in physical resilience – where the stakes are protection against natural disasters – is an open and economically important question.

In this paper, I provide the first large-scale evidence that political orientation affects household investment in climate adaptation. I study wind-related adaptation in single-family homes in Florida, where hurricane risk is highly salient and resilience depends largely on individual homeowners. I construct a novel property–owner–year panel of approximately 61 million observations covering the years 2014–2024 by merging the extensive dataset of building permits from Cotality (formerly CoreLogic) with property characteristics, deed-based ownership histories, voter registration records from L2 Data, and household income estimates from Data Axle. Using textual analysis of permit descriptions, I identify approximately 580,000 wind-adaptation permits – installations of impact-resistant windows, storm shutters, hurricane straps, and structural reinforcements – observed at the time they are undertaken. Exploiting variation within zipcode and year (so that Republican and Democratic homeowners face identical local hazard conditions and building code requirements), I find that the probability that Republicans file a wind-adaptation permit is 6.5% lower than that of Democrats, controlling for income, property characteristics, and a rich set of demographic controls. The effect persists when identification is sharpened to a two-way fixed-effects specification that adds property fixed effects on top of the zip code × year fixed effects, exploiting ownership transitions within the same dwelling: even comparing Republicans and Democrats who own the same house at different points in time, the gap is −4.6%. Crucially, the partisan gap is specific to climate

[1] Pew Research Center, "What the data says about Americans' views of climate change," August 2023, https://www.pewresearch.org/short-reads/2023/08/09/what-the-data-says-about-americans-views-of-climate-change/.

adaptation: Republicans show no meaningful difference in overall permitting activity, ruling out explanations based on general differences in home-investment behavior.

The magnitude of the partisan gap is economically meaningful. The 6.5% effect is equivalent to moving approximately two to three income deciles – roughly $40,000-$60,000 in annual household income at the median – and comparable in size to the gender gap in adaptation (single males are less likely than single females to file a wind permit). It is also in line with other estimates of how partisan identity affects real decisions: Kempf and Tsoutsoura (2021) find that partisan affiliation shifts credit rating analysts' expected downgrades by about 11% of the baseline rate.

I then turn to studying the mechanisms driving the documented partisan adaptation gap. In general, it is difficult to distinguish whether the partisan gap is due to differences in climate beliefs that are connected with political identity (I refer to this as a beliefs/political identity mechanism), or to other unobservable channels that might correlate with political identity (I refer to these as non-belief channels, for example, differential enforcement of building codes, or differential access to materials and labor for adaptation between Republicans and Democrats). I therefore present four pieces of evidence that are all consistent with a beliefs/political identity channel.[2] First, I exploit federal campaign contribution records to show that the adaptation gap is larger among FEC donors – households with the strongest revealed partisan engagement – than among non-donors, consistent with stronger political beliefs amplifying the effect on real investment. Second, I show that the gap is present both in areas where Florida's building code regulates some of the households' wind-protection decisions, and in areas where no such regulations apply and every adaptation investment is entirely voluntary (given grandfathering rules, there is still substantial discretion left even in the more regulated areas, but of course there is more discretion where regulations do not apply): this helps rule out mechanisms based on different enforcement of the building code regulations. Third, the time series of the gap tracks the political salience of climate change with striking precision: the gap is absent in 2014–2016, emerges sharply in 2017 at the start of the Trump administration, deepens during 2020–2021, and then narrows beginning in 2022 – coinciding with the relaunch of Florida's *My Safe Florida Home* program, which provides matching grants for wind-hardening investments framed around insurance savings rather than climate risk. Fourth, I show that the experience of a hurricane passing nearby (but not producing direct damages) does induce both Republicans and Democrats to adapt more; however, Democrats respond more than Republicans, suggesting that political views act as an anchor to learning from experience. Together, these results are consistent with a belief channel in which the partisan gap reflects how political identity shapes homeowners' subjective assessments of climate risk, and in which the gap responds to changes in the salience and polarization of climate as a political issue (Dunlap et al., 2016). They also suggest that financially framed subsidy programs may help depoliticize adaptation investment.

The results survive a battery of robustness checks. Restricting the sample to properties that had never previously filed a wind-adaptation permit yields estimates that are statistically and economi-

[2]Ideally, one would also want to distinguish between the pure beliefs explanation (Republicans hold different beliefs about climate risks) from a political identity explanation (they may have similar beliefs but act differently to follow the political line). I cannot identify this distinction with my data.

cally similar to the baseline; Excluding permits associated with new construction leaves the estimate essentially unchanged. Restricting to mortgage-financed purchases, where homeowner's insurance is required by the lender, produces a similar estimate, confirming that the gap is not driven by differential insurance coverage between Democrats and Republicans. The results also hold under logit and discrete-time hazard specifications. Finally, I show that the results are entirely driven by the extensive margin (the probability that Republicans file a wind-adaptation permit) and not the intensive margin (the cost of the wind permits undertaken).

In the final part of the paper, I quantify the welfare stakes of the partisan adaptation gap. Valuing avoided hurricane losses with a market-based catastrophe risk loading calibrated to catastrophe-bond prices (and, as an alternative, under CRRA utility), I estimate that closing the partisan gap – having Republicans adapt at the same rate as Democrats – would generate a net benefit of about $205 million in Florida. The order of magnitude of this welfare loss is comparable to the entire budget of the original *My Safe Florida Home* program, which was appropriated about $250 million in 2006–2007 and financed roughly 400,000 wind-mitigation inspections and 32,000 home-hardening grants before being defunded. Florida law mandates that insurers return mitigation savings to homeowners as premium credits; I estimate that in practice about 83% of that value is captured privately by the households themselves. Finally, an upper-bound benchmark in which every remaining positive-NPV mitigation opportunity in Florida is undertaken would be worth about $32 billion ($72 billion when extrapolated nationally).

The paper is organized as follows. After a brief literature review, I describe the data in Section 2. Section 3 presents the main results and reports a number of robustness checks. Section 4 provides evidence on the mechanisms behind the partisan gap. Section 5 quantifies the welfare cost of the partisan adaptation gap. Section 6 concludes.

Related Literature

This paper contributes to several interconnected literatures in climate finance, household finance, and political economy.

Climate finance and adaptation. Giglio et al. (2021a) provide a comprehensive overview of the economics of climate risk, reviewing how climate risks are priced in financial markets and emphasizing the importance of understanding climate-related behavior at the household, firm, and investor levels. A large body of work documents that climate risks affect asset prices across asset classes (for example, see Giglio et al. (2021b), Engle et al. (2020), and Bolton and Kacperczyk (2021)). Survey evidence confirms that institutional investors view climate risks as financially material (Krueger et al., 2020). Most of this literature has focused on mitigation and asset pricing rather than adaptation. Much of the literature on climate impacts and adaptation has focused on agriculture (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Mendelsohn, 2009; Fisher et al., 2012) or government-led adaptation through infrastructure and regulation (Gandhi et al., 2022; Lu and Nakhmurina, 2024). Barreca et al. (2016) show that the U.S. temperature–mortality relationship declined by 75 percent over the twentieth century, driven almost entirely by residential air conditioning – a powerful ex-

ample of private adaptation. At the aggregate level, hurricanes impose large fiscal costs through non-disaster transfer programs (Deryugina, 2017), severe disasters increase out-migration and lower property values (Boustan et al., 2020), and cyclone damages are lower in countries with more intense storm climates, suggesting costly but effective adaptation (Hsiang and Narita, 2012). Desmet and Rossi-Hansberg (2015) develop a spatial equilibrium model showing that global warming will shift population and production northward, with labor mobility serving as an important adaptation channel. In the residential sector, Meyer et al. (2014) document hurricane risk perceptions using survey evidence, and Hovekamp and Wagner (2023) study the role of mandated house elevation in reducing flood damages. Insurance plays a complementary role: Kousky (2019) reviews evidence that insurance improves post-disaster recovery, while Kousky et al. (2018) find that federal disaster aid partially crowds out private flood insurance. Bellon et al. (2024) study the uptake of PACE loans for clean-energy and resilience investments in Florida using permit text data. My contribution is to provide the first systematic study of voluntary household climate adaptation using building permit data, which allows adaptation investments to be observed at the time they occur rather than at the point of sale (if they are disclosed in the listings).

Political identity, beliefs, and financial behavior. Party affiliation has become an increasingly important determinant of economic beliefs and attitudes in the United States (Bertrand and Kamenica, 2018; Gentzkow et al., 2019; Mian et al., 2023), and Howe et al. (2015) document substantial geographic variation in climate opinions. A growing literature documents that these belief differences have real financial consequences. Meeuwis et al. (2022) show that following the 2016 election, likely-Republicans increased equity exposure while likely-Democrats shifted to safe assets, consistent with divergent models of the economy. Cookson et al. (2020) find similar partisan divergence during the COVID-19 pandemic, and Kempf and Tsoutsoura (2021) demonstrate that political orientation affects credit rating analysts' professional judgment. Kostovetsky et al. (2024) show that exposure to local climate-related news affects household and firm behavior. Attention and salience are important mediating mechanisms: Choi et al. (2020) show that warm temperatures increase attention to global warming and shift portfolios away from carbon-intensive stocks, and Gallagher (2014) finds that flood insurance take-up spikes after a local flood and then decays. This paper provides direct evidence that partisan differences in climate beliefs translate into differences in real, costly investment in physical resilience – extending the literature from financial markets and professional judgment to household-level decisions with tangible risk-management consequences.

Climate risk and real estate. Objective exposure to climate hazards depresses property values (Bernstein et al., 2019), and the effect varies with beliefs: Baldauf et al. (2020) find that climate risk is capitalized into house prices only in communities that believe in climate change, while Bakkensen and Barrage (2022) show that belief heterogeneity drives coastal home price dynamics. Barrage and Furst (2019) find that new housing construction in sea-level-rise-exposed areas is lower in high-climate-concern communities. Keys and Mulder (2020) document a recent emergence of sea-level-rise discounts in coastal Florida, Ortega and Taspinar (2018) show that Hurricane Sandy generated persistent price declines for properties in flood zones, and climate exposure affects municipal borrowing

costs (Painter, 2020; Goldsmith-Pinkham et al., 2023). Bernstein et al. (2022) find that Republicans are significantly more likely than Democrats to own properties exposed to sea-level rise. Housing market shocks can in turn affect political behavior: McCartney (2021) shows that house price changes influence voter turnout, and Hall et al. (2021) document that foreclosures reduce voter participation. While these papers study how climate risk and political identity interact through asset prices, sorting, and capitalization, my paper studies the real investment margin – whether homeowners actually harden their properties against climate risk – and shows that political identity shapes not just where people live or how they price risk, but how they invest in physical resilience.

2 Data

This section describes the institutional details of Florida building permits regulations, as well as the datasets used in the analysis and the procedures followed to construct the panel, which combines building permit records, property characteristics and ownership histories, voter registration data, and household financial information. The unit of observation of the final panel is a property–owner–year (that is, a property owned by an individual in a given year), and the time period covered is 2014–2024 (constrained primarily by the availability of voter registration data). The data appendix (Section A) provides step-by-step details of all data processing procedures.

2.1 Building Permits

2.1.1 Institutional Setting

Building permits in the U.S. operate within a multi-level regulatory framework. State and local governments adopt and enforce building codes – often based on model codes such as the International Building Code (IBC) for commercial structures and the International Residential Code (IRC) for residential buildings – to ensure that construction meets minimum safety standards (International Code Council, 2021). The federal government plays a limited direct role in private building regulation, setting standards for federal buildings and manufactured homes but not imposing a national building code. Federal agencies such as FEMA nonetheless influence local practices through model guidelines and hazard-mitigation incentives – for example, FEMA's floodplain regulations under the National Flood Insurance Program require communities to adopt certain construction restrictions in flood-prone areas (FEMA, 2020a).

At the state level, building codes are typically established through state law or building commissions, often mandating the latest IBC/IRC with state-specific amendments. These codes cover structural integrity, fire safety, electrical and plumbing standards, and – increasingly – energy efficiency and resilience to natural hazards (NAHB, 2022). At the local level, city or county building departments are responsible for issuing permits, reviewing plans for code compliance, and conducting inspections (NCSL, 2021).

A building permit is an official approval required before construction or substantial renovation can begin. Obtaining a permit typically involves submitting plans to the local building department

and paying applicable fees. By law, most new construction, major alterations, and repairs affecting structural elements or life-safety systems must go through the permit process (see, e.g., Florida Building Commission, 2020, Chapter 1, "Scope and Administration"). Not all housing investments require a permit, however: minor repairs and cosmetic changes are generally exempt. As discussed in Section 2.1.3, the types of hurricane-adaptation investments studied in this paper do typically require permits.

Once a permit is issued, the project must undergo inspections at key stages – e.g., foundation, framing, electrical, plumbing, and final – where inspectors verify that the work complies with approved plans and code requirements. A project that passes all inspections receives a certificate of occupancy or final approval.

In summary, the institutional framework involves model codes promulgated at the national level, adopted and sometimes amended by states, and enforced locally through permits and inspections.

2.1.2 Building Permit Data

Cotality (formerly CoreLogic)[3] provides a suite of linked housing-related datasets with nationwide geographic coverage, aggregating, cleaning, and normalizing information from county tax assessors, city building departments, and multiple listing services, some of which I discuss more below. Cotality's datasets include property characteristics, ownership records, tax assessments, and sales histories. In this paper I exploit the less widely used dataset on building permits. Each permit record contains information about the property (address, property type), the permit itself (a short textual project description – typically 20 to 30 words – together with effective and expiration dates, status, and in some cases the dollar value of the project). The highly standardized language of permit descriptions is what makes the keyword-based classification approach described in Section 2.1.4 feasible.

The full dataset includes roughly 330 million permits across the United States, of which about 152 million correspond to single-family residential properties. Nationally, counties covered by Cotality account for roughly 80% of the U.S. population. Coverage is uneven across localities, however, with the data most complete for larger municipalities and more populous states. I focus on Florida, where the dataset is exceptionally comprehensive: it covers approximately six million unique single-family residential properties and contains roughly 13 million single-family residential permits in the 2014–2024 period used in the analysis. This depth of coverage makes Florida particularly well suited for studying household adaptation decisions. Temporal coverage varies by location: for some cities, permit information goes back to the 1970s and 1980s, but coverage improves markedly over time. The analysis window in this paper is restricted to 2014–2024 because political registration data from the L2 voter file (described below) is available beginning in 2014.

Two limitations of the data are noteworthy. First, the data do not cover every municipality: smaller localities are less likely to have their permit records collected by Cotality. Incomplete coverage could bias the results if the absence of data correlates with both climate risk and political

[3]CoreLogic rebranded to Cotality in 2024. I use "Cotality" throughout.

orientation in ways that the controls do not capture. That said, counties with no permit data account for only about 9% of Florida's population, suggesting that coverage is broadly representative.[4] In addition, I apply county-level data quality filters that drop county-years with insufficient permit reporting, so that the analysis relies only on locality-periods with adequate coverage (see Appendix A for details).

A second potential limitation is that not all housing investments require a permit: permits are generally required only for major interventions, and the precise threshold varies across localities. An important question, therefore, is whether the climate adaptation investments studied here, and discussed in greater detail below, typically require a permit. The answer is that they generally do – impact-resistant windows, storm shutters, and structural reinforcements all involve permanent modifications to the building envelope – and I indeed observe a large number of such permits in the data.

Finally, it is worth noting that permit data offer a key advantage over other data sources such as transaction prices or listings, for the purpose of studying adaptation investments: whereas housing investments remain invisible in price and listings data until a property is sold, permits are recorded at the time they are obtained, providing an immediate and granular measure of household resilience efforts.

2.1.3 Wind Adaptation Investments

Next, I discuss in this section the main ways in which households can protect their homes against wind damage. Section 2.1.4 then details the keyword-based procedure used to identify adaptation permits among the approximately 13 million single-family residential permits for Florida in the Cotality data.

A wide range of weather-related hazards are associated with climate change, but their relevance for households depends critically on geographic location. Along the Atlantic and Gulf coasts, hurricane risk is particularly important. Housing represents a central component of household wealth and is directly exposed to climate hazards, making it a natural context in which to study household adaptation decisions.

Importantly, climate risks differ not only in their physical characteristics but also in who bears responsibility in practice for managing them. Flood risk, for instance, is largely addressed through government interventions – e.g. through floodplain management and large-scale infrastructure – leaving households with relatively limited scope for individual action. By contrast, protection against wind damage from hurricanes depends primarily on household-level decisions. Investments such as impact-resistant windows, storm shutters, reinforced roofs, and structural tie-downs are typically undertaken by individual homeowners. This distinction makes Florida a particularly well-suited setting for studying household climate adaptation: the state faces persistent hurricane risk year after year, making wind damage an economically significant and recurring threat, and it offers

[4]Relatedly, Brummet et al. (2016) compared Consumer Expenditure data with the Cotality dataset for 2014 and found that single-family residential homes matched in approximately 83% of cases.

exceptionally rich building permit data that allow adaptation investments to be tracked at a granular level.

In addition to floods and wind, FEMA identifies drought, extreme heat, and wildfires as significant climate-related hazards in the United States. Drought is generally less relevant for residential properties than for agriculture. Extreme heat is excluded from my analysis because, while some heat-related adaptation investments are observable in permit data – most notably HVAC and air conditioning installations – these systems are not specific to climate adaptation, making it difficult to distinguish routine upgrades from investments motivated by resilience to rising temperatures. Wildfire risk can partly be mitigated by household-level decisions but also depends on institutional interventions such as forest management; I leave its analysis to future research, and, in this paper, focus on wind risk.

Although households cannot fully eliminate their exposure to hurricanes, they can undertake a range of modifications to reduce potential losses. FEMA and other public agencies provide guidance on recommended household-level adaptation measures (see, e.g., FEMA, 2020b). The main wind-related adaptation actions include replacing doors and windows with impact-resistant alternatives, installing storm shutters, reinforcing doors, and strengthening roofs through the use of straps or other structural reinforcements. These investments typically require building permits because they involve permanent modifications to the building envelope or structure, and I observe all of them in the permit data. By contrast, minor or temporary measures that do not alter the building structure – such as removable storm shutter panels – are generally exempt from permitting requirements.

An important institutional feature is that local building codes in riskier areas often mandate specific hurricane-resistance standards. In designated "Wind-Borne Debris Regions" – most notably the High-Velocity Hurricane Zone (HVHZ) comprising Miami-Dade and Broward counties – building codes require that when components of the building envelope are installed or replaced, they must meet heightened hurricane-resistance standards, such as impact-resistant windows, reinforced roofing, and approved storm shutters (International Code Council, 2018, Section 1609.2). This matters for the analysis not because such modifications would be missing from the data – permits would still be required – but because the decision to undertake these upgrades may not be entirely attributable to a household's voluntary choice to adapt.

Crucially, however, existing buildings are typically grandfathered into current codes. Homeowners are *not* required to upgrade the building unless they undertake renovation work, in which case only the specific modification must comply with prevailing standards (for example, replacing windows in a mandate area requires installing impact-resistant ones).[5] As a result, a house located in a Wind-Borne Debris Region may legally retain its original, non-code-compliant components indefinitely, unless the homeowner chooses to replace them. For example, many households choose to keep the original windows, which in general last indefinitely. Households therefore retain substantial discretion over whether and when to undertake adaptation projects: even in areas where building codes impose resilience requirements on upgrades, the *decision* to engage in these projects

[5]The requirement to bring an *entire* structure up to code triggers only when a renovation exceeds 50% of the building's value (FEMA, 2010). The types of investments studied here do not typically meet that threshold.

remains largely at the household level. This institutional structure allows the observed permit activity to be interpreted as reflecting individual household choices to adapt to climate risk, even in areas subject to the building code mandate. Comparing adaptation decisions across mandate and non-mandate areas will nevertheless allow me to better understand the mechanisms through which political affiliation shapes adaptation behavior (see Section 4).

To determine whether each property is subject to a building code mandate, I proceed as follows. First, all properties in the HVHZ (Miami-Dade and Broward counties) are classified as subject to the mandate. Second, outside the HVHZ, the Florida building code imposes the mandate on all properties with a basic wind speed of 140 mph or higher, based on the 2008 ASCE 7-05 wind zones (or, since 2022, the 2021 ASCE 7-22 wind zones), as well as on all properties within one mile of the coastline in areas with wind speeds between 130 and 140 mph. I obtain the wind-zone shapefiles from the ASCE website and use them to geocode each property.[6] In Section 4, I conduct my analysis separately for properties in mandate and non-mandate areas.

2.1.4 Identifying Wind Adaptation Permits

To identify which permits relate to hurricane adaptation, I parse the textual description of each of the approximately 13 million single-family residential permits (2014–2024) in the Cotality data for Florida and apply a keyword-based classification. The procedure has three stages. First, I compiled an initial list of candidate keywords associated with hurricane-related investments using FEMA guidance documents on residential wind retrofits.[7] There are three main types of adaptation investments covered in the FEMA documents: (1) impact-resistant windows and doors, (2) storm shutters, and (3) structural reinforcements (mostly for the roof). Original windows and doors, as well as the house's structural elements, generally last indefinitely, so permits for these upgrades are likely to capture voluntary adaptation. For roofs, I follow the FEMA document and focus on reinforcement retrofits – such as secondary water barrier installation and roof strapping – rather than full roof replacements, which are typically dictated by the natural lifecycle of the roofing material (20–30 years) and thus would *not* reflect voluntary adaptation decisions.[8]

This initial list included terms that are highly specific to adaptation (e.g., "hurricane shutters," "impact wind") but also terms that are insufficiently specific on their own (e.g., "wind," which also appears in permits for wind turbines or generators). The 14 keywords that appeared in this initial list are: *wind*, *hurricane*, *strap*, *clip*, *anchor*, *barrier*, *mitigation*, *resistant*, *shutter*, *storm*, *impact*, *shelter*, *safe room*, and *roof*.

[6] There is essentially no difference between the two vintages of the wind-zone maps.

[7] Specifically, I provided the FEMA guidance document "Protect your property from severe winds" (FEMA, 2020b) to GPT-4o and prompted it to extract keywords that could identify wind-adaptation investments in permit descriptions. The resulting list was extensive and served as a starting point for the manual curation described below.

[8] Indeed, in the data roof replacements permits appear with equal frequency in areas at high and low exposure to hurricanes (see Appendix B.2). Consistent with this, the FEMA guidelines recommend reinforcing existing roofs but do not recommend replacing an entire roof as an adaptation measure; they recommend to use impact-resistant materials only when a roof is already being installed, recognizing that full replacements are driven by the natural lifecycle of roofing materials.

To refine the classification, for each keyword I manually reviewed up to 1,000 randomly selected permits containing that keyword. Based on this review, I compiled – separately for each keyword – two lists: a list of *complementary* words whose co-occurrence with the keyword clearly identifies the permit as wind-adaptation-related, and a list of *exclusion* words whose co-occurrence clearly identifies the permit as unrelated. For example, the keyword *barrier* is associated with hurricane adaptation when it co-occurs with *wind*, *hurricane*, or *secondary* (referring to secondary water barriers installed under roof shingles), but not when it co-occurs with *vapor* or *moisture* (indicating vapor or moisture barriers unrelated to hurricane protection). Similarly, the keyword *wind* identifies adaptation permits when it appears alongside terms such as *impact*, *anchor*, *bracing*, or *tempered*, but not when it co-occurs with *turbine* or *generator*.[9] Third, I constructed an additional set of general exclusion words that are applied to all permits to identify which are definitely not related to wind adaptation, regardless of whether any other word in the permit description triggered the match.[10]

Finally, I remove permits that are clearly related to repairs for existing storm damage rather than proactive adaptation. A permit is flagged as a repair if its description contains any of the words *damage*, *damaged*, *dmg*, *repair*, or *rebuild*, or if it contains the name of a named Florida hurricane (e.g., Irma, Michael, Ian, Milton, Charley, or any of the other major storms to have made landfall in the state). These permits typically reflect reconstruction work following a hurricane rather than voluntary adaptation investments.

To summarize, a permit is flagged as related to wind adaptation if and only if: (1) it contains at least one of the 14 wind-related keywords; (2) it also contains at least one of the complementary words associated with that keyword; (3) it contains none of the exclusion words, whether from the keyword-specific list or the general list; and (4) it is not flagged as a storm-damage repair. The complete taxonomy of keywords, complementary words, and exclusion words is reported in Appendix Table B.2, and Appendix Table B.3 provides a few examples of permit descriptions for each major keyword pair.

While the full taxonomy involves a large number of possible keyword combinations, the highly standardized language of permit descriptions means that a small number of word pairs account for the vast majority of classified permits in practice. Table 1 shows the 12 most frequent keyword–complement pairs (sorted by frequency) and their frequency among the permits classified as wind-related.[11] Out of approximately 13 million single-family residential permits, 580,103 are identified as wind-related – about 4.5% of the total. The most frequent pairs are: *impact wind* (320,312 permits), *shutter wind* (112,529), *hurricane shutters* (39,374), *shutter storm* (22,877), *door impact* (18,140),

[9] Note that some complementary terms in the code are multi-word phrases (e.g., "storm window," "debris prot") rather than single words, which further sharpens the classification.

[10] The general exclusion list is: traffic, inspect, Stiltz, flood light, hvac, pool, spa, kitchen remodel, bathroom remodel, demolition, flood zone determination, elevator, fence, seismic, earthquake. Note that Stiltz is a brand of home elevators, unrelated to stilts.

[11] When a keyword and its complement can each serve as the other's match (e.g., "impact" as the keyword with "window" as complement, or vice versa), I group them together, ordering the two words alphabetically. A small number of keywords – such as *anchor* – are sufficiently specific that no complement is required, though keyword-specific exclusion words still apply.

roll shutter (11,329), *barrier secondary* (8,856), *anchor* (6,741), *roof truss* (6,582), *hurricane protection* (4,989), *impact shutter* (2,663), and *panel storm* (2,517). Together these 12 pairs account for 96% of all classified wind permits. The dominance of impact windows and storm shutters is consistent with standard hurricane protection practices in Florida, while the presence of roof truss reinforcement reflects the importance of roof-to-wall connections in hurricane-resistant construction.

Table 1: Wind-Related Adaptation Keywords and Frequencies

Climate Pair	Frequency	Cumulative Probability
impact wind	320,312	0.55
shutter wind	112,529	0.75
hurricane shutters	39,374	0.81
shutter storm	22,877	0.85
door impact	18,140	0.88
roll shutter	11,329	0.90
barrier secondary	8,856	0.92
anchor	6,741	0.93
roof truss	6,582	0.94
hurricane protection	4,989	0.95
impact shutter	2,663	0.96
panel storm	2,517	0.96

Note: Each row shows a keyword–complement pair used to classify building-permit descriptions as wind-related, and the frequency of this pair in the dataset. Repair permits are excluded. These 12 pairs account for 96% of all classified wind permits; the remaining 4% are distributed across approximately 90 less frequent pairs.

An alternative approach would be to use a large language model (LLM) to classify each permit directly. Two features of the data make this less attractive than it may seem. First, permit descriptions are very short – typically 10 to 30 words – giving the model limited context to distinguish wind-adaptation permits from unrelated ones. In a manual validation exercise, direct LLM classification yielded substantially more errors than the keyword-based procedure (mostly because LLM are not very conservative in flagging permits as relating to adaptation, resulting in many false positives). Second, because the language of permit descriptions is highly standardized, the marginal benefit of a more flexible classifier is small: as Table 1 shows, a handful of word pairs account for the vast majority of classified permits (carefully manually reviewed).

In addition to the wind-adaptation classification, I flag permits related to *new construction* by searching for the phrase "new const" in the permit description. This flags only a small fraction of the permits, as most of the permits are in fact not related to new construction. Wind permits on new construction projects reflect builder or developer choices typically driven by code compliance rather than by the homeowner's voluntary decision to adapt. I use this flag in robustness tests in Section 3.5, where I verify that the main results hold with or without those related to new construction.

2.2 Property Characteristics and Ownership Histories

I supplement the permit data with two additional Cotality datasets. The *property dataset* (tax assessor records) provides yearly characteristics for each parcel, including address, year built, and time-varying attributes such as assessed value, improvement value (the value of the structure), square footage, and number of bedrooms and bathrooms. The *ownership dataset* – constructed from deeds records – tracks ownership transitions and includes owner names, transaction dates and amounts, and indicators such as the presence of a mortgage. Using these two datasets, I reconstruct the full ownership history of each property and build a property–year–owner panel in which each observation corresponds to a specific individual (or multiple individuals) owning a certain property in a certain year. When ownership transitions occur within a calendar year, permits are assigned to the owner whose tenure interval contains the permit application date (which I take to be the date the household made the investment decision).

2.3 Political Identity (L2)

The L2 voter file is a commercially maintained, nationwide voter-registration database widely used in political science and applied microeconomics. It contains individual-level records including each registrant's full legal name, demographic attributes (age, gender, and race/ethnicity), residential address, and – crucially – party affiliation. For Florida, L2 also provides enhanced attributes such as education, estimated net worth, religion, primary language, and charitable or political donation histories for a subset of voters. Updated snapshots are released regularly; for Florida they are available beginning in 2014, which defines the start of the analysis window.

To link voters to property owners, I merge the L2 voter file with the Cotality ownership dataset. Because neither dataset offers a common unique identifier, the merge requires a structured two-step linkage procedure. First, I perform an exact address match using standardized address components – house number, street name (after normalization and abbreviation handling), city name, state, and five-digit ZIP code. Only records with perfectly coinciding standardized addresses are retained as candidate matches. Second, for each candidate address match, I compare the owner name in Cotality to the voter name in L2 using fuzzy-string similarity. Specifically, I apply the Token Set Ratio algorithm, which is robust to reordered name components (e.g., "Smith John A." vs. "John A. Smith") and partial matches involving middle initials. A pair is classified as a valid match if the similarity score is at least 80 percent (a standard threshold in name-matching applications). This step helps ensure that the individual owner – rather than another adult at the same address – is correctly linked to the corresponding voter record.

This procedure successfully matches at least one owner to the L2 voter file for approximately 72% of properties at some point in time during 2014–2024. For years in which a matched owner's L2 record is missing (e.g., because the voter file snapshot for that year is unavailable), I impute demographic and political attributes using forward and backward fill within each owner–property spell. The resulting dataset identifies the political affiliation and demographic characteristics of each property owner, enabling analysis of how political orientation shapes adaptation behavior.

I classify each property–owner–year into a party affiliation based on the registered affiliation of its owners. A property is classified as Republican if all matched owners are registered Republican, or if the household contains Republicans together with unaffiliated or independent voters; Democrats are classified analogously. All others are classified as "other".

This classification procedure necessarily identifies the political affiliation only of homeowners who are registered voters residing at the property. It will not identify the affiliation of renters, institutional owners, owners holding property via LLCs, owners of second homes, or unregistered voters. All such cases are classified as "other," and interpreting their adaptation propensity is difficult, which is why the analysis focuses on comparing Republicans and Democrats.

2.4 Estimated Household Income and Household Characteristics

Data Axle is a large-scale commercial consumer database that aggregates information from public records, credit headers, marketing files, and other proprietary sources. For each address-year, it provides household-level attributes including estimated household income and a children-in-household indicator, both of which I use as controls in the regressions. Data Axle reports up to five identifiable household members per address-year, which increases the likelihood of identifying the specific owner associated with a given property.

To integrate Data Axle with the Cotality ownership records, I apply the same two-step matching protocol used for the L2 voter file: exact address matching followed by fuzzy name comparison using the Token Set Ratio algorithm and the same 80-percent similarity threshold. This procedure matches approximately 81% of properties to a Data Axle record at some point during the sample period. As with the L2 data, I apply forward and backward fill within owner–property spells to impute missing years.

The resulting unified property–owner–year dataset combines Data Axle's estimated household income and children indicator with the political affiliation and demographic attributes obtained from the L2 voter files.

2.5 Summary Statistics

The final analytical dataset is constructed at the property–year–owner level and contains approximately 61 million observations spanning 2014–2024. Each observation represents a specific individual (or multiple individuals) owning a given property in a given year. About 7.7 million observations (12.7%) have at least one permit filed in that property-year by that owner; approximately 464,000 observations (0.76%) have a wind-related permit (sometimes, multiple wind-related permits are filed for the same property-year-owner; my indicator of wind adaptation measures whether at least one permit in a given property-year-owner is classified as wind-related).

Table 2 presents summary statistics comparing Republican and Democratic households across key dimensions. Republicans have higher average income ($101,134 vs. $81,706), own more valuable homes ($343,803 vs. $267,704), and live in slightly newer properties (1988 vs. 1984 average year built). The two groups are similar in average age (approximately 59 years) and in the probability of residing

in a building code mandate area (about 57–59%). Household composition differs substantially: Democratic households are more likely to be female-headed (34% vs. 22%) and more racially diverse.

Table 2: Household Characteristics by Political Affiliation

Variable	Republicans	Democrats	Diff. p-value
Owner age	59.27	59.40	0.00
Annual income ($)	101,134	81,706	0.00
Year built	1988	1984	0.00
Tenure at house (years)	10.68	11.57	0.00
House value ($)	343,803	267,704	0.00
Any wind permit (%)	0.94	0.88	0.00
Any permit (%)	14.16	13.18	0.00
Mandate area	0.57	0.59	0.00
Gender composition			
Female household	0.22	0.34	0.00
Mixed-gender (M/F)	0.49	0.38	0.00
Male	0.27	0.24	0.00
Male–Male (MM)	0.01	0.01	0.00
Female–Female (FF)	0.01	0.02	0.00
Race / ethnicity			
Hispanic	0.13	0.16	0.00
White	0.68	0.41	0.00
Black	0.01	0.23	0.00

Note: The table reports mean household characteristics for Republican and Democrat homeowners in Florida, 2014–2024. Political affiliation is assigned using L2 voter-file records; a property is classified as Republican if all matched owners are registered Republican or if the household contains Republicans together with unaffiliated or independent voters; Democrats are classified analogously. "Any permit" equals one if the owner of a property in a given year filed any permit applications; "Any wind permit" equals one if the owner filed any permit classified as wind-adaptation in that year. Both are expressed as unconditional annual averages in percentage points. "Mandate area" is the share of households located in a Florida Building Code Wind-Borne Debris Region. The final column reports the p-value from a two-sided t-test of equal means (proportions test for categorical variables).

Notably, in the raw data Republicans are *more* likely to have both wind permits (0.94% vs. 0.88%) and permits in general (14.16% vs. 13.18%). This unconditional difference reflects the fact that Republicans tend to have higher incomes and more valuable homes – characteristics strongly associated with permit activity. As shown in Section 3, this pattern reverses once observable household characteristics and local conditions are controlled for: conditional on income, home value, and fine geographic fixed effects, Republicans are significantly *less* likely to file wind-adaptation permits than Democrats.

2.6 Validation: Wind Permits and Hurricane Risk

Next, I turn to validating the wind-adaptation measure extracted from the permit data. To do so, I examine whether it lines up with hurricane risk: a necessary condition for the permit-based measure to capture genuine climate adaptation is that properties facing higher hurricane risk should file more

wind-adaptation permits, while general permitting activity – which reflects routine maintenance and renovation unrelated to climate – should be largely unresponsive to hurricane risk.

As a first, more informal, step, Figure 1 maps permitting activity across Florida census tracts. Panel (a) reports, for each tract, the share of property–owner–year observations with a wind-adaptation permit; panel (b) does the same for all non-wind permits. To make the two panels comparable, the color bins of each map are defined as multiples of the corresponding statewide average rate (ranging from one-sixth of the average to six times the average). The figure shows that general permitting rates are much more uniform across the state, whereas wind-related permits concentrate along the southern coasts, which are known to be more exposed to hurricane risk.

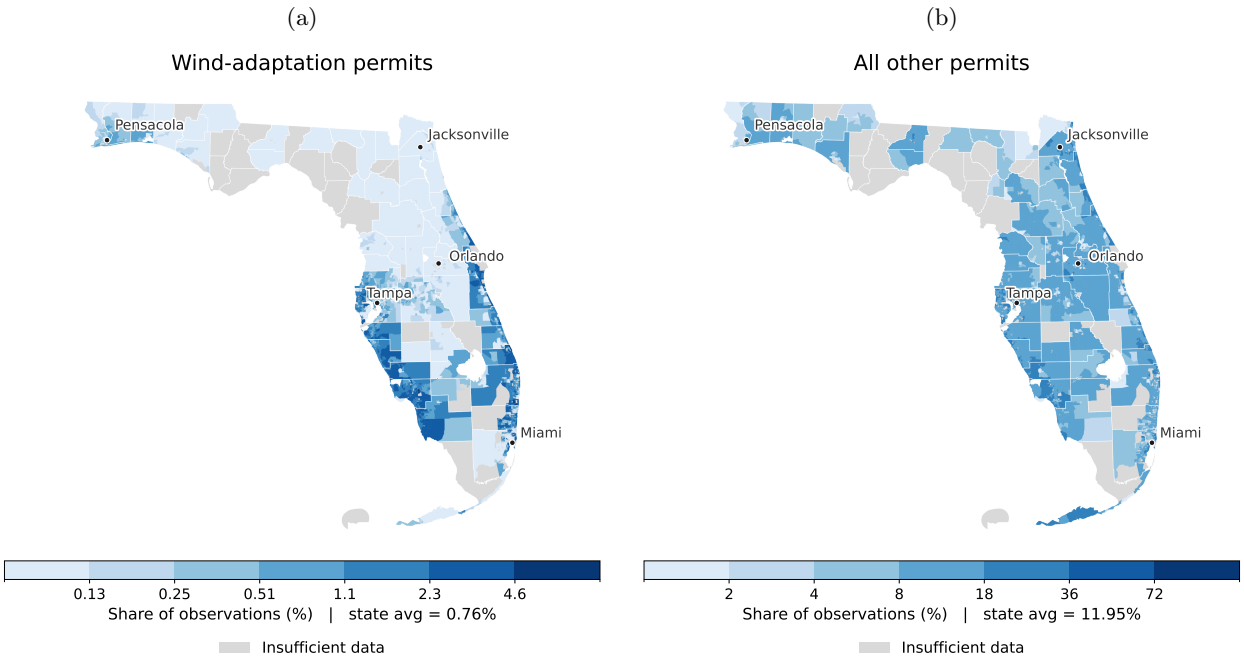
To study the relation between adaptation and risk more formally, I measure hurricane risk using the FEMA National Risk Index (NRI), a publicly available dataset that provides hazard risk metrics at the census-tract level, and follow the FEMA's definition of expected annual loss to build a hurricane risk measure at the property level.[12]

Figure 2 plots the wind-adaptation permit rate (left panel) and the non-wind permit rate (right panel) by decile of hurricane risk. The contrast is striking. Wind-adaptation permits rise sharply and monotonically across the risk distribution: properties in the top decile file wind permits at roughly 25 times the rate of those in the bottom decile. Non-wind permits, by contrast, are close to flat across the risk distribution, with a slight upward gradient that likely reflects the fact that higher-risk coastal properties tend to be more valuable and thus more likely to undergo renovations of all types. Appendix B.2 replicates this exercise on a particularly informative subset of non-wind permits – roof-replacement permits, which are driven by the natural lifecycle of roofing materials (20–30 years) rather than by hurricane risk – and shows that they are similarly flat across the risk distribution, providing an additional placebo for the wind-adaptation measure.

While these patterns are a useful validation of the wind-adaptation measure, their interpretation is complicated by the fact that hurricane risk changes smoothly across space, so significant variation in risk only happens across geographies; but of course, many factors vary across geographies besides hurricane risk – including local building codes, insurance conditions, and demographic composition. Indeed, the main analysis of this paper will address these confounds by fixing tight geographic fixed effects (zip code × year, or zip code × year combined with property fixed effects in a two-way fixed-effects specification), which absorb all cross-sectional variation in risk. Nevertheless, the strong gradient in wind permits, combined with the much lower gradient in other, non-wind-related permits, provides reassurance that the wind-adaptation permit classification captures risk-responsive investment behavior.

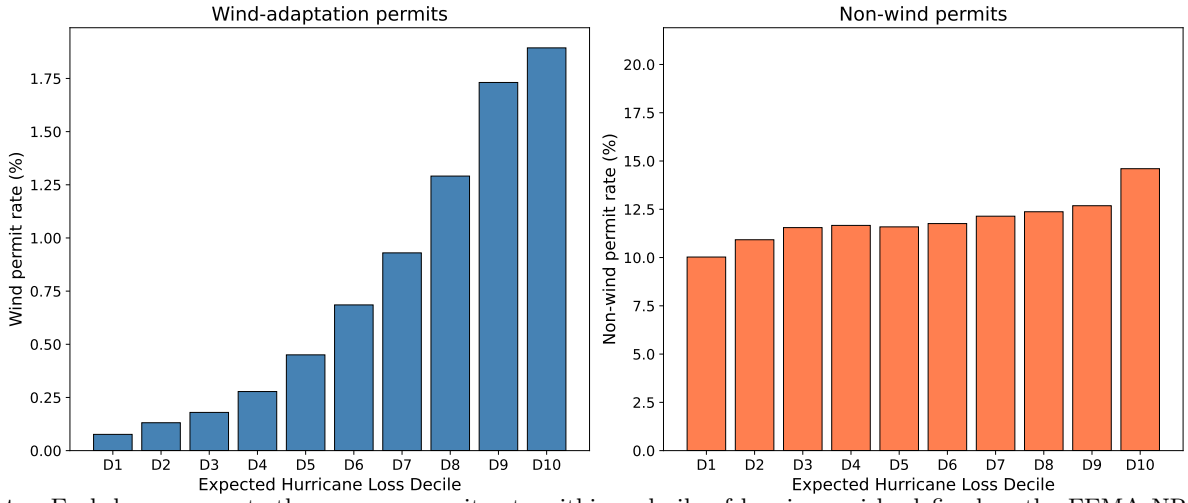
[12]The measure is constructed as the product of the estimated frequency of the events and the expected loss for each property given a hurricane event. Note that the measure is purely cross-sectional; hurricane risks change slowly over time, and the period of my analysis is too short to observe significant changes in risk; this is also evidenced by the fact that the hurricane risk maps used to define the building code mandates are essentially the same in 2008 and 2021.

Figure 1: Building permit activity across Florida census tracts



Note: Each panel maps census-tract-level permit activity over the full sample of approximately 61 million property–owner–year observations, 2014–2024. Panel (a) shows the share of observations with at least one wind-adaptation permit; panel (b) shows the share with at least one non-wind permit. In each panel, color bins are multiples of the corresponding statewide average rate (bin boundaries at 1/6, 1/3, 2/3, 1.5, 3, and 6 times the average, labeled in absolute percent), so that comparable shades indicate a comparable position relative to the state average. Tracts with fewer than 500 observations are shown in gray.

Figure 2: Wind-adaptation permits and hurricane risk



Note: Each bar represents the average permit rate within a decile of hurricane risk, defined as the FEMA NRI expected annual loss at the property level. The left panel plots the wind-adaptation permit rate; the right panel plots the rate for any non-wind building permit (i.e., property-years with at least one permit but no wind-adaptation permit). Deciles are computed over the full sample of approximately 61 million property-owner-year observations.

3 Results

This section presents the main results of the paper, studying how registered Republican and Democrat homeowners differ in their propensity to file wind-adaptation permits, controlling for many individual- and property-level characteristics.

3.1 Empirical Specification

The baseline estimating equation is:

$$WindPermit_{iot} = \alpha + \beta\, Republican_{iot} + \gamma\, X_{iot} + \delta_{g\times t} + \varepsilon_{iot},$$

where $WindPermit_{iot}$ is an indicator equal to one if owner o files at least one wind-adaptation permit for property i in year t, and $Republican_{iot}$ is an indicator equal to one if the owner o of property i is a Republican at time t (Democrats is the excluded category). The coefficient of interest, β, measures the difference in wind-permit filing rates between Republicans and Democrats, conditional on covariates and fixed effects.

The vector X_{iot} includes homeowner characteristics (separately for each owner) – income, gender, ethnicity, age, education, religion, language, net worth, presence of charitable contributions, presence of children, and presence of multiple owners – as well as property attributes such as assessed value, year built, years since last renovation, square footage, bedrooms, bathrooms, and ownership tenure, all entering with flexible nonparametric specifications (all reported in Table B.6 in the Appendix). Every variable has an extra category for missing values (or "other" for political affiliation). The term $\delta_{g\times t}$ denotes geography-by-year fixed effects. In the baseline specification, g is a zip code, so β is identified from variation across households within the same zip code and year: that is, among homeowners facing the same local hazard conditions and building codes. I also estimate a more demanding two-way fixed-effects specification that adds property fixed effects on top of the zip code $\times$ year fixed effects, exploiting differences across owners of the *same* property. The advantage of the latter specification is that it fully controls for any unobservable differences in property characteristics that is fixed over time; the disadvantage is that it identifies the results effectively from a much smaller universe of houses – those that are owned by both Democrats and Republicans at different points in time. Standard errors are clustered at the zip-code level throughout, and therefore account for potential error correlation within zipcode contemporaneously and across time.

3.2 Main Results

Table 3 presents the baseline results. Note that to make results comparable across different specifications (here and below), and to aid interpretation, all coefficients in the table and figures are expressed as a fraction of the baseline filing probability (0.76 percentage points per property-owner-year). Therefore, for example, a coefficient of -0.065 means Republicans have a probability of

adapting that is 6.5% lower than that of Democrats.[13]

Table 3: Effect of Political Affiliation on Wind Permit Adoption

	Dep. var.: Wind permit (% of baseline)	
	(1)	(2)
Republican	−0.065***	−0.046***
	(0.009)	(0.012)
Other/missing	−0.024***	−0.009
	(0.008)	(0.012)
Controls	Y	Y
Fixed effects	Zip × Year	Zip × Year + Property
Clustering	Zip	Zip
Observations	60,714,431	60,644,537
R^2 (overall)	0.018	0.111
R^2 (within)	0.002	0.001

Note: Table reports results of a regression of an indicator of wind-related permit filing on political affiliation, controls, and fixed effects. The dependent variable is an indicator equal to one if the property has at least one wind-related permit in a given year. Coefficients are expressed as a fraction of the baseline probability of filing a wind-related permit (0.76 percentage points); for example, −0.065 means that the probability that Republicans file a wind-adaptation permit is lower than that of Democrats, by 6.5% of the baseline. The omitted party category is Democrat. Controls include owner age, gender, household income, net worth, ethnicity, education, religion, language, charitable contribution indicators, presence of children, and multiple-owner status, as well as property value, year built, years since last renovation, square footage, bedrooms, bathrooms, and tenure at the property (square footage, bedrooms, and bathrooms are time-invariant and absorbed by the property fixed effects in column 2). Column (1) includes zip code × year fixed effects. Column (2) includes zip code × year fixed effects together with property fixed effects (a two-way fixed-effects specification). Standard errors clustered at the zip-code level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Full coefficient estimates are reported in Table B.6 in the Appendix.

Column (1) reports a first set of results, obtained using zip code × year fixed effects, and including all the controls mentioned above. The estimated coefficient on the Republican dummy variable indicates that the probability that Republicans file a wind-adaptation permit in a certain year is, indeed, 6.5% lower than that of Democrats. The "other/missing" party category shows a coefficient much closer to zero (but this coefficient is difficult to interpret because this group of owners is very heterogeneous).

Figure 3 plots the estimated coefficients on selected control variables from this baseline specification. Several patterns are noteworthy. Higher income is strongly associated with greater wind-adaptation activity: moving from the lowest to the highest income bin raises the wind filing probability by about 30% of the baseline, with an approximately linear gradient across bins (panel a). Property value shows a similar, mostly monotonic increasing, pattern (panel b). Tenure at the property is negatively associated with filing, consistent with the idea that homeowners are more likely

[13]More precisely, a coefficient of −0.065 means Republicans have a probability of adapting that is lower than that of Democrats, by an amount that is 6.5% of the baseline probability. To a first-order approximation, this is equivalent to stating that their probability is 6.5% lower than that of Democrats.

to do renovations in the early years of ownership (panel c).

Panel (d) reports the gender coefficients, with single-female owners as the excluded category. Single males are less likely to file wind permits than single females (-0.089, i.e., 8.9% of the baseline). All multi-owner categories – male-female (MF), female-female (FF), and male-male (MM) – show higher filing rates, with the MF category having the largest coefficient ($+0.128$). Full coefficient estimates for all controls are reported in Table B.6 in the Appendix (note that the Appendix table does not scale coefficients by the baseline probability of 0.76%).

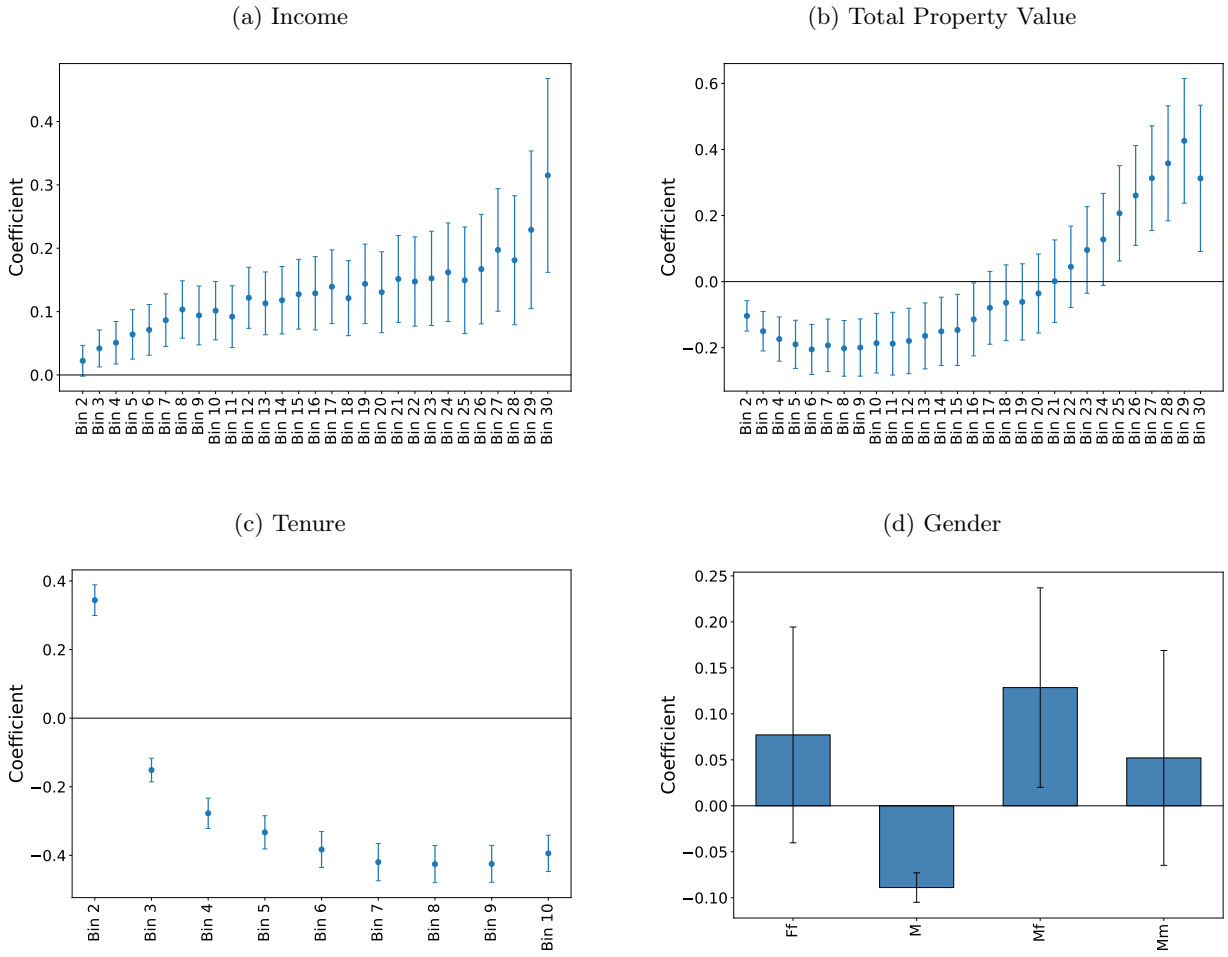
Column (2) tightens the comparison further by adding property fixed effects on top of the zip code $\times$ year fixed effects (a two-way fixed-effects specification). In this specification, identification comes from *within-property* variation across owners of different parties: when a Republican replaces a Democrat (or vice versa) in the same dwelling, does the new owner invest differently in climate adaptation? Even in this demanding specification, the Republican gap remains significant at -0.046 ($p < 0.01$), that is, 4.6% of the baseline rate. This specification is particularly powerful because it allows me to identify the effect of political views on climate adaptation by comparing the *same* property under different owners, thus eliminating the possibility that the results are driven by (observed or unobserved) differences in the properties themselves.

The difference between -6.5% in column (1) to -4.6% in column (2) can reflect two distinct channels. First, it could reflect unobserved property selection: Republicans might be more likely to buy houses within each zip code-year that are less likely to need adaptation; indeed, Republicans tend to buy systematically different properties, including more valuable and newer houses. Second, the sample from which the two-way fixed-effects specification is identified is different from (and significantly smaller than) the full sample, and the partisan gap could be smaller in that subsample because that sample differs in other dimensions. For this reason, I report the results both with and without property fixed effects.

To better understand the role of observable characteristics, Appendix Table B.4 reports the Republican coefficient from a "waterfall" of progressively richer specifications. Without any controls or fixed effects, Republicans are actually *more* likely to file wind permits than Democrats: the raw unconditional gap is positive, as noted in Table 2. Adding zip code $\times$ year fixed effects reduces the coefficient but it remains positive. The sharpest change occurs when property characteristics are added (assessed value, year built, years since renovation, square footage, bedrooms, bathrooms, tenure, and multiple-owner indicator): the Republican coefficient turns negative, indicating that much of the unconditional difference reflects the types of properties Republicans own. Adding demographic controls (gender, ethnicity, age, religion, language, children) further widens the gap, while adding socioeconomic controls (income, net worth, education, charitable contributions) produces only modest additional changes. The pattern is qualitatively similar across both fixed-effects structures (Panels A and B).

While the next section provides some more discussion of the economic magnitude of the results, it is useful to mention potential concerns with the interpretation of these results. The most important concern, naturally, is that the results may be driven by unobservable differences in the personal

Figure 3: Estimated coefficients on selected control variables – baseline specification



Note: Each panel plots the estimated coefficients and 95% confidence intervals on the indicated control variable from the baseline specification with zip code × year fixed effects (column 1 of Table 3). As in the table, coefficients are expressed as a fraction of the baseline filing probability (0.76 percentage points). The omitted categories are the lowest income bin, the lowest property-value bin, the shortest tenure group, and single female, respectively.

characteristics of Republicans and Democrats, or the kind of houses they buy, that correlate with their hurricane-related investment choices. Indeed, we have already seen that controlling for observable characteristics is important in determining the results, since unconditionally Republicans are more likely to invest in permits of all types, including wind adaptation permits: this suggests that a variety of house and individual characteristics do matter for climate adaptation investment, and they do differ systematically between Republicans and Democrats.

Among these concerns, the possibility that Republicans and Democrats may systematically buy different properties that in turn require different types of investments is addressed by specification (2) of the table, with property fixed effects. Another possibility is the omission of relevant individual-level variables. I try to address this concern as best as possible by including, as described above, a large variety of household-level characteristics, including estimated income and net worth.

A plausible alternative explanation for my results worth discussing explicitly – precisely based on an omitted individual characteristic – is that Republicans may be more likely to buy property insurance (which includes wind coverage) than Democrats, and they therefore have less incentive to adapt. Unfortunately, we cannot directly see insurance coverage in the data. To directly address this concern, however, in Section 3.5 I report results from a robustness check that restricts the sample to properties purchased with a mortgage that are within 20 years of the purchase date. In these properties, the mortgage is likely to still be active, therefore requiring insurance from homeowners. The results hold in this subsample with similar economic magnitudes, suggesting that the different propensity for adaptation between Republicans and Democrats is not driven by differential insurance coverage.

Another possibility that I can directly exclude is that (conditional on observables) Republicans are simply less likely to do the kind of investments that require permits in general, and, as a mechanical consequence, they may end up doing fewer wind-related investments as well. I address this possibility in section 3.4, where I show that in fact, the propensity of Republicans to file permits of any kind is similar to that of Democrats (or, in specifications where it is lower, it is just slightly so), while they are strongly less likely to file wind-related permits.

Finally, it is worth noting that while even a very extensive list of controls cannot fully dispel a concern for omitted variable, the additional results exploring the mechanism in section 4 provide further evidence that lines up with the interpretation of the results as reflecting the effect of political views on climate adaptation investment.

3.3 Magnitudes

The estimated gap of 4.6–6.5% of the probability of filing a wind-adaptation permit between Democrats and Republicans may appear modest overall (given a baseline probability of 0.76 percentage points per property-owner-year). In this section, I make some comparisons that can help put it in context.

First, the effects of political views on climate adaptation are comparable to the effects of moving roughly two to three income deciles. As shown in Figure 3a, each income decile is associated with an increase of about 2.5% of the baseline rate, and a back of the envelope calculation reveals that the

6.5% estimated Republican gap is equivalent in magnitude to a difference of about $40,000–$60,000 in annual household income at the median.

Second, the effect of politics is similar in magnitude to the gender gap. Single-male owners are 8.9% less likely than single-female owners to file a wind-adaptation permit (Table B.6, column 1), roughly the same magnitude as the partisan gap.

Third, these magnitudes are very much in line with other studies documenting the real effects of political attitudes. Kempf and Tsoutsoura (2021), for example, find that partisan affiliation shifts credit rating analysts' expected downgrades in a quarter by about 1/100th of a notch; that is, 11% of the baseline rate – the same order of magnitude as the effects documented here.

3.4 Accounting for Permitting Activity

A potential concern with the previous results is that Republicans may simply invest less in home maintenance overall, filing fewer permits in general, and fewer wind-related permits among them. Table 4 addresses this concern with additional analyses.

The table has two panels, corresponding to the two fixed-effects structures from Table 3: zip code × year fixed effects in Panel A, and the two-way fixed-effects specification with zip code × year and property fixed effects in Panel B.

Column (1) of each panel reproduces the baseline wind-permit regression from Table 3: the dependent variable here is the indicator for filing at least one wind-related permit, again scaled by the baseline probability.

Column (2) replaces the dependent variable with an indicator for filing a *non-wind* building permit, i.e., a permit is filed but no wind-related permit (94% of the permit observations). This isolates Republicans' propensity to engage in home-improvement activity that is unrelated to wind adaptation. The number here is much smaller, −1.8% (again, scaled by the proper baseline) in Panel A and indistinguishable from zero in Panel B, therefore substantially smaller than the wind-permit gap. Appendix B.2 repeats this analysis on the particular subset of roof-replacement permits (a natural placebo, since roof replacements are driven by the lifecycle of roofing materials rather than by forward-looking climate preparedness considerations), and finds a similarly small Republican coefficient that flips sign across the two specifications – in sharp contrast to the uniformly negative wind-adaptation gap.

To better understand the difference, column (3) runs again the baseline wind-permit regression, but adds an indicator for any permitting activity as a control. One way to interpret these results is that this regression helps control for omitted variables that affect the propensity to file a wind permit by inducing a different propensity to file permits more generally. The Republican gap declines only modestly, to 4.4% in Panel A and 4.2% in Panel B. The bulk of the partisan difference in wind-adaptation permits cannot be attributed to general differences in home-improvement behavior.

Overall, these results suggest that the partisan gap in wind-adaptation permits is not driven by general differences in home-improvement behavior, but rather is specific to climate-related investment.

Table 4: Accounting for Permitting Activity

Panel A: Zip code × Year fixed effects

	(1) Wind permit (% of baseline)	(2) Non-wind permit (% of baseline)	(3) Wind permit (% of baseline)
Republican	−0.065***	−0.018***	−0.044***
	(0.009)	(0.002)	(0.008)
Other	−0.024***	−0.008***	−0.014**
	(0.008)	(0.002)	(0.007)
Any permit control			Y
Observations	60,714,431	60,714,431	60,714,431
R^2 (overall)	0.018	0.039	0.066
R^2 (within)	0.002	0.009	0.051

Panel B: Zip code × Year + Property fixed effects

	(1) Wind permit (% of baseline)	(2) Non-wind permit (% of baseline)	(3) Wind permit (% of baseline)
Republican	−0.046***	−0.001	−0.042***
	(0.012)	(0.003)	(0.010)
Other	−0.009	0.008***	−0.016
	(0.012)	(0.003)	(0.010)
Any permit control			Y
Observations	60,644,537	60,644,537	60,644,537
R^2 (overall)	0.111	0.137	0.152
R^2 (within)	0.001	0.007	0.047

Note: The dependent variable in columns (1) and (3) is an indicator for filing at least one wind-related permit; in column (2) it is an indicator for filing a non-wind building permit (i.e., a permit is filed but no wind-related permit). Coefficients are expressed as a fraction of the respective baseline probability: 0.76 percentage points for wind permits (columns 1 and 3) and 11.9 percentage points for non-wind permits (column 2). Column (3) adds an indicator for any permit as a control. The excluded party category is Democrat. All specifications include the same controls as in Table 3 and standard errors are clustered at the zipcode level. Panel A uses zip code × year fixed effects; Panel B uses a two-way fixed-effects specification with zip code × year and property fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.5 Robustness

This section reports a number of robustness checks on the baseline results. Table 5 presents two panels corresponding to the two main fixed-effects specifications: zip code × year fixed effects in Panel A, and the two-way fixed-effects specification with zip code × year and property fixed effects in Panel B. Results are qualitatively similar across both panels. The baseline specification is reproduced in column (1) of each panel, whereas the remaining columns report the following robustness results.

Block × year fixed effects. Column (2) of Panel A reports the baseline result with census block × year fixed effects in place of zip code × year fixed effects, restricting identification to households in the same close neighborhood and year. The Republican coefficient is -0.063 ($p < 0.01$), virtually unchanged from the zip-code-by-year baseline of -0.065, demonstrating that the result is robust to the choice of geographic fixed effects.

Never previously adapted. Column (3) of Panel A and column (2) of Panel B restrict the sample to properties that have not previously filed any wind-adaptation permit. Therefore, this column focuses the estimation on first-time adaptation decisions. The Republican coefficient is similar in absolute value to the baseline in Panel A (-6.6%) and significantly larger in Panel B (-7.6% vs. -4.6%). As discussed above, this is consistent with the partisan gap being more pronounced in the first-time adaptation decisions.

Excluding new construction. Column (4) of Panel A and column (3) of Panel B exclude permits flagged as new construction – defined as having a "new construction" keyword in the permit description or being observed within two years of the property's year built. The Republican coefficient is essentially unchanged from the baseline, consistent with the fact that this is a small fraction of the sample (it is also plausible that for new construction, not every component of the project is filed a separate permit with a full description of the work).

Mortgage purchases only. As discussed above, homeowner's insurance coverage is a potential confounding factor in the estimation. Here, I repeat in column (5) of Panel A and column (4) of Panel B the estimation on properties purchased with mortgages, for which insurance is typically required by the lender. I also restrict the sample to properties purchased within the 20 years prior to the permit application date, to ensure that the mortgage is still active and therefore insurance is required. The Republican gap remains significant in both panels: -6.5% in Panel A ($p < 0.01$) and -4.3% in Panel B ($p < 0.05$), with magnitudes similar to the baseline. Overall, the test suggests that the partisan gap is not primarily driven by omitted insurance variation.

Logit and discrete-time hazard specifications. The last two columns of each panel replace the linear probability model with nonlinear alternatives. The Logit column estimates a logit model:

$$\Pr(\mathit{WindPermit}_{iot} = 1) \;=\; \Lambda(\beta\, \mathit{Republican}_{ot} \;+\; \gamma\, X_{iot} \;+\; \delta_{g\times t})\,,$$

where $\Lambda(\cdot)$ is the logistic function, and β is a log-odds ratio. The Hazard column estimates a discrete-time hazard model using a complementary log-log link (implemented via Poisson regression) on the

at-risk sample – that is, property-owner-years up to and including the first wind permit:[14]

$$\Pr(\mathit{WindPermit}_{iot} = 1 \mid \text{at risk}) \;=\; 1 - \exp\big(-\exp(\beta\, \mathit{Republican}_{ot} \;+\; \gamma\, X_{iot} \;+\; \delta_{g\times t} \;+\; h(d_{iot}))\big),$$

where $h(d_{iot})$ is a flexible function of spell duration (implemented as duration dummies) and β is a log-hazard ratio.

Because the baseline filing probability is very low (0.76%), the log-odds ratio from the logit and the log-hazard ratio from the hazard model both approximate the proportional change in the probability of adaptation. Specifically, for small β, $\exp(\beta) \approx 1+\beta$, so a coefficient of -0.050 implies approximately a 5% lower probability (logit) or hazard (cloglog) of filing a wind-adaptation permit.

In Panel A, the Republican coefficient is -0.049 (Logit) and -0.048 (Hazard), both with $p < 0.001$, implying approximately a 5% lower probability/hazard of adaptation – similar to the linear probability model estimates of 6.5%. In Panel B (with property fixed effects), the Logit coefficient is -0.045 ($p < 0.001$) and the Hazard coefficient is -0.057 ($p < 0.001$), implying roughly a 4.5–5.7% lower probability/hazard of adaptation.

Both nonlinear models require dropping observations in fixed-effect groups with no outcome variation (separation), which reduces the sample. This reduction is modest for Panel A (to 49 million for logit and 48 million for the hazard model) but substantial for Panel B (property fixed effects), where only 5.1 million (logit) and 3.6 million (hazard) observations survive, because most properties never file a wind permit. Despite this, the partisan gap remains significant.

Intensive margin. In addition to studying the extensive margin of adaptation, a natural question is whether the partisan gap extends to the *intensive margin* – that is, do Republicans spend differently on housing investments, and specifically on wind-adaptation projects, conditional on making them? I investigate this by looking at the value of the permits reported in the Cotality data. Unfortunately permit values are often noisy (most likely because of inaccurate reporting to the municipalities), with a substantial share of missing or implausible values. In addition, often multiple permits referring to different parts of the projects get assigned the same (large) value, most likely the value of the total project. To address these measurement issues, I winsorize the values at the 90th percentile, or at both the 10th and 90th percentiles. Finally, this analysis is conducted at the individual permit level rather than the property-owner-year level used in the rest of the paper: each observation is a single permit. The sample includes all non-repair permits with positive reported values (approximately 7.5 million permits). The average reported value is about $10,000.

Appendix Table B.5 presents the results of a regression of individual permit value on all the usual controls and fixed effects, plus the party indicator, the indicator of wind-adaptation permit, as well as the interaction between party and wind-adaptation indicator. The table has four columns, corresponding to the two fixed-effect specifications for the two winsorization cases (10% both sides

[14] The complementary log-log model is the natural link for discrete-time hazard data because it maps directly to an underlying continuous-time proportional hazards model. The Poisson regression is numerically equivalent for rare events (see, e.g., Cameron and Trivedi, 2005). The at-risk sample restricts to observations where no prior wind permit has been filed within the ownership spell, and includes spell-duration dummies to capture the nonparametric baseline hazard.

and 10% on the upper end only). In the zip code × year specification, Republicans spend about $75 more on permits than Democrats (roughly 1% of the mean permit value). In the more demanding specification with both zip code × year and property fixed effects, the Republican coefficient drops to essentially zero (about −$16) and is not statistically distinguishable from Democrats' spending. Across all four specifications, the Republican × wind interaction is negative (−$35 to −$41), indicating that Republicans spend relatively *less* on wind-adaptation permits, but it is small in magnitude and not statistically significant. From a quantitative standpoint, all the intensive margin effects of political orientation are at or below 1% of the mean permit value, indicating that the primary channel for political views to affect adaptation is on the extensive, not the intensive margin. It is also useful to remark that it is not clear whether differences in the price paid for a household adaptation investment translates into differences in adaptation effectiveness or quality: they could instead capture aesthetic differences, especially given the fact that the building standards require certain levels of protections to qualify.

4 Mechanisms

The previous sections establish that Republican homeowners are significantly less likely than Democrats to file wind-adaptation permits, and that this gap is specific to climate-related investment. A natural next question is *why* political affiliation predicts adaptation. Understanding the mechanism matters not only for interpreting the results but also for policy design: if the gap reflects differences in climate-risk beliefs, then programs that reframe adaptation around private financial returns (as the My Safe Florida Home program does) – rather than climate risk – may be effective at closing it; if instead it reflects other determinants like differences in adaptation opportunities (e.g. access to materials and labor), different policy interventions would be needed.

We can think of two main reasons for the observed patterns. First, Republicans may hold different beliefs about climate risk and therefore see less value in protective investment, or they may behave as if they held these beliefs driven by political identity (for example, to follow the party line on climate); I refer to this as the *political identity/belief channel*.[15] Second, Republicans and Democrats may differ along some other dimensions, like different access to the material or labor needed for adaptation, different enforcement of permitting regulation, or other unobservable confounders that vary across political parties and incidentally correlate with wind-adaptation behavior; I'll refer to these as the *non-belief channel*.

This section presents four pieces of evidence that help narrow the set of plausible explanations: an analysis of the partisan gap by political intensity, an analysis of adaptation in areas with more or less stringent building code regulation, an analysis of the time variation in the partisan gap, and an analysis of how the gap responds to direct, first-hand hurricane experience. These results are all consistent with the belief/political identity channel. While they do not exhaustively rule out the various non-belief stories, they do rule out at least some versions of them. For example, the fact

[15] While the two are themselves different, it is not possible to distinguish the two with my data.

Table 5: Robustness Checks

Panel A: Zip code × Year fixed effects

	(1) Baseline (0.76%)	(2) Block × Year FE (0.76%)	(3) Never adapted (0.62%)	(4) No new constr. (0.73%)	(5) Mortgage only (0.82%)	(6) Logit	(7) Hazard
Republican	−0.065***	−0.063***	−0.066***	−0.066***	−0.065***	−0.049***	−0.048***
	(0.009)	(0.008)	(0.010)	(0.010)	(0.009)	(0.006)	(0.006)
Other/missing	−0.024***	−0.022***	−0.019**	−0.026***	−0.033***	−0.022***	−0.021***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.006)	(0.006)
Observations	60,714,431	60,713,180	56,218,294	58,313,788	25,519,469	49,291,149	47,832,517

Panel B: Zip code × Year + Property fixed effects

	(1) Baseline (0.76%)	(2) Never adapted (0.62%)	(3) No new constr. (0.73%)	(4) Mortgage only (0.82%)	(5) Logit	(6) Hazard
Republican	−0.046***	−0.076***	−0.048***	−0.043***	−0.045***	−0.057***
	(0.012)	(0.016)	(0.012)	(0.016)	(0.013)	(0.015)
Other/missing	−0.009	−0.037***	−0.007	−0.021	−0.005	−0.018
	(0.012)	(0.013)	(0.012)	(0.016)	(0.013)	(0.016)
Observations	60,644,537	56,126,514	58,230,610	25,290,953	4,782,305	3,360,998

Note: The dependent variable is an indicator for filing at least one wind-related permit in a given year. Columns reporting linear probability model (LPM) estimates express coefficients as a fraction of the respective sample baseline filing probability, shown in parentheses below each column heading. The Logit column reports logit coefficients (log-odds ratios) and the Hazard column reports discrete-time hazard model coefficients (log-hazard ratios); both can be interpreted as approximate proportional effects on the probability/hazard of adaptation (see text). All specifications include the same controls as in Table 3. In Panel A the "Block × Year FE" column reports the baseline result with census block × year fixed effects in place of zip code × year fixed effects, demonstrating robustness to the choice of geographic fixed effects. The "Never adapted" column restricts to property-years where the property had not previously filed any wind-adaptation permit. The "No new constr." column excludes property-years flagged as new construction (permit keyword or within two years of year built). The "Mortgage only" column restricts to properties purchased with a mortgage within the previous 20 years. The Logit column estimates a logit model; observations in fixed-effect groups with no outcome variation (separation) are dropped. The Hazard column estimates a discrete-time hazard model via Poisson regression on an at-risk sample (property-owner-years up to and including the first wind permit), with spell-duration dummies for the nonparametric baseline hazard; separated observations are also dropped. Standard errors clustered at the zip-code level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

that the partisan gap is stronger for those Republicans that donate to the party, and is stronger during the first Trump administration, is harder to square with a differential access to adaptation opportunities (materials and/or labor) between Republicans and Democrats.

4.1 Political Intensity

If the partisan gap in adaptation reflects politically-mediated beliefs about climate risk, one would expect the gap to be larger among homeowners who are more politically engaged. To test this, I exploit federal campaign contribution records from the FEC, which are available in the L2 voter file. Approximately 3.4% of the sample has at least one FEC donation on record – 7.2% of Republicans and 5.3% of Democrats. I split each party into donors and non-donors, creating four categories: Republican donor, Republican non-donor, Democrat donor, and Democrat non-donor.

Table 6 reports the results, with the omitted category being Democrat donor. The pattern is striking. Republican FEC donors – those with the strongest revealed partisan engagement – show the largest adaptation gap: their probability of filing a wind-adaptation permit is 18.8% lower than that of Democrat donors in the zip×year specification (column 1), and 13.2% lower in the two-way fixed-effects specification with zip×year and property fixed effects (column 2). Republican non-donors show a smaller gap of 9.7% (column 1) and 11.8% (column 2). Democrat non-donors fall in between, with a statistically insignificant gap of 3.9% (column 1) and 7.7% (column 2) relative to Democrat donors.

The ordering – Democrat donors adapt the most, followed by Democrat non-donors, then Republican non-donors, then Republican donors – maps directly onto the intensity of partisan identity, consistent with a belief channel in which deeper political engagement amplifies the influence of party-aligned views on climate risk.

4.2 Mandate vs. No-Mandate Areas

Florida's building code imposes mandatory wind-protection standards – including requirements for hurricane straps, impact-resistant windows, and reinforced roofing – in designated Debris Regions along the coast, as discussed in Section 2. Properties outside the mandate boundary face no such requirements; any wind-adaptation investment is purely voluntary. Figure 4 displays the geographic distribution of properties in the sample, distinguishing mandate areas (blue) from no-mandate areas (green). The mandate zone follows the coastline, covering the southeastern coast, the Keys, the Tampa Bay area, and portions of the Panhandle – the regions most exposed to hurricane-force winds.

Before turning to the partisan gap in these two subsamples, Figure 5 replicates the validation exercise from Section 2.6 separately within mandate and no-mandate areas. The positive gradient between hurricane risk and wind-adaptation permits holds in both subsamples, confirming that the permit-based measure captures risk-responsive behavior regardless of the regulatory environment. The gradient is steeper in no-mandate areas, where all wind adaptation is voluntary, than in mandate areas, where code requirements create a baseline level of adaptation activity that partially compresses

Table 6: Political Intensity: FEC Donors vs. Non-Donors

	Dep. var.: Wind permit (% of baseline)	
	(1)	(2)
Republican, FEC donor	−0.188***	−0.132**
	(0.034)	(0.056)
Republican, non-donor	−0.097***	−0.118*
	(0.038)	(0.067)
Democrat, non-donor	−0.039	−0.077
	(0.035)	(0.065)
Controls	Y	Y
Fixed effects	Zip × Year	Zip × Year + Property
Clustering	Zip	Zip
Observations	60,714,431	60,644,537
R^2 (overall)	0.017	0.111
R^2 (within)	0.002	0.001

Note: Table reports results of a regression of wind-permit filing on party affiliation interacted with FEC donor status. The omitted category is Democrat FEC donor. Coefficients are expressed as a fraction of the baseline probability of filing a wind-related permit (0.76 percentage points). An indicator for FEC donor status (any party) is included as a separate control but not reported. "FEC donor" is defined as either owner having at least one federal campaign contribution recorded in FEC filings (approximately 3.4% of the sample). Column (1) includes zip code × year fixed effects; column (2) is a two-way fixed-effects specification with zip code × year and property fixed effects. All specifications include the same controls as in Table 3. Standard errors clustered at the zip-code level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

the risk–permit relationship. Non-wind permitting activity, shown in the right panels, remains flat across the risk distribution in both subsamples.

Table 7 reports the results. Panel A reports estimates with zip code × year fixed effects, and Panel B reports estimates from the two-way fixed-effects specification with zip code × year and property fixed effects. Column (1) of each panel reproduces the full-sample estimate; columns (2) and (3) split the sample at the 2008 mandate boundary. In mandate areas (column 2), the baseline filing rate is 1.2% – roughly twelve times the rate in no-mandate areas (0.10%, column 3) – reflecting the much greater volume of code-required adaptation activity, but also the much greater risk in those areas.

In Panel A, the Republican coefficient in mandate areas is −0.052, indicating that Republicans have a probability of filing that is 5.2% of the baseline lower than Democrats; in no-mandate areas, the Republican coefficient is −0.084: Republicans are a significant 8.4% of the baseline less likely to adapt. In Panel B, the corresponding coefficients are −0.049 in mandate areas and −0.075 in no-mandate areas.[16] Across both specifications, the partisan gap is larger in the no-mandate subsample as in the mandate subsample, though this difference is not statistically significant (mostly due to the fact that the no-mandate subsample has low precision).

[16]Note that because each number is scaled by the baseline probability of its own sample, the full-sample scaled estimate is not just a linear combination of the two subsample estimates.

Table 7: Political Affiliation and Wind Adaptation: Mandate vs. No-Mandate Areas

Panel A: Zip code × Year fixed effects

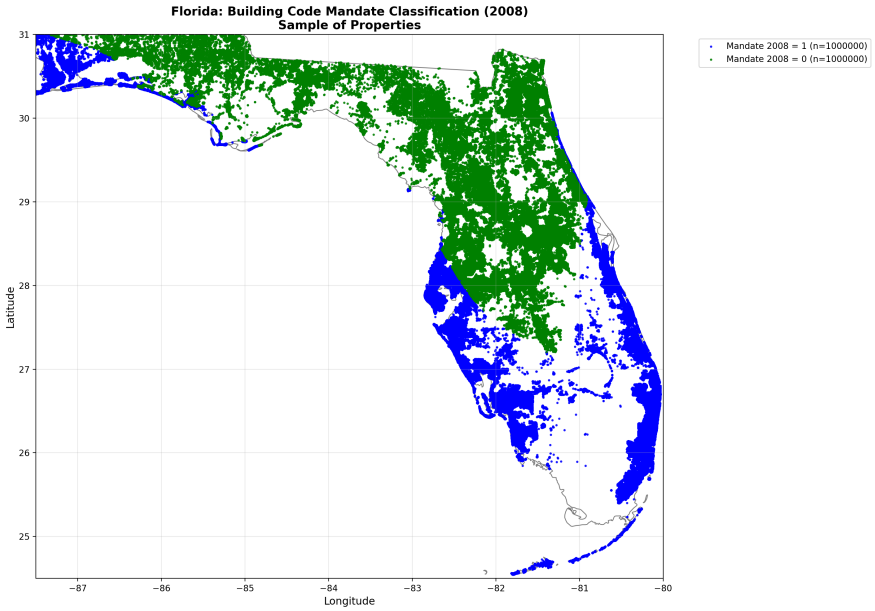
	(1) Full sample (0.76%)	(2) Mandate (1.25%)	(3) No mandate (0.11%)
Republican	−0.065***	−0.052***	−0.084***
	(0.009)	(0.008)	(0.028)
Other/missing	−0.024***	−0.023***	−0.019
	(0.008)	(0.007)	(0.028)
Observations	60,714,431	34,952,939	25,761,407
R^2 (overall)	0.018	0.015	0.004
R^2 (within)	0.002	0.003	0.000

Panel B: Zip code × Year + Property fixed effects

	(1) Full sample (0.76%)	(2) Mandate (1.25%)	(3) No mandate (0.11%)
Republican	−0.046***	−0.049***	−0.075**
	(0.012)	(0.012)	(0.037)
Other/missing	−0.009	−0.015	−0.019
	(0.012)	(0.011)	(0.037)
Observations	60,644,537	34,918,059	25,726,406
R^2 (overall)	0.111	0.108	0.099
R^2 (within)	0.001	0.001	0.000

Note: The dependent variable is an indicator for filing at least one wind-related permit in a given year. Coefficients are expressed as a fraction of the respective sample baseline filing probability, shown in parentheses below each column heading. The omitted party category is Democrat. Column (1) reproduces the baseline specification from Table 3. Column (2) restricts the sample to properties in areas where the Florida Building Code mandates wind-protection upgrades (the High-Velocity Hurricane Zone and surrounding buffer, as defined by the 2008 code boundary). Column (3) restricts to properties outside the mandate area. All specifications include the same controls as in Table 3. Standard errors are clustered at the zip-code level. Panel A uses zip code × year fixed effects; Panel B uses a two-way fixed-effects specification with zip code × year and property fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 4: Florida building code mandate areas



Note: The figure maps properties in the sample by their location relative to the 2008 Florida Building Code wind-protection mandate boundary. Blue points denote properties in the mandate area, where the code requires wind-adaptation measures such as hurricane straps, impact-resistant windows, and reinforced roofing. Green points denote properties outside the mandate area, where wind-adaptation investment is entirely voluntary.

The no-mandate subsample is particularly informative because it isolates a setting where every wind-adaptation permit reflects a purely voluntary household decision – there is no regulatory requirement that could compel adaptation as a byproduct of other renovation activity. The finding of a large partisan gap in this subsample (where, it is useful to keep in mind, risk is significantly lower) helps rule out explanations based on differential enforcement of regulations between Republican and Democratic homeowners. It is, instead, consistent with a belief channel.

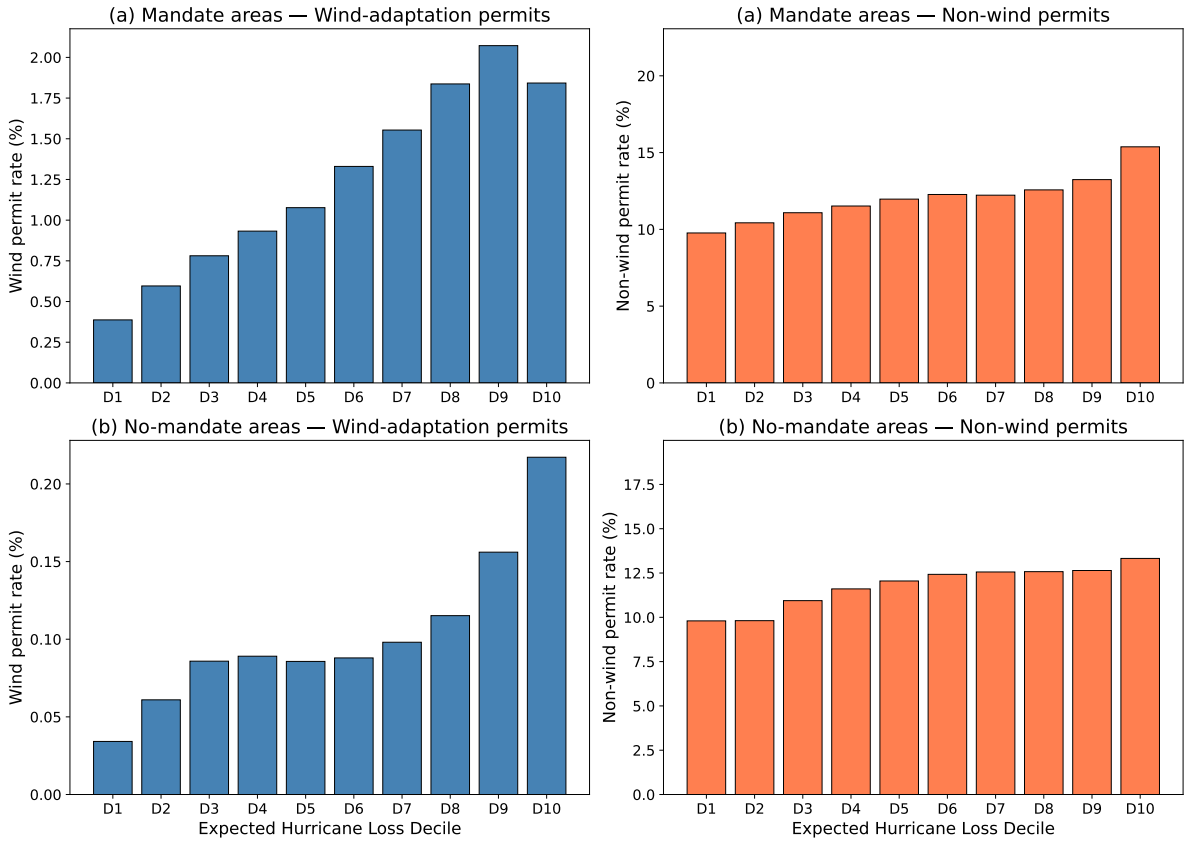
4.3 Time Variation in the Partisan Gap

The third piece of evidence exploits time variation in the partisan gap. If the partisan gap reflects political identity and its associated beliefs, it should respond to changes in the salience and polarization of climate as a political issue. To test this, I interact the Republican indicator with year dummies and estimate the model with zip code × year fixed effects (column 1 of Table 3), absorbing the level of zip-code-by-year variation while allowing the partisan gap to vary across years. Each coefficient measures the Republican effect in a given year relative to Democrats, again expressed as a percentage of the baseline filing rate.[17]

Figure 6 plots the results. Three distinct phases emerge. First, in 2014–2016 (the final years of the Obama administration) the Republican coefficient hovers near zero and is not statistically dis-

[17] Appendix B.1 reports an alternative version of the figure that scales each year's Republican coefficient by the year-specific baseline filing rate rather than the constant overall baseline; the pattern is similar.

Figure 5: Wind-adaptation permits and hurricane risk: mandate vs. no-mandate areas



Note: Each bar represents the average permit rate within a decile of expected hurricane dollar loss, computed separately within each subsample. The left panels plot the wind-adaptation permit rate; the right panels plot the rate for any non-wind building permit (i.e., property-years with at least one permit but no wind-adaptation permit). Panel (a) restricts to properties in the 2008 Florida Building Code wind-protection mandate area; panel (b) restricts to properties outside the mandate area.

tinguishable from the Democrat rate. The partisan gap in wind-adaptation investment is essentially absent during this period.

Second, a sharp decline begins in 2017, coinciding with the start of the Trump administration. The Republican effect falls progressively from 2017 onwards, reaching its trough during the 2020–2021 period. This timing aligns with the documented surge in partisan polarization over climate and environmental issues during the Trump presidency. Gallup surveys show that the partisan gap in environmental concern, stable at around 27 percentage points through 2013, widened to an average of 45 points during 2017–2019, driven by a combination of increased Democratic urgency and decreased Republican concern (Dunlap et al., 2016; Dunlap, 2019). The withdrawal from the Paris Climate Agreement in 2017, the rollback of EPA regulations, and the broader politicization of climate science appear to have deepened the identity-based divide, with consequences extending beyond stated attitudes to real investment behavior.

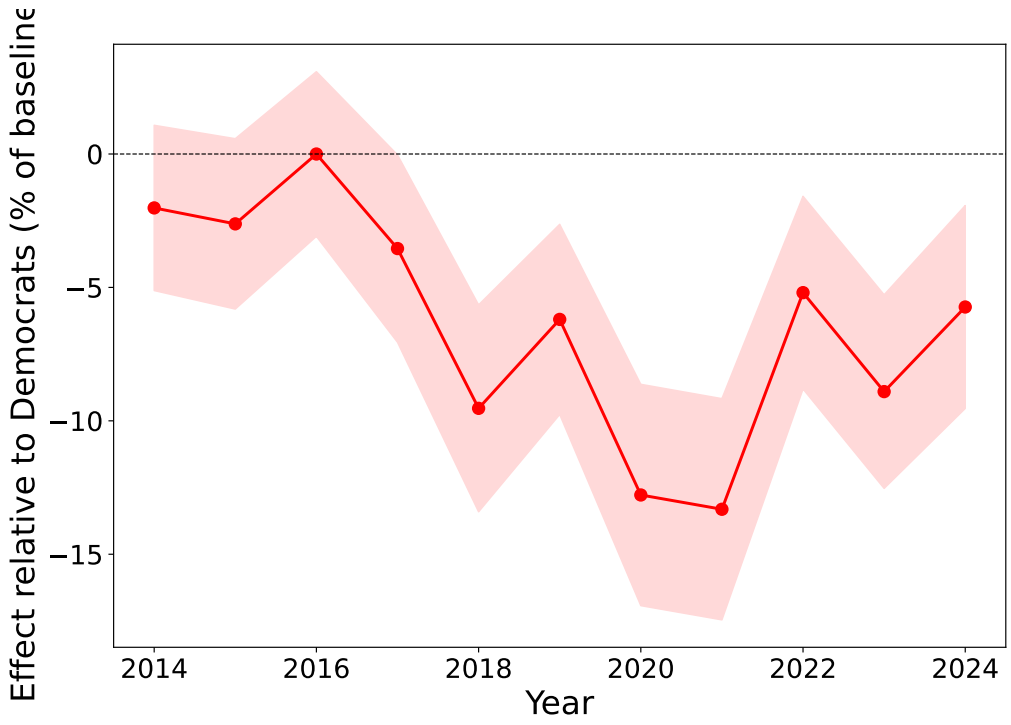
Third, the gap narrows sharply beginning in 2022. A likely contributor to this reversal is the relaunch of the *My Safe Florida Home* program. Originally created in 2006 with $250 million in appropriations following the devastating 2004–2005 hurricane seasons, the program was defunded after its initial allocation was exhausted and remained dormant for fifteen years. In May 2022, Governor DeSantis signed SB 2-D as part of a special legislative session on property insurance reform, reviving the program with $150 million in new funding. The program provides free wind-mitigation inspections and matching grants of up to $10,000 (on a 2-to-1 state-to-homeowner basis) for qualifying improvements such as hurricane straps, impact-resistant windows, and reinforced roofing – precisely the types of investment captured by the wind-adaptation permits studied here. By framing home hardening as a financial decision tied to insurance savings rather than a climate-motivated one, the program may have lowered the identity cost of adaptation for Republican homeowners, effectively depoliticizing the investment. Subsequent appropriations brought total program funding above $400 million by 2024, suggesting broad and sustained uptake.

The time-series pattern provides supportive evidence for a belief channel, whereas it is harder for non-belief channels to explain this timing.

4.4 Hurricane-Induced Attention and Wind Adaptation

I now explore how first-hand experience of hurricanes affects wind adaptation, and how it mediates the effects of political identity. A long literature (Gallagher, 2014; Bakkensen and Barrage, 2022; Hong et al., 2019; Baldauf et al., 2020) has highlighted the role of direct experience of climate events in shaping beliefs about climate change and household behavior, and related work shows that households and investors respond to realized climate shocks (Alekseev et al., 2021). I measure experience of hurricanes by observing whether a property is located *near* the path of a hurricane, but not in the precise area where damages are concentrated (the part that experiences hurricane-strength winds). I consider being in the area of the hurricane where damages are unlikely to occur, when the hurricane passes through, as an experience shock that potentially affects beliefs (or awareness) about hurricane risks without producing direct damage – the cleanest way to capture this kind of

Figure 6: Republican effect on wind-adaptation permits over time



Note: Each point plots the estimated coefficient on a Republican × year interaction from a regression with zip code × year fixed effects (column 1 of Table 3) and standard errors clustered at the zip-code level. Coefficients are expressed as a percentage of the baseline wind-adaptation filing rate (0.76 percentage points). Shaded bands indicate 95% confidence intervals. The omitted category is Democrat. The dashed line at zero indicates no difference from the Democrat filing rate. Figure B.1 in the Appendix reports an alternative version that scales the year-specific Republican coefficient by the year-specific Democrat baseline, taking into account that the overall filing rate varies over time.

belief shock (in the spirit of Dessaint and Matray, 2017).

The analysis will focus on understanding two questions. First of all, does the experience of a hurricane passing nearby (but not in the hurricane-strength area) affect the wind permitting activity of households compared to areas that are at similar hurricane risk, but that do not end up near the path of a hurricane? Second, do Republicans and Democrats respond differently? In other words: does the partisan gap increase or decrease with nearby hurricane experience? On the second question, there are two forces at play. To the extent Republicans under-invest partly because they have not personally confronted hurricane risk, living through a storm should raise their awareness about these risks and increase their adaptation disproportionately, therefore *narrowing* the gap. On the other hand, Republicans might have firmer, identity-anchored priors about climate risk, and therefore update less strongly than Democrats to the experience of a hurricane passing nearby. This section provides evidence that indeed both Republicans and Democrats do strongly increase their wind-adaptation investments following a hurricane passing nearby, but Republicans react less strongly, thus *widening* the partisan gap (lending support to the idea that Republicans might have stronger priors about climate risks).

To measure the experience of a hurricane passing nearby, I merge the property panel with storm-track data from NOAA's National Hurricane Center HURDAT2 Atlantic best-track database, used also by Kruttli et al. (2025), who study extreme-weather uncertainty and firm returns.[18] HURDAT2 records, at six-hour intervals along each storm's path, the position of the eye, and the radial extent of the strength of winds in each of the four geographic quadrants around the center (because a storm's wind field is asymmetric – typically strongest in the forward-right quadrant – using the information on radius by quadrant permits a far more accurate mapping of which locations actually experienced damaging winds than just the distance to the eye). I use this data to obtain a precise measure of whether any particular location experienced hurricane-strength winds (64 knots or more, which produce the vast majority of hurricane damages), or storm-strength winds (typically inducing little damage, from 34 to 64 knots) from each hurricane.

For every property in the sample and every year from 2014 to 2024, therefore, I determine whether the parcel fell inside each storm's 34- and 64-knot wind fields at any point during the year. I define *Hurricane Experience* as an indicator that the property experienced tropical-storm-force winds, but not hurricane-force winds: those that during the year were in the 34-knot to 64-knot field. Properties that were directly hit by hurricane-level winds of 64 knots and above (very close to the eye) are excluded from this analysis, as the effect of the experience on belief is confounded by the direct damages.[19] I lag the variable by one year (within the same owner) to capture the time it takes for homeowners to find contractors and organize the permit filing.

I then repeat the analysis of Table 3 adding two additional variables: the *Hurricane Experience* dummy and its interaction with the political party indicator. I also add a full set of quintiles or

[18] HURDAT2 (https://www.nhc.noaa.gov/data/hurdat/) is the National Hurricane Center's post-season "best-track" reanalysis of every Atlantic tropical cyclone.

[19] While my analysis directly excludes permits that explicitly mention repairs due to hurricane damage, it is plausible that some permits may not explicitly mention this, so it is conservative to exclude from the analysis properties that are likely to have sustained damage.

deciles of hurricane risk based on the FEMA measure (see Section 2.6) interacted with the political party indicators: as described in greater detail below, these allow me to compare properties that experienced a hurricane to properties of similar risk that did not experience a storm.

Table 8 reports the results, focusing on the two coefficients mentioned above. The coefficient on the hurricane experience variable is positive and large (10% to 20% of baseline depending on the specification), and highly significant. It shows that experience of a hurricane passing by strongly increases the wind adaptation activity of homeowners. Note that because the regressions have fine geographic fixed effects (including, in some specifications, property fixed effects), the coefficient is identified by the comparison of houses and years that experienced a hurricane passing nearby to houses and years that did not experience a hurricane, but are ex-ante equally exposed to hurricane risk (which is absorbed by the fixed effects).

The second coefficient in the table reports the interaction of *Hurricane Experience* with the Republican indicator. It is negative and significant, though not very large (about 2.5% of baseline in the property-fixed-effects specification), suggesting that Republicans react less strongly to the experience of a hurricane passing nearby than Democrats. The overall effect of experience for Republicans (the sum of the two coefficients in the table) is still positive and large; but Democrats react more strongly, thus slightly increasing the partisan gap. Note that, as mentioned above, the regression includes interactions of hurricane risk bin dummies with political party indicators. Therefore, the coefficient on the interaction of *Hurricane Experience* with the Republican indicator is identified by the comparison of the response for Republicans and Democrats in properties that experienced a hurricane to the response in properties *of similar ex-ante risk* that did not experience a storm.

This pattern helps adjudicate between the two forces discussed above. Were the partisan gap mainly due to lower awareness by Republicans, one would expect that the experience of the hurricane would close it, at least in part; were it mainly a matter of identity-anchored priors, one would expect Democrats to update their beliefs more strongly than Republicans, and the gap to become larger. The latter is what we see in the data, consistent with the identity-anchored-priors force dominating. This is also consistent with the time-series evidence presented above: the *My Safe Florida Home* program may have helped close much of the gap not by making the risk itself salient, but by reframing home hardening as a financially motivated decision tied to insurance savings.

Together, the four pieces of evidence in this section – political intensity, the mandate/no-mandate split, the time path of the gap, and the response to direct hurricane experience – point toward a mechanism rooted in how political identity shapes homeowners' subjective assessments of climate risk. The partisan gap widens with the strength of partisan engagement, persists where adaptation is purely voluntary, tracks the political polarization of climate change over time, and is not closed – if anything it is modestly widened – by first-hand experience of a storm, despite Republicans and Democrats both responding to it. This set of results is difficult to reconcile with the non-belief-based channels, but is fully consistent with a belief/political identity channel.

Table 8: Hurricane-Induced Attention and Wind Adaptation

	Dep. var.: Wind permit (% of baseline)			
	5 risk bins		10 risk bins	
	(1)	(2)	(3)	(4)
Hurricane Experience	0.115***	0.203***	0.116***	0.201***
	(0.023)	(0.020)	(0.023)	(0.020)
Hurricane Experience × R	−0.049***	−0.025**	−0.048***	−0.024**
	(0.012)	(0.012)	(0.012)	(0.012)
5 risk bins × R	✓	✓		
10 risk bins × R			✓	✓
Controls	Y	Y	Y	Y
Fixed effects	Zip×Yr	+Prop	Zip×Yr	+Prop
Clustering	Zip	Zip	Zip	Zip
Observations	53,270,755	53,194,250	53,270,755	53,194,250

Note: The dependent variable is an indicator for filing at least one wind-related permit in a given year. Coefficients are expressed as a fraction of the baseline filing probability (0.77%); e.g., a value of 0.203 means filing is 20.3% of baseline more likely. "Hurricane Experience" is an indicator that the property experienced storm-strength winds (inside the 34-knot wind field or stronger, excluding direct hits; see below) in the prior year, measured within the same owner spell so exposure under a previous owner does not carry over; "× R" is its interaction with the Republican indicator. The omitted party category is Democrat. Every column also includes party×risk-bin interactions; columns (1)–(2) use five risk bins and columns (3)–(4) use ten. Throughout, prior-year direct hits (the 64-knot "R64" field) are excluded so the estimate reflects non-damaging wind experience rather than mechanical damage repair. All specifications include the same controls as in Table 3. Standard errors clustered at the zip-code level are reported in parentheses. Odd columns use zip code × year fixed effects; even columns add property fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

5 Welfare losses from missed adaptation

This section presents back-of-the-envelope estimates of the welfare loss from forgone adaptation associated with political beliefs. I first discuss the relevant counterfactual: if the partisan adaptation gap disappeared, which households would change their behavior? I then value the benefits and costs of the resulting investments and combine them into an aggregate and a per-adopter NPV. Appendix C provides the full calculations and calibrations.

Building the counterfactual. I consider two counterfactuals. The first (and main) one assumes that all Republicans behave like Democrats with respect to wind adaptation. Recall that *both* Republicans and Democrats adapt at relatively low rates: just below 1% of households invest in wind adaptation per year. The rate is about 5 percent (more precisely, 4-7%) lower for Republicans. In my first counterfactual, I ask what would happen if Republicans behaved like Democrats, and undertook wind adaptation investments at a rate 5% higher. To do so, I sum up the total NPV of the wind-adaptation investments Republicans actually made in my sample, and then compute 5% of that as the additional NPV that is directly attributed to political beliefs. Of course, this assumes the marginal investments from Republicans turning Democrats that would resemble those actually undertaken; because adopters self-select, this is likely an overestimate; Appendix C also constructs

a similar counterfactual sampling from matched non-adapters, with similar albeit slightly smaller results.[20]

This first counterfactual ignores two indirect channels that are relevant to understand the effects of politics on adaptation: the low baseline adaptation rate of *both* parties may itself reflect the climate skepticism that has dominated the political debate, and the fact that even small belief differences can have large effects through policy (for example, by building regulations that affect all households). I therefore also report another benchmark, an upper bound on the total effects of political beliefs: the total net welfare improvement from every remaining positive-NPV mitigation opportunity. This can be thought of as a theoretical optimal-adaptation ceiling, not an estimate of the welfare loss directly caused by partisanship.

I value future benefits in two complementary ways: applying the market-based catastrophe risk loading λ to expected annual losses, as is typical in the insurance industry, and valuing the benefits under CRRA utility. Both approaches confront the fact that hurricane damages are fat-tailed: most damages come from high-wind events that are rare but devastating.

Calculating the NPV: market-based risk loading. For each property i with a wind adaptation investment, I obtain the cost C_i from the permit value (winsorized, since permit values in Cotality are noisy; see Appendix C), and construct expected annual loss, EAL_i, from FEMA hurricane risk tables combined with Cotality structure value. From the building engineering literature (FEMA, 2025; Orooji et al., 2022) I calibrate that opening protection reduces expected losses from severe hurricanes by an average of 33%. This is captured by a parameter $\rho = 0.33$.

Because mitigation is a hedge, the risk-adjusted present value of its benefits exceeds their expectation; following insurance-industry practice, I capture this by discounting expected annual losses at the risk-free rate and multiplying by a "risk-loading factor" $(1 + \lambda)$, which can be calibrated directly from catastrophe-bond and reinsurance prices, and is responsible for the entirety of the risk adjustment (therefore, it encapsulates both for distribution of damages and risk preferences). The resulting formula is:

$$\text{NPV}_i \;=\; (1+\lambda)\,\rho\,\text{EAL}_i \sum_{t=1}^{T} \frac{(1+g)^{\,t-1}}{(1+r_f)^{\,t}} \;-\; C_i.$$

Given the centrality of the discount rate and risk premium for the NPV results, I compute the results using a central value of $\lambda = 3.5$, but also report $\lambda = 2.7$ and 5.3 for robustness; all three are observed market prices (Artemis, 2024; Froot, 2001). I choose maturity of $T = 30$ years (averaging the longer lifespan of impact windows and structural reinforcement and the shorter lifespan of hurricane shutters), a real risk-free rate of 1%, and $g = 0$ to be conservative; Appendix C details these calibrations.

[20] As Appendix C describes in detail, the differences between Republicans that adapt and those that don't adapt but live in the same area and have similar property value are quite small, so matching on those two quantities alone makes the NPV numbers similar.

Calculating the NPV: CRRA utility. Market prices for λ are affected by market frictions which tend to bias them upwards (see Tomunen, 2026), so as an alternative I value the same decision under CRRA utility, taking a "disaster" view that reflects the fat-tailed nature of hurricane losses: in a representative year, a household with structure value V faces with probability p a serious wind event that destroys a share x of V, and adaptation reduces that conditional loss to $(1-\rho)xV$. I compute the certainty equivalent of the adaptation investment, by calibrating both the loss distribution and risk aversion (instead of λ as in the previous approach), and assuming the house is the only asset of the household. I directly calibrate severity (conditional loss) x_i from the Florida Public Hurricane Loss Model (FPHLM, 2025) as a function of the wind speeds of the area where the property is located, and, using that, I invert the expected annual loss obtained from FEMA to compute the annual probability p_i: $p_i = \text{EAL}_i/(x_i V_i)$. I report the results for different levels of risk aversion, $\gamma \in \{2, 4, 10\}$; Appendix C provides more details.

Results: total NPV. Table 9 reports the estimated total welfare benefits for the two counterfactuals: the direct one in which Republicans behave like Democrats ("R adapts like D") and the optimal-adaptation benchmark in which both Democrats and Republicans adapt ("Optimal adaptation"). Each row corresponds to a different value of λ (for the market-based estimate) or γ (for the CRRA calibration). As a main estimate, bolded, I take the central value ($\lambda = 3.5$) of the market-based approach, as this directly incorporates market information on the pricing of this exact type of risks.

Under the central case, the *realized* adaptation investments in my sample (by both Republicans and Democrats) generate a statewide present-value benefit of about $16.7 billion, against $5.2 billion of spending: a net welfare gain of roughly $11.4 billion and a gross benefit-cost ratio of 3.19 (consistent with ranges estimated in the wind-mitigation literature; TDI, 2024).

Closing the political bias as in the first counterfactual would then increase the investments made by Republicans by about 5%, yielding a **total NPV of $205 million**, or **$27,300 per marginal adopter**. Despite the low baseline adaptation rate, that closing the political gap raises by 5%, the total net present value from eliminating the gap is almost as high as the entire budget of the first My Safe Florida Home program: the program was appropriated about $250 million in 2006–2007, enough for roughly 400,000 inspections and 32,000 home-hardening grants before it was defunded in 2008.

Turning to the second counterfactual, I compute the total NPV of adaptation in Florida (assuming that all and only positive-NPV adaptation projects get undertaken); I obtain a central calibration of **$32.3 billion** (Table 9). These gains are not directly caused by political bias, but they are indirectly connected insofar as politics shapes regulation and incentive programs (like the My Safe Florida Home program; Florida House of Representatives, 2024) aimed at filling this gap.

The table shows that the central estimates for the market-based calibration are in line with those from the CRRA utility approach with relatively low values of risk aversion (around $\gamma = 3$). The table also shows that the aggregate NPVs are economically large across the entire set of robustness calibrations.

Total NPV	R adapts like D	Optimal adaptation
$\lambda = 2.7$ (market)	\$153 million	\$23.6 billion
$\lambda = 3.5$ **(market)**	**\$205 million**	**\$32.3 billion**
$\lambda = 5.3$ (market)	\$322 million	\$53.3 billion
$\gamma = 2$ (CRRA)	\$103 million	\$14.4 billion
$\gamma = 4$ (CRRA)	\$474 million	\$65.3 billion
$\gamma = 10$ (CRRA)	\$6.1 billion	\$918 billion

Table 9: Welfare cost of the Republican adaptation gap and aggregate net benefit if all remaining positive-NPV mitigation opportunities are undertaken, under the market-loading and CRRA approaches.

Finally, we can also compute the break-even values of the parameters, under which the NPV drops to zero. Those numbers are low: they are achieved for $\lambda^* \approx 0.41$ or for $\gamma^* \approx 0.6$, much below what is typically estimated to be households' attitude toward risk.

Private vs. social benefits. The calculations so far computed the total value of adaptation, i.e., the *social* value; given that many households are insured, they do not necessarily capture the entirety of this benefit (some of the benefit accrues to the insurers). There are two ways in which insured households internalize the benefits from adaptation: through the deductible (which is specifically higher for hurricane risk than for all other risks, typically 2% or 5% of the value of the house), and by obtaining reductions in premia from insurers. In Florida, the law mandates that the share π of insurer savings returned as premium credits should be 1 (§627.0629, F.S.; Florida Legislature, 2025), that is, insurers are supposed to pass along *all* risk improvements to homeowners. In that case, the social benefit is equal to the private benefits: households capture the entire benefit-cost ratio (BCR) of 3.19. In practice, this pass-through may be lower, due to various frictions. Appendix C calibrates the benefits that accrue to individuals if the pass-through is lower than that; with an estimated pass-through ratio of $\pi = 0.73$, about 83% of the welfare benefits are captured by individual households, with a private BCR of 2.6. Adaptation is thus privately profitable even with incomplete pass-through, so low take-up – and the partisan gap in particular – looks less like a wedge between private and social returns than a problem of salience, information, and trust, precisely the margin where political identity can operate.

A national extrapolation. Finally, I construct a national analogue of the optimal-adaptation counterfactual: I assign each single-family home in Cotality's national data an expected annual wind loss from its structure value and its county's hurricane loss rate in FEMA's National Risk Index (FEMA, 2023), impute adaptation status from my Florida panel (trying to estimate based on observables the probability that a house is already adapted), and value protection with the same formula as above. The national total I compute is \$72.1 billion in the central case (of which, recall, \$32.3 billion come from Florida alone). Just like for the second counterfactual (which this one extends nationally), this measures the value a policy or belief shift that unlocked adaptation nationally could create, not a loss directly attributable to partisan bias; Appendix C details the

construction.

6 Conclusion

This paper shows that political orientation affects household investment in climate adaptation. Using a novel property–owner–year panel of approximately 61 million observations that includes coverage of building permits in Florida from 2014 to 2024, I find that Republican homeowners' probability of filing a wind-adaptation permit is 6.5% lower than that of Democrats, conditional on income, property characteristics, and a rich set of demographic controls. The gap is robust to a more demanding two-way fixed-effects specification that adds property fixed effects on top of the zip code × year fixed effects, exploiting ownership transitions within the same dwelling, where the gap is 4.6%. The partisan divide is specific to climate adaptation – Republicans show little difference in overall permitting activity, ruling out a general reluctance to invest in home maintenance. The effect is economically meaningful, comparable in magnitude to moving two to three income deciles or to the gender gap in adaptation. Four pieces of evidence point toward a beliefs channel for the partisan gap: the gap is roughly twice as large among FEC campaign donors as among non-donors, consistent with stronger partisan engagement amplifying the effect; the gap is larger in areas outside the building-code mandate (where wind adaptation is fully voluntary) as in mandate areas; the gap widens sharply in 2017 with the start of the Trump administration, deepens during 2020–2021, and then narrows after the relaunch of Florida's *My Safe Florida Home* program (which tried to de-politicize adaptation investments in Florida); and the gap slightly widens after households are exposed to nearby hurricanes, suggesting that while both Republicans and Democrats respond to it by adapting more, Republicans respond less strongly, potentially anchored by their political views. This lack of adaptation has large economic consequence: I estimate the welfare loss to be $200m, as large as the entire *My Safe Florida Home* original budget.

Looking forward, these findings have especially important implications because climate damages are expected to keep growing and mitigation alone is insufficient to prevent them. As hurricane intensity and frequency increase along the Atlantic and Gulf coasts, household-level adaptation becomes an essential complement to public infrastructure and building code regulation. If political beliefs create systematic under-investment in physical resilience among a large share of homeowners, the welfare consequences are potentially substantial: higher damage costs, larger insurance claims, and greater fiscal exposure through disaster aid programs (Deryugina, 2017; Kousky et al., 2018).

Several directions for future research emerge from this work. First, adaptation decisions may exhibit peer effects – neighbors' visible investments (such as storm shutters or impact windows) could shift the perceived norm and reduce the political stigma of climate-related spending, a channel that the permit data assembled here are well suited to test. Second, studying whether financially framed subsidy programs can help narrow the partisan gap could open the door to alternative approaches to address future climate risks.

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A Data Appendix: Processing Pipeline and Construction Details

This appendix documents the data processing workflow step by step.

A.1 Permit extraction and wind classification

1. In the permit data, I retain only observations with a valid Cotality property identifier (clip).

2. From the separate permit *status* file, I extract the earliest status record and earliest date for each permit ID.

3. Permit descriptions are parsed using a keyword taxonomy. For each keyword (wind, hurricane, strap, clip, anchor, barrier, mitigation, resistant, shutter, storm, impact, shelter, safe room, roof), I apply: complements (to increase precision) and exclusions (to drop unrelated uses such as "wind turbine" or "roof leak"). If any keyword plus complement is present and no exclusion applies, the permit is classified as wind adaptation. Each permit is also independently flagged as a storm-damage repair if its description contains any of the substrings *damag* (matching both "damage" and "damaged"), *dmg*, *repair*, or *rebuild*, or if it contains the name of a Florida hurricane (e.g., Irma, Michael, Ian, Milton, Charley, Andrew, and others). Repair permits are excluded from the wind-adaptation measure. I also flag "new construction" permits by searching for the phrase "new const" in the description. Additionally, permits are classified as single-family residential based on land-use codes and textual land-use strings in the permit record.

4. A cleaning script resolves duplicates, drops permits with invalid dates (outside the 1970–2025 range), and collapses multiple entries per clip and permit number, preserving the earliest date and consistent indicators. When exactly two records share a clip and permit number, the script retains the earliest date, the latest permit value, and the maximum of each binary indicator. When more than two records exist, it further distinguishes permits by their reported dollar value before collapsing. The aim of this procedure is to try and clean up errors in the permit data, such as multiple entries for the same permit.

A.2 Property (tax) data

1. I keep single-family residential land uses based on land-use codes and textual land-use strings. I retain a standardized set of variables (address, coordinates, land use, year built, values, and structural characteristics).

2. I create three outputs: a *static* property file with the modal (most frequent non-null) address and geographic coordinates; a *dynamic* property file with annual assessed value, square footage, bedrooms, bathrooms, year built, and effective year built (which captures the last major renovation); and an *ownership names* file extracting owner names by clip and tax year.

A.3 Owner transfer (deeds) data and ownership history

1. I parse buyer and seller names, splitting combined fields when two owners are embedded in a single string.

2. When multiple transfers occur on the same day for a property, I use buyer-seller name overlaps to order events and to identify the appropriate buyer and seller for that day.

3. I construct an ownership history at the property-year-owner level, with start and end dates, owner order, and transaction attributes. For the first recorded deed of each property, the seller is treated as a pre-existing owner whose tenure begins before the sample period and ends at the first sale date.

4. For property-years in which no deed-based owner is observed, the owner name is filled from the tax assessor records.

5. I restrict the panel to property-years classified as single-family residential in either the deeds, the tax records, or the permit data. I also drop observations missing any core address component (house number, street name, city, state, or ZIP code) or missing the property FIPS (county) code, since these cannot be matched to voter or consumer records.

A.4 L2 voter registration data

1. I combine yearly L2 voter registration files into a single Florida L2 panel, and map categorical fields (party, marital status, etc.) to standardized codes.

2. I standardize addresses and create full-name strings to prepare for matching.

A.5 Data Axle consumer data

1. I standardize addresses and construct full-name strings for all household members

2. From each annual Data Axle file (2006–2023), I retain estimated household income and a children-in-household indicator – the two variables used as controls in the regressions – in addition to the name and address fields used for matching.

A.6 Matching owners to L2 and Data Axle

1. I standardize owner addresses in the ownership history and standardize addresses in L2 and Data Axle using consistent functions (expanding abbreviations such as "St" to "Street," "Ave" to "Avenue," and similar).

2. I match on exact address (house number, standardized street, standardized city, ZIP, and year). This produces candidate pairs for name matching.

3. I compute fuzzy name similarity using the Token Set Ratio algorithm and keep matches above a 0.8 threshold. When a property has two owners on the deed, the matching is performed separately for each owner. I select the best match (highest similarity) per clip-year-owner and record match types.

4. The matched identifiers (LALVOTERID and FAMILYID) are merged into the property-year-owner panel.

A.7 Geographic joins and risk measures

1. Using parcel-level coordinates (with block-level coordinates as a fallback), I assign census tracts to properties via spatial join with TIGER 2023 tract shapefiles.

2. I merge FEMA National Risk Index (NRI) data at the census-tract level, providing hurricane risk metrics (expected annual frequency, expected building loss, and composite risk score) for each property. When the parcel-level tract assignment yields a match, I use it; otherwise I fall back to the block-level tract assignment.

3. I construct wind mandate zones using 2008 (ASCE 7-05) and 2021 (ASCE 7-22) wind contour shapefiles. For each vintage, I extract the 130 and 140 mph contour lines and construct two polygons: one covering the area seaward of the 140 mph contour (wind speed $\geq$ 140 mph) and one covering the area inland of the 130 mph contour (wind speed $\leq$ 130 mph). Properties falling in neither polygon are in the 130–140 mph band. I also construct a one-mile coastal buffer using a 10 m-resolution coastline shapefile.

4. A property is classified as subject to the building code mandate if it falls within the $\geq$ 140 mph polygon, *or* if it falls in the 130–140 mph band and is within the one-mile coastal buffer. Properties inland of the 130 mph contour are classified as non-mandate. The same logic is applied separately for the 2008 and 2021 wind zone vintages, yielding two mandate indicators.

A.8 County-level data quality filtering

1. Permit data are not available for all counties and years. To ensure that the analysis uses only county-years with adequate reporting, I apply county-level data quality filters.

2. I first require that a county have at least 1,000 cumulative permits over the entire study period. Counties that fail this threshold are excluded entirely.

3. For the remaining counties, I compute the average annual permit volume over 2019–2022 as a recent baseline. Counties with fewer than 10 average annual permits in this period are also excluded.

4. For each surviving county, I identify the first and last year in which total permits exceed 5% of the 2019–2022 baseline. Only observations falling within this window (inclusive) are retained; early years with clearly incomplete reporting and trailing years with data gaps are dropped.

5. These filters remove counties and county-years with sporadic or clearly incomplete permit reporting, while retaining the vast majority of properties and population.

A.9 Permit assignment and panel construction

1. I merge cleaned permits to the property-year-owner panel using clip and year. If a property-year has a single owner, all permits in that year are assigned to that owner. If multiple owners exist, permits are assigned based on whether the permit date falls within the owner's tenure interval.

2. I aggregate to a property-year-owner dataset with indicators for whether the owner had any permit or any wind permit in that year.

3. I merge in L2 voter attributes (party affiliation, gender, age, ethnicity, education, religion, language, net worth, and charitable and political contribution indicators) and forward/back-fill within each property-owner spell to minimize missingness from match gaps. Where age is missing in some years but observed in others, I impute by computing the difference between the observation year and the earliest year with a non-null age.

4. I merge Data Axle household attributes (estimated income, children indicator) using the same forward/back-fill procedure within owner spells.

5. I merge annual property characteristics (assessed value, square footage, bedrooms, bathrooms, and year of most recent renovation, a.k.a. effective year built) from the tax assessor records. These are forward-filled (but not back-filled) within each property.

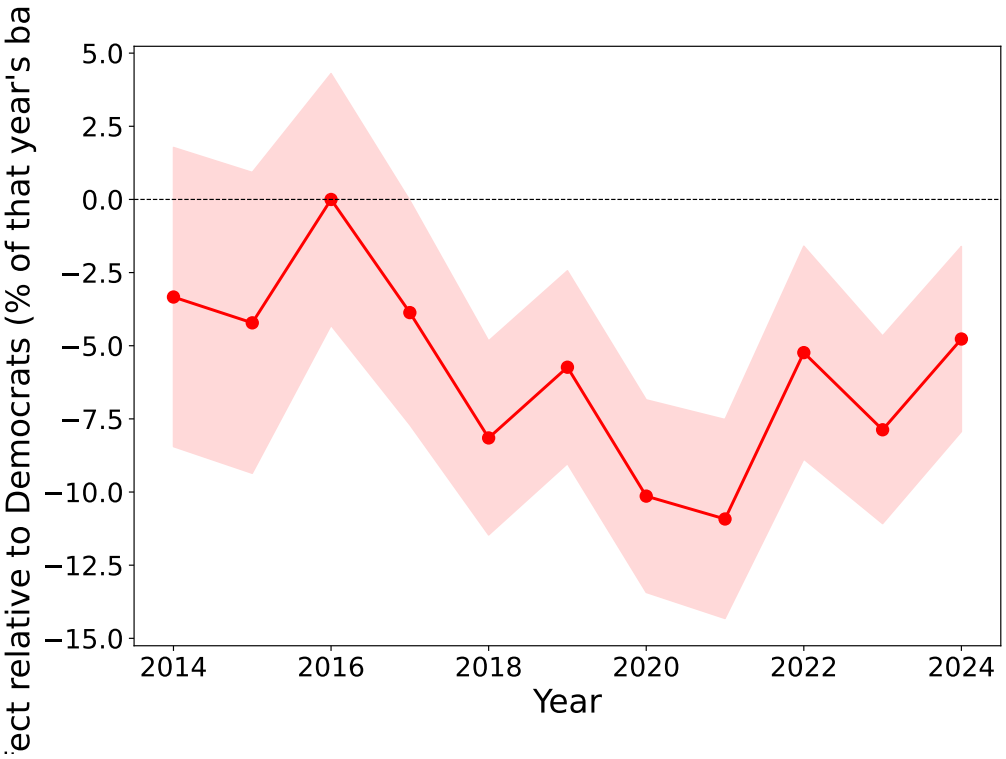
6. I construct several derived variables used in the analysis:

   - *Latest renovation year*: the maximum of year built and effective year built that does not exceed the observation year, used to compute years since last renovation.
   - *Tenure*: years since the owner's start date.
   - *Party group*: a property-year is classified as Republican (R) if all matched owners are registered Republican, or if the household contains a Republican together with a voter who is registered as neither Republican nor Democrat; Democrat (D) is defined analogously; all other cases are classified as "other."

7. For each property-year-owner observation in which *any* permit is flagged as a storm-damage repair, the wind-adaptation indicator is set to zero. This is more conservative than excluding individual repair permits: it ensures that all wind-related activity for an owner in a year that also involves repair work is excluded, since the wind permits may have been motivated by recent storm damage rather than proactive adaptation.

8. The final analysis panel spans 2014–2024 (the period with L2 coverage), with political affiliation, demographics, property characteristics, risk exposure, and permit outcomes.

Figure B.1: Republican effect on wind-adaptation permits over time, scaled by year-specific baseline



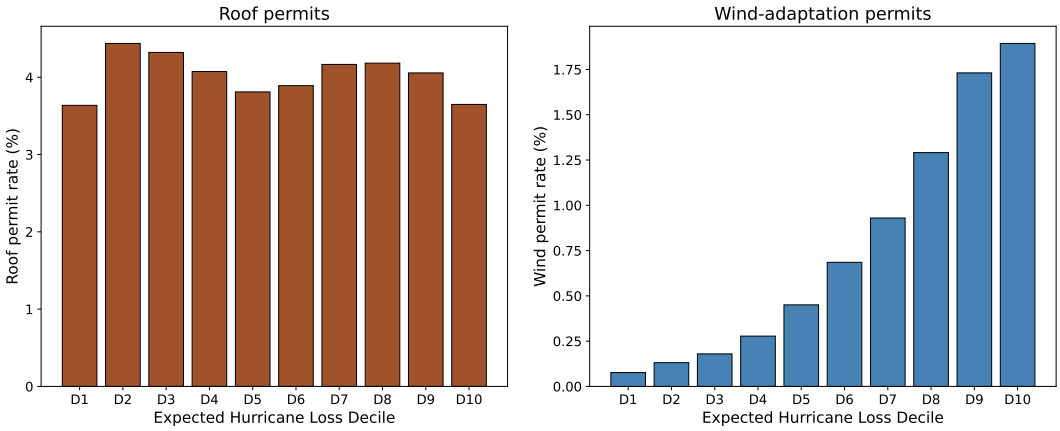
Note: Each point plots the estimated coefficient on a Republican × year interaction from a regression with zip code × year fixed effects, scaled by the year-specific filing rate (the unconditional mean of the wind-permit indicator in that year). Standard errors clustered at the zip-code level. Shaded bands indicate 95% confidence intervals. The omitted category is Democrat.

B Additional Figures and Tables

B.1 Time variation in the partisan gap: alternative scaling

Figure 6 in Section 4 scales each year's Republican × year interaction coefficient by the constant overall baseline rate (0.76%). Because the rate at which homeowners file wind-adaptation permits varies substantially over the sample period – it rises in the wake of Hurricane Irma (2017), peaks during the 2020–2021 period, and recedes thereafter – an alternative scaling is to express each year's Republican coefficient as a fraction of the *year-specific* baseline. Figure B.1 reports this alternative scaling. The qualitative pattern is identical to the constant-baseline figure – low gap during 2014–2016, sharp widening from 2017 through 2020–2021, and narrowing thereafter.

Figure B.2: Roof permits and hurricane risk



Note: The figure plots the average roof-permit rate within deciles of expected hurricane dollar loss (left) alongside the average wind-adaptation permit rate (right). Roof permits are essentially flat across the risk distribution, while wind-adaptation permits exhibit a sharp positive gradient.

B.2 Roof permits

This section repeats the analysis using an important subsample of non-wind-related permits: those that relate to roofing. The vast majority of roof-related permits are roof replacements (the structural reinforcement are a tiny fraction of the total in the data, and they are classified as wind-adaptation permits). As discussed in the text, roof replacements occur typically due to aging of the roof (roofs need to be replaced every 20-30 years) and damage. Neither of these can be thought of as "voluntary climate adaptation" in the same way as impact windows and doors and hurrican shutters are. We would therefore not expect to see neither a relation between hurrican risk and roof permits, nor a partisan gap in roof replacements. This section verifies this in the data.

Figure B.2 replicates the hurricane-risk validation exercise (Section 2.6) using roof permits as the dependent variable: unlike the wind-adaptation permits, which display a sharp positive gradient with hurricane risk, roof permit filings are essentially flat across the risk distribution. This pattern confirms that generic roof work is not risk-responsive and is therefore a sensible placebo for the wind-adaptation analysis.

Table B.1 reports the analog of the main partisan-gap regression with roof permits as the dependent variable. The estimated Republican coefficient is small in magnitude (about 2% of the baseline in one specification and about 1% in the other) and – tellingly – changes sign across specifications: it is -1.3% in the zip code $\times$ year specification (column 1) and $+2.2\%$ in the two-way fixed-effects specification with zip code $\times$ year and property fixed effects (column 2). This pattern stands in sharp contrast to the wind-adaptation gap, which is uniformly negative and economically larger across both specifications (-6.5% and -4.6%, respectively).

The placebo evidence supports the interpretation that the partisan gap in wind-adaptation permits reflects a real, voluntary investment decision directly about climate-related adaptation rather

Table B.1: Roof permits as a placebo: Republican coefficient (% of baseline)

	Dep. var.: Roof permit (% of baseline)	
	(1)	(2)
Republican	−0.013***	0.022***
	(0.002)	(0.004)
Other/missing	−0.009***	0.006
	(0.002)	(0.004)
Controls	Y	Y
Fixed effects	Zip × Year	Zip × Year + Property
Clustering	Zip	Zip
Observations	60,714,431	60,644,537
Baseline (mean)	4.02%	4.02%

Note: Table reports the Republican and Other/missing coefficients from a regression where the dependent variable is an indicator for filing at least one roof permit (any roofing keyword) in a given year, scaled by the baseline filing rate of 4.02 percentage points. The sample, controls, and clustering are identical to Table 3. Column (1) includes zip code × year fixed effects; column (2) is the two-way fixed-effects specification with zip code × year and property fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

than a general partisan difference in home-improvement spending.

Table B.2: Wind-Adaptation Keyword Taxonomy

Keyword	Complements	Exclusions
Wind	high wind, high-wind, wind load, wind speed, wind pressure, anchor, uplift, bracing, impact, tempered, storm window, storm prot, debris prot	turbine, generator
Hurricane	shutters, impact, panels, protection, accordion, screens, straps, clips, foamseal, bracing, proof, fabric, resistant, shield, wind, retrofit, mitigation, shelter	due to
Strap	adhesive, bracing, anchor, storm, panels, wind, retrofit, mitigation, hurricane	earthquake, electrical, solar
Clip	adhesive, bracing, truss, anchor, storm, panels, wind, retrofit, mitigation, hurricane, uplift, foamseal, sheat, strap	earthquake, electrical, solar
Anchor	bracing, truss, anchor, wind, retrofit, mitigation, hurricane, clips, uplift, foamseal, sheat, strap, wall, roof	earthquake, electrical, solar
Barrier	hurricane, wind, secondary, uplift	vapor, moisture, leak
Mitigation	hurricane, shutter, impact, wind	earthquake, radon, insp
Resistant	impact, hurricane resistant, hurricane-resistant, high-wind, high wind, weather resistant, weather-resistant, wind resistant, wind-resistant	–
Shutter	hurricane, impact, storm, wind, debris, pressure, heavy-duty, heavy duty, reinforced, aluminum, roll, steel, polycarbonate, fiberglass, fiber glass	decorative
Storm	storm drain, storm sewer, storm shutter, stormwater drain, storm water drain, storm panel, storm shelter, stormshelter, door	–
Impact	window, door	–
Shelter	storm, hurricane	–
Safe Room	safe room	–
Roof	high velocity, hvhz, mph, strap, clip, anchor, truss, uplift, bracing, reinforc, tie down, tiedown, impact	leak, coating, solar, gutter, antenna, satellite, hvac, vent, cleaning, paint, skylight

Note: A permit description is classified as wind-related if it contains at least one keyword *and* at least one of that keyword's complement words, *and* none of the keyword-specific exclusion words listed above. In addition, a set of general exclusion words is applied to all permits before keyword matching begins: *traffic, inspect, Stiltz, flood light, floodlight, hvac, pool, spa, kitchen remodel, bathroom remodel, demolition, flood zone determination, elevator, fence, seismic, earthquake.* These general exclusions remove permit descriptions that are clearly unrelated to wind adaptation. A " – " in the Exclusions column indicates no keyword-specific exclusions beyond the general list. Permits flagged as storm-damage repairs (containing *damag, dmg, repair, rebuild*, or a named Florida hurricane) are excluded from the wind-adaptation count even if they match a keyword–complement pair.

Table B.3: Sample Wind-Adaptation Permit Descriptions

impact, wind

- Replace 5 windows with impact
- Install 9 impact windows
- Replace windows & doors with impact
- Replace (13) windows S/S and (2) doors all impact FL7286-R1; FL9747-R1; FL# 261-R2; FL6707-R1
- Replace 14 windows impact and clear panels over 1 opening 2 supermas 2 manual rolldown shutter FL17791.1 17733.1 9520.2 17794.1 17793.3 12246.1 16380.1 1435.5

shutter, wind

- Wind retro-fit hurricane shutters
- Storm shutters to comply with wind mitigation standards
- Installation of 14 hurricane shutters – wind load calculations attached
- Install hurricane shutters on common area openings – wind loads and schedule forms submitted
- Storm shutters – resd wind retrofit – install steel panels FL13583.1 – new hr entry door FL 4904.1 – add 1 clip FL 101 – retrofit post FL 102

hurricane, shutters

- Hurricane shutters
- Install hurricane shutters
- Install hurricane pulldown shutters to 4 window openings on front of home
- Install of hurricane accordion shutters to 7 window and slider openings on side and rear of home
- Installation hurricane protection installing accordion style shutters FL13987.1 back of home – lanai – doors and transom

shutter, storm

- Install storm shutters
- Install 6 accordion storm shutters
- Install storm shutters on 3 openings
- Shutters – (10) manual roll and (6) accordion storm – FL13987-R5.1 – FL10564-R5.1
- Installing 13 accordion shutters FL# 1850.3 and 3 motorized storm catcher rolldown screens FL# 11291.1

door, impact

- Install impact door
- Replace front door w impact
- 2 PGT impact sliding glass doors
- Replace garage door size for size impact rated FL 31372.39
- Remove existing non impact sliding glass doors and replace with new impact sliding glass doors

roll, shutter

- Install 2 roll down shutter w/el
- Motorized roll-down shutters
- Install (4) manual roll-down shutters
- Roll type shutters
- Install 2 motorized roll up shutters FL 17000.1 install 2 remote fabric roll up shutters FL 12830.5 and 5 mesh screens FL16380.1

barrier, secondary

- Re-roof with secondary water barrier underlayment
- Re-roof with asphalt shingles and secondary water barrier
- Re-roof GAF dimensional shingles with secondary water barrier
- Tear off and re-roof with secondary water barrier and OC duration shingles in brownwood and a 3ply SBS mod bit on the rear flat
- Remove existing shingle down to wood deck nail all decking install peel-and-stick secondary water barrier replace drip edge replace roof vents install dimensional shingles

anchor

- Building hurribolt framing anchor system submittal
- M/H anchor retrofit
- Place anchor tie down pre fab shed according to code
- Reroof tile 6/12 polyanchor, tuplus, eagle malibu foam attached
- Addition & roof over includes row orig permit. Plan alteration: P/C tie beams/anchors

roof, truss

- Reinforce roof trusses
- Re-roof entire roof – truss retrofit
- Flat roof to slope w trusses
- Trusswork sheathing roofing soffit
- Trusses over flat roof

hurricane, protection

- Installation of hurricane protection
- Install hurricane protection at 6 openings
- Hurricane protection – accordions 11 openings
- Hurricane protection – 4 EZ screen (FL# 14110) & 6 fabric shield (FL# 3227)
- Install accordion hurricane protection on ten openings. Install storm catcher hurricane protection on twelve openings. Install manual roll down storm catcher hurricane protection on four openings

impact, shutter

- Installation of impact shutters
- Install 1 impact bahama shutter
- Aluminum impact accordion shutter install (11)
- Installation of 3 motorized roll down shutters impact rated
- Install 4 rolling shutters (1 crank/3 motorized electric) & 15 impact colonial shutters

panel, storm

- Install storm panels
- Storm panels on 8 openings
- Install fabric storm panels on 3 openings
- Replace (5) windows size/size & cover w/fabric storm panels FL14994.9; FL15208.1
- Installation of 15 vinyl replacement windows FL# 6208 & installation of 26 storm panels on all window openings FL# 515

Note: Each entry shows a verbatim excerpt from the Cotality permit record.

Table B.4: Waterfall: Progressive Addition of Controls

Panel A: Zip code × Year fixed effects

	Republican	SE	Observations	R^2
Party only	0.078*	(0.041)	60,714,544	0.000
+ Geo × Year FE	0.048***	(0.010)	60,714,431	0.016
+ Property	−0.027***	(0.009)	60,714,431	0.017
+ Demographics	−0.059***	(0.008)	60,714,431	0.017
+ Socioeconomic	−0.065***	(0.009)	60,714,431	0.018

Panel B: Zip code × Year + Property fixed effects

	Republican	SE	Observations	R^2
Party only	0.078*	(0.041)	60,714,544	0.000
+ Zip × Year + Property FE	0.010	(0.012)	60,644,537	0.110
+ Property chars	−0.014	(0.012)	60,644,537	0.110
+ Demographics	−0.048***	(0.012)	60,644,537	0.111
+ Socioeconomic	−0.046***	(0.012)	60,644,537	0.111

Note: Each row reports the Republican coefficient from a regression of wind-permit filing on party affiliation with progressively richer controls. Coefficients are expressed as a fraction of the baseline probability (0.76 percentage points); the omitted category is Democrat. "Party only" includes only the party indicators with no controls or fixed effects. Panel A adds zip code × year fixed effects; Panel B adds the two-way zip code × year and property fixed effects. "+ Property" (Panel A) and "+ Property chars" (Panel B) add property characteristics: assessed value, year built, years since last renovation, tenure at the property, and multiple-owner indicator; in Panel A, square footage, bedrooms, and bathrooms are also included as controls, while in Panel B these are time-invariant and absorbed by the property fixed effects. "+ Demographics" adds gender, ethnicity, age, religion, language, and presence of children. "+ Socioeconomic" adds income, net worth, education, and charitable contribution indicators. Standard errors clustered at the zip-code level in parentheses. R^2 is the overall R^2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table B.5: Permit Value: Party × Wind Interactions (Permit-Level)

	W10% Both Sides		W10% Upper Only	
	(1)	(2)	(3)	(4)
	Zip × Year	Zip × Yr + Prop.	Zip × Year	Zip × Yr + Prop.
Republican	75***	−16	75***	−16
	(17)	(32)	(17)	(32)
Other/missing	30**	27	30**	29
	(15)	(31)	(15)	(31)
Wind permit	853***	1,349***	885***	1,377***
	(122)	(127)	(123)	(128)
R × Wind	−35	−41	−40	−44
	(95)	(106)	(95)	(106)
Other × Wind	52	−30	49	−33
	(73)	(78)	(73)	(78)
Controls	Y	Y	Y	Y
Fixed effects	Zip × Yr	Zip × Yr + Prop.	Zip × Yr	Zip × Yr + Prop.
Clustering	Zip	Zip	Zip	Zip
Observations	7,496,967	6,407,314	7,496,967	6,407,314
Mean (dep. var.)	$10,321	$10,321	$10,265	$10,265

Note: Each observation is an individual building permit. The dependent variable is permit value in dollars (winsorized as indicated). The sample includes all non-repair permits with positive reported values. The omitted party category is Democrat × non-wind permit. Columns (1) and (3) include zip code × year fixed effects; columns (2) and (4) are two-way fixed-effects specifications with zip code × year and property fixed effects. All specifications include the same controls as in Table 3. Standard errors clustered at the zip-code level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table B.6: Full Coefficient Estimates – Part I

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Party affiliation (excluded: Democrat)		
Republican	−0.050***	−0.035***
	(0.007)	(0.009)
Other/missing	−0.018***	−0.007
	(0.006)	(0.009)
Gender (excluded: Female)		
Female–Female (FF)	0.059	−0.084
	(0.046)	(0.095)
Male (M)	−0.068***	−0.030***
	(0.006)	(0.009)
Male–Female (MF)	0.098**	0.093
	(0.042)	(0.092)
Male–Male (MM)	0.040	−0.023
	(0.046)	(0.095)
No gender info	−0.178***	−0.102
	(0.043)	(0.094)
Owner age, owner 1 (excluded: 25–30)		
Owner 1: <25	−0.026	−0.022
	(0.018)	(0.020)
Owner 1: 30–35	0.075***	0.089***
	(0.012)	(0.013)
Owner 1: 35–40	0.096***	0.118***
	(0.012)	(0.015)
Owner 1: 40–45	0.115***	0.139***
	(0.014)	(0.017)
Owner 1: 45–50	0.120***	0.146***
	(0.015)	(0.018)
Owner 1: 50–55	0.136***	0.169***
	(0.016)	(0.020)
Owner 1: 55–60	0.204***	0.229***
	(0.018)	(0.023)
Owner 1: 60–65	0.294***	0.296***
	(0.023)	(0.029)
Owner 1: 65–70	0.367***	0.335***
	(0.028)	(0.032)
Owner 1: 70–75	0.318***	0.265***
	(0.028)	(0.031)
Owner 1: >75	0.081***	0.084***
	(0.023)	(0.027)
Owner 1: Age unknown	0.108**	0.037
	(0.043)	(0.096)

Note: This table reports the full set of coefficient estimates from the baseline regressions summarized in Table 3. The dependent variable is an indicator equal to one if the property has at least one wind-related permit in a given year, expressed in percentage points (mean: 0.76%). Column (1) includes zip code × year fixed effects; column (2) zip code × year fixed effects together with property fixed effects (a two-way fixed-effects specification). Coefficients are in raw percentage points (not rescaled). Standard errors clustered at the zip-code level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The table continues over the following pages.

Table B.7: Full Coefficient Estimates – Part II

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Owner age, owner 2 (excluded: 25–30)		
Owner 2: <25	−0.062**	−0.077***
	(0.024)	(0.028)
Owner 2: 30–35	0.080***	0.105***
	(0.015)	(0.017)
Owner 2: 35–40	0.081***	0.122***
	(0.016)	(0.020)
Owner 2: 40–45	0.100***	0.145***
	(0.016)	(0.021)
Owner 2: 45–50	0.132***	0.184***
	(0.018)	(0.024)
Owner 2: 50–55	0.173***	0.222***
	(0.021)	(0.027)
Owner 2: 55–60	0.257***	0.302***
	(0.025)	(0.032)
Owner 2: 60–65	0.350***	0.396***
	(0.031)	(0.039)
Owner 2: 65–70	0.435***	0.481***
	(0.036)	(0.042)
Owner 2: 70–75	0.392***	0.445***
	(0.036)	(0.040)
Owner 2: >75	0.189***	0.306***
	(0.027)	(0.034)
Owner 2: Age unknown	0.146***	0.068
	(0.047)	(0.094)
Ethnicity, owner 1 (excluded: Black)		
Hispanic	−0.018	0.019
	(0.012)	(0.017)
White	0.050***	0.049**
	(0.013)	(0.019)
Other	0.019	0.016
	(0.013)	(0.022)
Missing	0.065***	0.081***
	(0.017)	(0.027)
Ethnicity, owner 2 (excluded: Black)		
Hispanic	0.033**	0.039
	(0.015)	(0.024)
White	0.068***	0.066***
	(0.014)	(0.024)
Other	0.021	0.046*
	(0.015)	(0.027)
Missing	0.081***	0.113***
	(0.018)	(0.030)

Table B.8: Full Coefficient Estimates – Part III

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Language, owner 1 (excluded: blank)		
Arabic	−0.038	0.063
	(0.044)	(0.108)
English	0.031**	0.043*
	(0.014)	(0.023)
German	0.154**	0.216
	(0.068)	(0.141)
Hindi	−0.114**	−0.169
	(0.049)	(0.117)
Italian	−0.018	0.103
	(0.042)	(0.093)
Portuguese	−0.070**	0.037
	(0.030)	(0.076)
Spanish	−0.002	0.078***
	(0.015)	(0.028)
Vietnamese	−0.151***	−0.102
	(0.035)	(0.090)
Other	−0.121***	0.068
	(0.026)	(0.060)
Missing	0.003	−0.037
	(0.016)	(0.025)
Language, owner 2 (excluded: blank)		
Arabic	−0.121	0.065
	(0.099)	(0.185)
English	−0.038**	−0.030
	(0.019)	(0.034)
German	0.086	0.196
	(0.130)	(0.276)
Hindi	0.018	0.081
	(0.069)	(0.180)
Italian	−0.107	0.047
	(0.087)	(0.166)
Portuguese	−0.078	0.275**
	(0.055)	(0.124)
Spanish	−0.080***	−0.011
	(0.020)	(0.039)
Vietnamese	−0.085	0.210
	(0.062)	(0.154)
Other	−0.098**	−0.005
	(0.039)	(0.081)
Missing	−0.027	−0.044
	(0.023)	(0.037)

Table B.9: Full Coefficient Estimates – Part IV

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Religion, owner 1 (excluded: blank)		
Buddhist	−0.196***	−0.229***
	(0.025)	(0.056)
Catholic	−0.097***	−0.215***
	(0.014)	(0.027)
Eastern Orthodox	−0.069**	−0.147**
	(0.030)	(0.071)
Greek Orthodox	−0.136***	−0.284***
	(0.045)	(0.093)
Hindu	−0.152***	−0.179**
	(0.033)	(0.090)
Islamic	−0.205***	−0.159**
	(0.029)	(0.066)
Jewish	−0.086***	−0.178***
	(0.019)	(0.031)
Protestant	−0.097***	−0.211***
	(0.014)	(0.025)
Other	−0.047	−0.053
	(0.048)	(0.102)
Missing	−0.095***	−0.103***
	(0.017)	(0.026)
Religion, owner 2 (excluded: blank)		
Buddhist	−0.194***	−0.363***
	(0.032)	(0.077)
Catholic	−0.079***	−0.180***
	(0.017)	(0.031)
Eastern Orthodox	−0.036	−0.269***
	(0.046)	(0.098)
Greek Orthodox	−0.118**	−0.294**
	(0.059)	(0.117)
Hindu	−0.182***	−0.184*
	(0.045)	(0.096)
Islamic	−0.092**	−0.147
	(0.042)	(0.093)
Jewish	−0.063**	−0.100**
	(0.025)	(0.046)
Protestant	−0.116***	−0.196***
	(0.016)	(0.028)
Other	−0.133**	−0.368***
	(0.064)	(0.138)
Missing	−0.080***	−0.126***
	(0.022)	(0.034)

Table B.10: Full Coefficient Estimates – Part V

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Net worth, owner 1 (excluded: $0)		
$1-4999	0.051**	0.119**
	(0.025)	(0.052)
$10,000 - $24,999	0.064**	0.075
	(0.027)	(0.055)
$100,000 - $249,999	0.106***	0.194***
	(0.022)	(0.045)
$10000-24999	0.031	0.081*
	(0.022)	(0.045)
$100000-249999	0.056**	0.091**
	(0.023)	(0.044)
$25,000 - $49,999	0.052**	0.116**
	(0.025)	(0.051)
$250,000 - $499,999	0.171***	0.262***
	(0.025)	(0.051)
$25000-49999	0.037*	0.134***
	(0.022)	(0.045)
$250000-499999	0.021	−0.052
	(0.024)	(0.046)
$499999+	−0.052*	−0.339***
	(0.030)	(0.068)
$5,000 - $9,999	0.048	0.134
	(0.036)	(0.083)
$50,000 - $99,999	0.070***	0.145***
	(0.023)	(0.050)
$5000-9999	0.074***	0.177***
	(0.025)	(0.052)
$50000-99999	−0.008	0.124***
	(0.021)	(0.046)
Greater than $499,999	0.323***	0.451***
	(0.031)	(0.056)
Less than $1	0.037*	0.085*
	(0.022)	(0.045)
missing	0.082***	0.186***
	(0.021)	(0.043)

Table B.11: Full Coefficient Estimates – Part VI

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Net worth, owner 2 (excluded: $0)		
$1-4999	0.165***	0.139*
	(0.034)	(0.072)
$10,000 - $24,999	0.095***	0.087
	(0.036)	(0.080)
$100,000 - $249,999	0.137***	0.168**
	(0.031)	(0.067)
$10000-24999	0.091***	0.115
	(0.032)	(0.072)
$100000-249999	0.136***	0.187***
	(0.029)	(0.066)
$25,000 - $49,999	0.053	0.056
	(0.035)	(0.073)
$250,000 - $499,999	0.222***	0.325***
	(0.034)	(0.069)
$25000-49999	0.134***	0.188***
	(0.028)	(0.066)
$250000-499999	0.133***	0.099
	(0.031)	(0.069)
$499999+	0.196***	0.052
	(0.037)	(0.075)
$5,000 - $9,999	0.124**	0.117
	(0.051)	(0.102)
$50,000 - $99,999	0.105***	0.129*
	(0.033)	(0.073)
$5000-9999	0.121***	0.100
	(0.036)	(0.083)
$50000-99999	0.082***	0.134**
	(0.029)	(0.068)
Greater than $499,999	0.421***	0.539***
	(0.040)	(0.076)
Less than $1	0.067**	0.084
	(0.030)	(0.064)
missing	0.185***	0.238***
	(0.030)	(0.065)

Table B.12: Full Coefficient Estimates – Part VII

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Education, owner 1 (excluded: Attended Vocational/Technical Extremely Likely)		
Attended Vocational/Technical School Likely	0.086	0.034
	(0.137)	(0.241)
Bach Degree - Extremely Likely	0.143***	0.169**
	(0.052)	(0.085)
Bach Degree - Likely	0.135**	0.178**
	(0.053)	(0.088)
Completed College Likely	0.200***	0.253***
	(0.056)	(0.091)
Completed Graduate School Likely	0.333***	0.405***
	(0.065)	(0.100)
Completed High School Likely	0.180***	0.246***
	(0.056)	(0.093)
Did Not Complete High School Likely	0.009	0.020
	(0.095)	(0.135)
Grad Degree - Extremely Likely	0.191***	0.150*
	(0.051)	(0.088)
Grad Degree - Likely	0.150***	0.186**
	(0.053)	(0.086)
HS Diploma - Extremely Likely	0.074	0.151*
	(0.053)	(0.086)
HS Diploma - Likely	0.082	0.150*
	(0.053)	(0.086)
Less than HS Diploma - Ex Like	0.281**	0.492**
	(0.128)	(0.232)
Less than HS Diploma - Likely	0.049	0.117
	(0.053)	(0.087)
missing	0.123**	0.135
	(0.052)	(0.086)
Some College - Likely	0.118**	0.171**
	(0.052)	(0.086)
Some College -Extremely Likely	0.188***	0.207**
	(0.053)	(0.088)
Vocational Technical Degree - Extremely Likely	0.175***	0.137
	(0.066)	(0.115)

Table B.13: Full Coefficient Estimates – Part VIII

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Education, owner 2 (excluded: Attended Vocational/Technical Extremely Likely)		
Attended Vocational/Technical School Likely	−0.357**	−0.316
	(0.147)	(0.221)
Bach Degree - Extremely Likely	−0.088	−0.093
	(0.081)	(0.118)
Bach Degree - Likely	−0.089	−0.080
	(0.081)	(0.116)
Completed College Likely	−0.032	0.015
	(0.081)	(0.117)
Completed Graduate School Likely	0.077	0.084
	(0.096)	(0.146)
Completed High School Likely	−0.062	−0.073
	(0.086)	(0.123)
Did Not Complete High School Likely	−0.158	−0.083
	(0.160)	(0.268)
Grad Degree - Extremely Likely	−0.082	−0.097
	(0.081)	(0.120)
Grad Degree - Likely	−0.083	−0.082
	(0.081)	(0.118)
HS Diploma - Extremely Likely	−0.141*	−0.103
	(0.081)	(0.116)
HS Diploma - Likely	−0.122	−0.089
	(0.080)	(0.116)
Less than HS Diploma - Ex Like	−0.070	−0.110
	(0.184)	(0.321)
Less than HS Diploma - Likely	−0.172**	−0.141
	(0.082)	(0.118)
missing	−0.073	−0.056
	(0.081)	(0.117)
Some College - Likely	−0.108	−0.092
	(0.081)	(0.117)
Some College -Extremely Likely	−0.072	−0.047
	(0.080)	(0.116)
Vocational Technical Degree - Extremely Likely	−0.119	−0.084
	(0.097)	(0.155)

Table B.14: Full Coefficient Estimates – Part IX

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Charitable contributions (excluded: missing)		
Owner 1: Unknown	0.075***	0.081***
	(0.011)	(0.017)
Owner 1: Yes	0.069***	0.041**
	(0.011)	(0.017)
Owner 2: Unknown	0.041***	0.061***
	(0.014)	(0.022)
Owner 2: Yes	0.033**	0.033
	(0.015)	(0.022)
Years since last renovation (excluded: Decile 1)		
Decile 2	−0.034	0.038
	(0.028)	(0.025)
Decile 3	−0.092***	0.054**
	(0.030)	(0.024)
Decile 4	−0.136***	0.070***
	(0.031)	(0.025)
Decile 5	−0.165***	0.097***
	(0.032)	(0.027)
Decile 6	−0.187***	0.123***
	(0.034)	(0.027)
Decile 7	−0.220***	0.128***
	(0.036)	(0.029)
Decile 8	−0.252***	0.105***
	(0.038)	(0.032)
Decile 9	−0.232***	0.084**
	(0.040)	(0.035)
Decile 10	−0.209***	0.066*
	(0.041)	(0.038)
Other controls		
Has children	−0.021***	−0.011
	(0.007)	(0.007)
Multiple owners	0.033***	0.021***
	(0.008)	(0.007)

Table B.15: Full Coefficient Estimates – Part X

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Year built, bins 2–16 (excluded: Bin 1)		
Bin 2	0.048*	0.176*
	(0.025)	(0.091)
Bin 3	0.032	0.128
	(0.020)	(0.117)
Bin 4	0.028	0.050
	(0.021)	(0.148)
Bin 5	0.032	0.028
	(0.024)	(0.123)
Bin 6	0.060***	0.020
	(0.022)	(0.133)
Bin 7	0.089***	0.246
	(0.027)	(0.168)
Bin 8	0.116***	0.080
	(0.024)	(0.159)
Bin 9	0.136***	−0.170
	(0.025)	(0.161)
Bin 10	0.168***	−0.111
	(0.026)	(0.219)
Bin 11	0.173***	0.268
	(0.027)	(0.255)
Bin 12	0.147***	−0.222
	(0.028)	(0.247)
Bin 13	0.149***	0.165
	(0.026)	(0.201)
Bin 14	0.178***	0.434
	(0.028)	(0.390)
Bin 15	0.183***	0.186
	(0.028)	(0.230)
Bin 16	0.190***	0.298
	(0.030)	(0.242)

Table B.16: Full Coefficient Estimates – Part XI

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Year built, bins 17–30 (excluded: Bin 1)		
Bin 17	0.176***	0.321
	(0.034)	(0.320)
Bin 18	0.147***	0.383
	(0.041)	(0.251)
Bin 19	0.077**	0.170
	(0.035)	(0.275)
Bin 20	−0.005	0.088
	(0.030)	(0.216)
Bin 21	−0.060*	1.019**
	(0.033)	(0.428)
Bin 22	−0.095***	0.772**
	(0.032)	(0.363)
Bin 23	−0.186***	0.508**
	(0.034)	(0.235)
Bin 24	−0.247***	0.268
	(0.034)	(0.173)
Bin 25	−0.311***	0.310
	(0.035)	(0.245)
Bin 26	−0.384***	0.272
	(0.038)	(0.213)
Bin 27	−0.439***	0.024
	(0.041)	(0.173)
Bin 28	−0.523***	−0.791**
	(0.057)	(0.322)
Bin 29	−0.639***	−0.267**
	(0.064)	(0.109)
Bin 30	−0.676***	−0.302***
	(0.069)	(0.115)
Missing	−0.270**	−0.308*
	(0.119)	(0.172)

Table B.17: Full Coefficient Estimates – Part XII

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Property value, bins 2–16 (excluded: Bin 1)		
Bin 2	−0.079***	−0.118***
	(0.018)	(0.027)
Bin 3	−0.115***	−0.181***
	(0.023)	(0.038)
Bin 4	−0.133***	−0.221***
	(0.026)	(0.045)
Bin 5	−0.145***	−0.251***
	(0.028)	(0.051)
Bin 6	−0.157***	−0.285***
	(0.030)	(0.055)
Bin 7	−0.147***	−0.303***
	(0.031)	(0.059)
Bin 8	−0.155***	−0.331***
	(0.033)	(0.063)
Bin 9	−0.153***	−0.351***
	(0.034)	(0.066)
Bin 10	−0.142***	−0.362***
	(0.035)	(0.069)
Bin 11	−0.144***	−0.387***
	(0.037)	(0.073)
Bin 12	−0.137***	−0.399***
	(0.039)	(0.076)
Bin 13	−0.126***	−0.412***
	(0.039)	(0.078)
Bin 14	−0.115***	−0.433***
	(0.040)	(0.081)
Bin 15	−0.112***	−0.449***
	(0.042)	(0.085)
Bin 16	−0.087**	−0.451***
	(0.043)	(0.088)

Table B.18: Full Coefficient Estimates – Part XIII

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Property value, bins 17–30 (excluded: Bin 1)		
Bin 17	−0.061	−0.452***
	(0.043)	(0.090)
Bin 18	−0.049	−0.468***
	(0.045)	(0.093)
Bin 19	−0.047	−0.499***
	(0.045)	(0.096)
Bin 20	−0.028	−0.511***
	(0.047)	(0.099)
Bin 21	0.001	−0.518***
	(0.049)	(0.103)
Bin 22	0.034	−0.528***
	(0.048)	(0.103)
Bin 23	0.073	−0.536***
	(0.051)	(0.109)
Bin 24	0.097*	−0.554***
	(0.054)	(0.113)
Bin 25	0.158***	−0.550***
	(0.056)	(0.118)
Bin 26	0.199***	−0.567***
	(0.059)	(0.123)
Bin 27	0.239***	−0.615***
	(0.062)	(0.130)
Bin 28	0.274***	−0.675***
	(0.068)	(0.138)
Bin 29	0.326***	−0.752***
	(0.074)	(0.145)
Bin 30	0.239***	−0.976***
	(0.086)	(0.157)
Missing	0.551***	0.274
	(0.161)	(0.231)

Table B.19: Full Coefficient Estimates – Part XIV

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Household income, bins 2–16 (excluded: Bin 1)		
Bin 2	0.017*	0.010
	(0.009)	(0.009)
Bin 3	0.032***	0.021*
	(0.011)	(0.011)
Bin 4	0.039***	0.028**
	(0.013)	(0.012)
Bin 5	0.049***	0.036***
	(0.015)	(0.012)
Bin 6	0.054***	0.036***
	(0.016)	(0.012)
Bin 7	0.066***	0.045***
	(0.016)	(0.012)
Bin 8	0.079***	0.055***
	(0.018)	(0.013)
Bin 9	0.072***	0.049***
	(0.018)	(0.013)
Bin 10	0.078***	0.045***
	(0.018)	(0.013)
Bin 11	0.070***	0.029**
	(0.019)	(0.013)
Bin 12	0.093***	0.053***
	(0.019)	(0.013)
Bin 13	0.086***	0.045***
	(0.019)	(0.013)
Bin 14	0.090***	0.053***
	(0.021)	(0.013)
Bin 15	0.097***	0.047***
	(0.021)	(0.013)
Bin 16	0.098***	0.056***
	(0.023)	(0.014)

Table B.20: Full Coefficient Estimates – Part XV

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Household income, bins 17–30 (excluded: Bin 1)		
Bin 17	0.106***	0.053***
	(0.023)	(0.013)
Bin 18	0.093***	0.039***
	(0.023)	(0.014)
Bin 19	0.110***	0.049***
	(0.024)	(0.015)
Bin 20	0.100***	0.048***
	(0.025)	(0.014)
Bin 21	0.116***	0.057***
	(0.027)	(0.014)
Bin 22	0.113***	0.056***
	(0.027)	(0.014)
Bin 23	0.116***	0.060***
	(0.029)	(0.016)
Bin 24	0.124***	0.071***
	(0.030)	(0.015)
Bin 25	0.114***	0.050***
	(0.033)	(0.016)
Bin 26	0.128***	0.074***
	(0.034)	(0.016)
Bin 27	0.151***	0.083***
	(0.038)	(0.018)
Bin 28	0.138***	0.073***
	(0.040)	(0.017)
Bin 29	0.175***	0.082***
	(0.049)	(0.022)
Bin 30	0.241***	0.072**
	(0.060)	(0.029)
Missing	0.052**	−0.051***
	(0.022)	(0.011)

Table B.21: Full Coefficient Estimates – Part XVI

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Square footage (excluded: missing)		
Bin 1	0.177	
	(0.135)	
Bin 2	0.227*	
	(0.136)	
Bin 3	0.250*	
	(0.137)	
Bin 4	0.281**	
	(0.137)	
Bin 5	0.307**	
	(0.137)	
Bin 6	0.321**	
	(0.138)	
Bin 7	0.359**	
	(0.140)	
Bin 8	0.380***	
	(0.141)	
Bin 9	0.382***	
	(0.141)	
Bin 10	0.328**	
	(0.144)	
Bedrooms (excluded: 1)		
2	0.063***	
	(0.021)	
3	0.065***	
	(0.023)	
4	0.038	
	(0.024)	
5	0.040	
	(0.029)	
6	0.041	
	(0.041)	
7	−0.175**	
	(0.069)	
8	0.166**	
	(0.078)	
9	0.015	
	(0.126)	
10+	−0.005	
	(0.066)	
Missing	0.086***	
	(0.032)	
Bathrooms (excluded: 1)		
2	0.029**	
	(0.012)	
3	−0.010	
	(0.018)	
4	−0.067**	
	(0.028)	
5+	−0.146***	
	(0.042)	
Missing	−0.100***	
	(0.037)	

Note: Square footage, number of bedrooms, and number of bathrooms are fixed property characteristics and are absorbed by the property fixed effects in column (2).

Table B.22: Full Coefficient Estimates – Part XVII

	Dep. var.: Wind permit (%)	
	(1)	(2)
	Zip × Year	Zip × Yr + Property
Ownership tenure (excluded: Decile 1)		
Decile 2	0.263***	0.285***
	(0.017)	(0.018)
Decile 3	−0.116***	−0.108***
	(0.013)	(0.013)
Decile 4	−0.212***	−0.222***
	(0.017)	(0.018)
Decile 5	−0.254***	−0.283***
	(0.019)	(0.020)
Decile 6	−0.293***	−0.343***
	(0.020)	(0.023)
Decile 7	−0.321***	−0.392***
	(0.021)	(0.025)
Decile 8	−0.325***	−0.412***
	(0.021)	(0.026)
Decile 9	−0.325***	−0.411***
	(0.021)	(0.025)
Decile 10	−0.301***	−0.375***
	(0.021)	(0.026)
Fixed effects	Zip × Year	Zip × Yr + Property
Clustering	Zip	Zip
Observations	60,714,431	60,644,537
R^2 (overall)	0.018	0.111
R^2 (within)	0.002	0.001
RMSE	8.633	8.605

C Details of the welfare calculations

This appendix collects the details behind the welfare calculations in the main text.

Calibration of the market-based risk loading. In the market-based approach, I value the benefits of mitigation by discounting expected annual losses at the risk-free rate and applying the risk-loading factor $(1 + \lambda)$. Note that this multiplier captures both equilibrium risk attitudes and the perceived risk distribution (i.e. it does the entirety of the risk adjustment); it can be calibrated directly from observed catastrophe-bond and reinsurance prices. Catastrophe-bond multiples $(1+\lambda)$ averaged 4.5× in 2023 and 3.7× in 2024 (Artemis, 2024), while Froot (2001) documents a California Earthquake Authority remote-layer reinsurance placement priced at 6.3× expected loss. I therefore use three observed prices: $\lambda = 2.7$ (the 2024 average), $\lambda = 3.5$ (the 2023 average and my central case), and $\lambda = 5.3$ (Froot's remote-layer example).

The remaining parameters are a horizon of $T = 30$ years, averaging the shorter service life of hurricane shutters and the longer service life of impact windows and structural reinforcements; a real risk-free rate of 1%; and $g = 0$. This conservative choice for g does not incorporate two forces that could increase future benefits in real terms (increasing g and therefore making the benefits higher): real building costs have tended to grow faster than overall inflation, and hurricane-related damages are expected to increase further due to climate change, especially via projected increases in hurricane intensity (IPCC, 2021).

Investment costs in the main text are taken from permit values, which are quite noisy in Cotality; I winsorize them between \$3,000 and \$30,000, typical ranges for shutter and impact window investments.

Calculating the NPV assuming CRRA utility. The λ-loading approach above is attractive because it needs only the mean loss (EAL_i) plus one observed market price. An alternative approach is to compute the certainty equivalent using a specified utility function; this requires knowing the distribution of losses, not just their expectation, in addition to calibrating the risk aversion parameter. In the utility-based calibration, I value the same decision directly under a household's utility function, taking a realistic "disaster" representation of hurricane risks, that assumes that losses occur only in relatively serious wind events. Within this framework, I back out the annual probability of such an event from each home's own expected annual loss, together with an estimate of the damage level conditional on a hurricane event.

Specifically, a household with structure value V faces a two-state hurricane risk: with probability p a serious wind event occurs and destroys a fraction x of V; with probability $1-p$, nothing happens. Mitigation reduces the loss conditional on the event from x to $(1-\rho)x$ but leaves the residual risk in place. The household's certainty-equivalent annual willingness to pay P for the mitigated position solves

$$(1-p)\,u(V-P) \;+\; p\,u\big(V-P-(1-\rho)xV\big) \;=\; (1-p)\,u(V) \;+\; p\,u\big(V(1-x)\big), \qquad u(c)=\frac{c^{1-\gamma}}{1-\gamma}.$$

After solving for P_i, I calculate $\text{NPV}_i^{\text{CRRA}} = P_i A(r_f, g, T) - C_i$ using the same horizon, growth rate, and discount rate as in the market-based calculation.

I take the estimate of x from the Florida Public Hurricane Loss Model's (FPHLM) vulnerability curves (FPHLM, 2025), in the tables for mean damage ratio versus wind speed, averaged across masonry and timber construction, for unmitigated properties. I match wind zones in Florida (based on the building code maps) to the wind speeds in the tables, averaging within the observed ranges: the non-mandate area has wind speeds 130–140 mph (averaged severity 0.35, that is, 35% loss). The high-velocity-hurricane (mandate) zone has wind speeds above 140 mph up to Florida's highest design speeds (Monroe, Miami-Dade, and Broward), and although the curve keeps climbing well past 200 mph – reaching about 0.8 by 250 mph – I deliberately choose the conservative value $x = 0.50$ for that zone (50% conditional loss) rather than the higher full-range average. Given x, I back out p_i for each home so the expected annual loss matches the number reported by FEMA: $p_i = \text{EAL}_i/(x_i V_i)$.

Matched non-adopter counterfactual. Because households that adapted selected into doing so, the marginal investments unlocked by closing the partisan gap need not resemble those actually undertaken. As a robustness check, I therefore also construct the counterfactual directly from non-adopters. For each Republican adopter observation, I draw a never-adapted Republican home from the same census tract, falling back to the county where necessary, and value a representative retrofit at the median adopter cost. At the central $\lambda = 3.5$, this exercise yields \$152 million rather than \$205 million. The matched homes have similar risk profiles but lower structure values than adopters. Matching to the never-adapted home closest in structure value within the same geography raises the estimate to \$181 million.

Private vs. social benefits. The calculations in the main text value the avoided physical losses in full: they measure the *social* benefit of mitigation. For an insured homeowner, however, some of the avoided loss initially accrues to the insurer, and flows back to the household only insofar as mitigation lowers the insurance premium (or is already borne by the household via the deductible). The private benefit therefore has three components. First, the avoided losses the household retains directly – the share of expected loss below the hurricane deductible, s_{ded}; Second, the insurer-layer savings returned as premium reductions, where Florida law mandates actuarially based mitigation credits (§627.0629, F.S.; Florida Legislature, 2025); I denote the realized pass-through by π. Third, for the fraction u of single-family owners without wind coverage, the entire avoided loss. The ratio of private to social benefit is then $u + (1-u)\left[s_{ded} + (1 - s_{ded})\,\pi\right]$.

I calibrate these parameters as follows. s_{ded} is calibrated from two ingredients: the distribution of hurricane deductibles from the Florida Hurricane Catastrophe Fund ratemaking data call (FHCF, 2026) (showing that 82% of policies have a 2% deductible, and 13% have a 5% deductible), and the share of expected annual wind loss falling below each deductible, by region, from Applied Research Associates (2002) and FPHLM (2025), which agree closely (≈0.20 at the 2% deductible in the highest-risk zone, ≈0.33 elsewhere; roughly 15 points higher at 5%). Weighting the loss shares by the deductible mix gives 0.22 in the mandate zone and 0.35 in the rest of the state.

The uninsured share u is computed by looking at a number of different estimates: the Insurance Information Institute places Florida homeowners without property insurance at 15–20% (III, 2024), and an ACS-based proxy – owner-occupied homes reporting under $100 of annual insurance spending, which need not coincide with the share lacking wind coverage specifically – puts Florida at about 19% (LendingTree, 2026). I therefore calibrate u at 18%.

The pass-through $\pi = 0.73$ is estimated from the incomplete credit take-up data (showing that by 2009 about 40% of all residential policies received mitigation credits, while 55% of the homes inspected under the My Safe Florida Home program qualified without further improvement, see FCHLPM, 2010). The estimated π is computed as 0.4/0.55.

National extrapolation. Florida is not the only state exposed to hurricane wind risk, so I construct a national analogue of the optimal-adaptation counterfactual, using the SFR homes in the national Cotality files. For each home outside Florida, I assign expected annual wind loss equal to its structure value times its county hurricane loss rate from the FEMA National Risk Index (FEMA, 2023). To parallel the Florida calculation, tract risk is hurricane annual frequency times the conditional building-loss rate; I aggregate it to counties weighting by exposed building value. I then value protection with the same formula as above – $(1 + \lambda)\,\rho\,\mathrm{EAL}_i\,A(r_f, g, T)$, and use the median cost from the Florida permits to estimate the cost.

The one ingredient I do not observe outside Florida is whether a home has already adapted. I impute it from Florida: using my main sample, I estimate the probability that a home has never adopted wind protection within cells defined by county hurricane risk (eight bins), structure value (eight bins), and construction vintage (five bins), requiring at least 200 Florida homes per cell and falling back to coarser cells otherwise. The assumption is that, conditional on these three characteristics, homes outside Florida are unprotected at Florida's rates.

This assumption is likely conservative. Florida has some of the strictest wind-related building codes and one of the most active retrofit markets in the country, so Florida's protection rates likely overstate protection in states without comparable mandates, biasing the imputed national figure downward. Under this raw current-stock calibration, the national present-value benefit is **$72.1 billion** in the central case ($32.3 billion in Florida plus $39.8 billion elsewhere), with a $52.4–$120.5 billion range across the market-observed λ grid.