Political Orientation and Household Climate Adaptation: Evidence from Building Permits

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Abstract

I study how political orientation affects households' decisions to invest in climate adaptation, focusing on wind-related 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 4–7% lower than that of registered Democrats, controlling for extensive individual, property, and geographic 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 on the mechanism point toward a beliefs channel: the partisan gap in adaptation doubles among FEC campaign donors, consistent with stronger partisan identity amplifying the effect; it is stronger in areas where building codes are less stringent and therefore leave household decisions less constrained; it widens sharply at the start of the first Trump administration before narrowing after the relaunch of Florida's My Safe Florida Home subsidy program; and it narrows during periods of high local climate news coverage, widening when attention fades.

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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 66 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 6.7% lower than that of Democrats, controlling for income, property value, and a rich set of owner and property characteristics. The effect persists when identification is sharpened to census-block-by-year fixed effects (−6.4%) and to property fixed effects that exploit ownership transitions within the same dwelling by including property fixed effects (−3.8%), therefore comparing Republicans and Democrats that own the same house at different points in time. Crucially, the partisan gap is specific to climate adaptation: Re-

[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/.

publicans 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 6.7% 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 climate beliefs that are connected with political identity, or to other components of political identity that affect adaptation but not through beliefs. However, four pieces of evidence point toward a channel rooted in partisan differences in climate-risk beliefs. First, I exploit federal campaign contribution records to show that the adaptation gap is roughly twice as large among FEC donors – households with the strongest revealed partisan engagement – as 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 purely 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): indeed, where adaptation is purely voluntary, the partisan gap is larger. 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 to roughly −13% to −14% by 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, using the newspaper-based climate attention index of Kostovetsky et al. (2024), I show that the partisan gap narrows sharply in periods of high local climate news coverage—when objective risk is salient and harder to dismiss—and widens when attention recedes. Within a given property, the Republican gap is −8.2% in low-attention periods but closes almost entirely when attention is high, and this result strengthens when I control for the aggregate trends in the partisan gap and for differences in the partisan gap across geographies. 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 can 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 economically similar to the baseline, ruling out the possibility that the gap reflects differential prior

adaptation. 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. The results also hold under logit and discrete-time hazard specifications. Finally, 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).

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 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 adaptation literature 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; Goldsmith-Pinkham et al., 2023; 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 example 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

I begin from a description of the institutional setting for building permits in the U.S. and Florida more specifically, as well as the Cotality dataset I use to identify hurricane-related 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.[2] 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.[3]

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.[4] At the local level, city or county building departments are responsible for issuing permits, reviewing plans for code compliance, and conducting inspections.[5]

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.[6] 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 ap-

[2] International Code Council (ICC), International Building Code (IBC), 2021 Edition.

[3] Federal Emergency Management Agency (FEMA), "Building Codes Save: A Nationwide Study of Loss Prevention," 2020.

[4] National Association of Home Builders (NAHB), "State and Local Building Codes," 2022.

[5] National Conference of State Legislatures (NCSL), "Building Codes and State Enforcement," 2021.

[6] See, e.g., Florida Building Commission, *Florida Building Code*, 7th Edition (2020), Chapter 1, "Scope and Administration."

proved 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)[7] 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. 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 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.[8] 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

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

[8] 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.

important question, therefore, is whether the climate adaptation investments studied here 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: 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 a more immediate and granular measure of household resilience efforts.

2.1.3 Wind Adaptation Investments

This subsection describes 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 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 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 weather-related hazards in the United States. Drought is generally less relevant for residential properties than for agriculture. Extreme heat is excluded 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.

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.[9] 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.[10] 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).[11] 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. And, indeed, many households choose to keep the original windows and shutters, 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* 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.

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

[9] See, for example, FEMA, "Protect your property from severe winds," https://www.fema.gov/sites/default/files/2020-11/fema_protect-your-property_severe-wind.pdf.

[10] International Code Council, International Building Code, Section 1609.2, 2018 Edition.

[11] The requirement to bring an *entire* structure up to code triggers only when a renovation exceeds 50% of the building's value. See Federal Emergency Management Agency, *Substantial Improvement/Substantial Damage Desk Reference*, FEMA P-758, May 2010. The types of investments studied here do not typically meet that threshold.

the ASCE website and use them to geocode each property.[12] In Section 4, I conduct the 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 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.[13] 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). Windows, doors, and shutters generally last indefinitely, so permits for these upgrades are likely to capture voluntary adaptation. For roofs, we 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.[14]

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

Second, 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*.[15] Third, I constructed an additional set of general exclusion words that are applied to all permits to identify which are definitely not

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

[13] Specifically, I provided the FEMA guidance document "Protect your property from severe winds" 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.

[14] Indeed, in the data roof replacements permits appear with equal frequency in areas at high and low exposure to hurricanes. 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.

[15] 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.

related to wind adaptation, regardless of which keyword triggered the match.[16]

Fourth, 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.1, and Appendix Table B.2 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.[17] 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* (320,311 permits), *shutter wind* (112,552), *hurricane shutters* (39,374), *shutter storm* (22,877), *door impact* (18,140), *roll shutter* (11,311), *barrier secondary* (8,856), *anchor* (6,741), *roof truss* (6,584), *hurricane protection* (4,991), *impact shutter* (2,666), and *panel storm* (2,518). 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.

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. 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.

[16] 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.

[17] 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), the alphabetical ordering groups them together. A small number of keywords—such as *anchor*—are sufficiently specific that no complement is required, though keyword-specific exclusion words still apply.

Table 1: Wind-Related Adaptation Keywords and Frequencies

Climate Pair	Frequency	Cumulative Probability
impact wind	320,311	0.55
shutter wind	112,552	0.75
hurricane shutters	39,374	0.81
shutter storm	22,877	0.85
door impact	18,140	0.88
roll shutter	11,311	0.90
barrier secondary	8,856	0.92
anchor	6,741	0.93
roof truss	6,584	0.94
hurricane protection	4,991	0.95
impact shutter	2,666	0.96
panel storm	2,518	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.

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 our without permits 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, 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, 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 ensures 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 66 million observations spanning 2014–2024. Each observation represents a specific individual (or multiple individuals) owning a given property in a given year. About 8 million observations (12%) have at least one permit filed in that property-year by that owner; approximately 497,000 observations (0.75%) 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 ($97,527 vs. $79,162), own more valuable homes ($343,360 vs. $265,478), 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 58–59%). Household composition differs substantially: Democratic households are more likely to be female-headed (35% vs. 23%) and more racially diverse.

Notably, in the raw data Republicans are *more* likely to have both wind permits (0.94% vs. 0.87%) and permits in general (14.01% vs. 13.00%). 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

Table 2: Household Characteristics by Political Affiliation

Variable	Republicans	Democrats	Diff. p-value
Owner age	59.47	59.52	0.00
Annual income ($)	97,527	79,162	0.00
Year built	1988	1984	0.00
Tenure at house (years)	10.49	11.33	0.00
House value ($)	343,360	265,478	0.00
Any wind permit (%)	0.94	0.87	0.00
Any permit (%)	14.01	13.00	0.00
Mandate area	0.58	0.59	0.00
Gender composition			
Female household	0.23	0.35	0.00
Mixed-gender (M/F)	0.48	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	0.42	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).

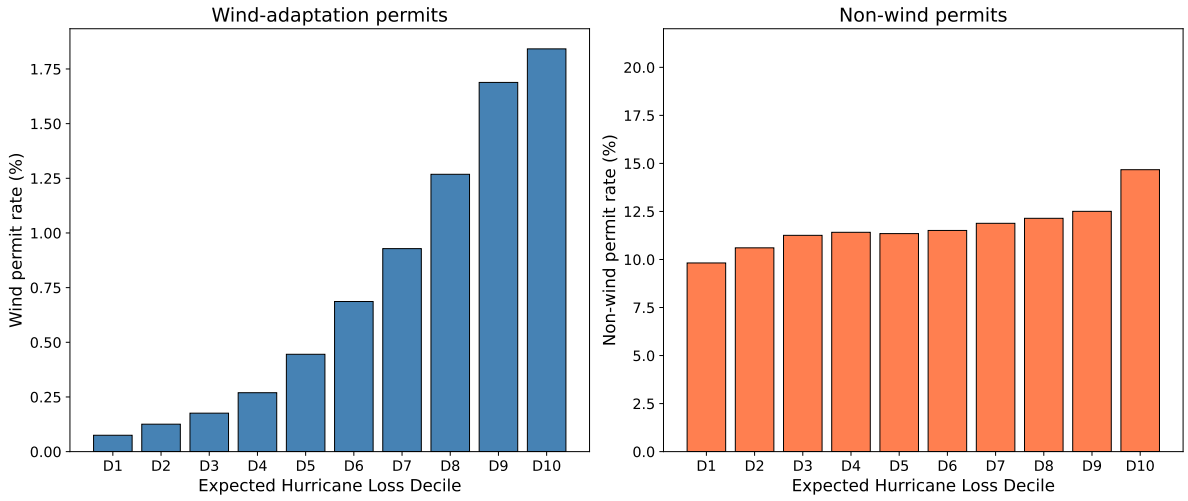
wind-adaptation permits, while general permitting activity—which reflects routine maintenance and renovation unrelated to climate—should be largely unresponsive to hurricane risk.

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.[18]

Figure 1 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

[18]Source: `https://hazards.fema.gov/nri/`. 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 our 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: 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 66 million property-owner-year observations.

higher-risk coastal properties tend to be more valuable and thus more likely to undergo renovations of all types.

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, census block × year, or even individual property fixed effects), 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.

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.

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—income, gender, race, age, and education—as well as property attributes such as assessed value, year built, and ownership tenure. 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 specifications using census-block-by-year fixed effects and property and year fixed effects, the latter exploiting differences across owners of the same property. 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 (0.75 percentage points per property-owner-year). Therefore, for example, a coefficient of -0.067 means Republicans have a probability of adapting that is 6.7% (not percentage points) lower than that of Democrats.

Column (1) reports a first set of results, obtained using zip code $\times$ year fixed effects. The estimated coefficient on the Republican dummy variable indicates that the probability that Republicans file a wind-adaptation permit in a certain year is 6.7% lower than for Democrats. The "other/missing" party category shows a coefficient much closer to zero.

Figure 2 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 filing probability by about 25% of the baseline, with an approximately linear gradient across bins (panel a). Property value shows a similar monotonically increasing pattern (panel b). Tenure at the property is negatively associated with filing, consistent with the idea that homeowners are more likely 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 (-0.095, or about 9.5% of the baseline). All multi-owner categories—male-female (MF), female-female (FF), and male-male (MM)—show substantially higher filing rates, with the MF category having the largest coefficient ($+0.187$). Full coefficient estimates for all controls—including age, ethnicity, education, net worth, charitable and political contributions, and the missing-value indicators—are reported in Table B.5 in the Appendix (note that the Appendix table does not scale coefficients by the baseline probability

Table 3: Effect of Political Affiliation on Wind Permit Adoption

	Dep. var.: Wind permit (% of baseline)		
	(1)	(2)	(3)
Republican	−0.067***	−0.064***	−0.038***
	(0.009)	(0.008)	(0.012)
Other/missing	−0.013*	−0.012*	0.001
	(0.008)	(0.007)	(0.012)
Controls	Y	Y	Y
Fixed effects	Zip × Year	Block × Year	Property + Year
Clustering	Zip	Zip	Zip
Observations	66,194,785	66,189,501	66,120,781
R^2 (overall)	0.017	0.021	0.108
R^2 (within)	0.002	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 (0.75 percentage points); for example, −0.067 means that the probability that Republicans file a wind-adaptation permit is 6.7% lower than that of Democrats. The excluded party category is Democrat. Controls include owner age, gender, household income, net worth, property value, year built, tenure at the property, ethnicity, education, charitable contribution indicators, FEC donor status, presence of children, and multiple-owner status. Column (1) includes zip code × year fixed effects; column (2) census block × year fixed effects; column (3) property and year fixed effects. 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.5 in the Appendix.

of 0.75%).

Columns (2) and (3) of the table progressively tighten the geographic comparison. Column (2) replaces zip code × year with census block × year fixed effects, restricting identification to households in the same close neighborhood and year. The Republican coefficient is −0.064 ($p < 0.01$), virtually unchanged. Column (3) introduces property fixed effects, so identification comes entirely from ownership transitions within the same dwelling: when a Republican replaces a Democrat (or vice versa), does the new owner invest differently in climate adaptation? Even in this demanding specification, the Republican gap remains significant at −0.038 ($p < 0.01$), or roughly 4% of the baseline rate. The attenuation relative to column (1) reflects time-invariant selection of Republicans into different types of homes.

To better understand the role of observable characteristics, Appendix Table B.3 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 × 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, 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, children) further widens the gap, while adding socioeconomic controls (income, net worth, education, charitable and political contributions) produces only modest additional changes. The pattern is qualitatively similar across all three fixed-effects structures (Panels A–C).

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 characteristics of Republicans and Democrats, or the kind of houses they buy, that correlate with their household 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.

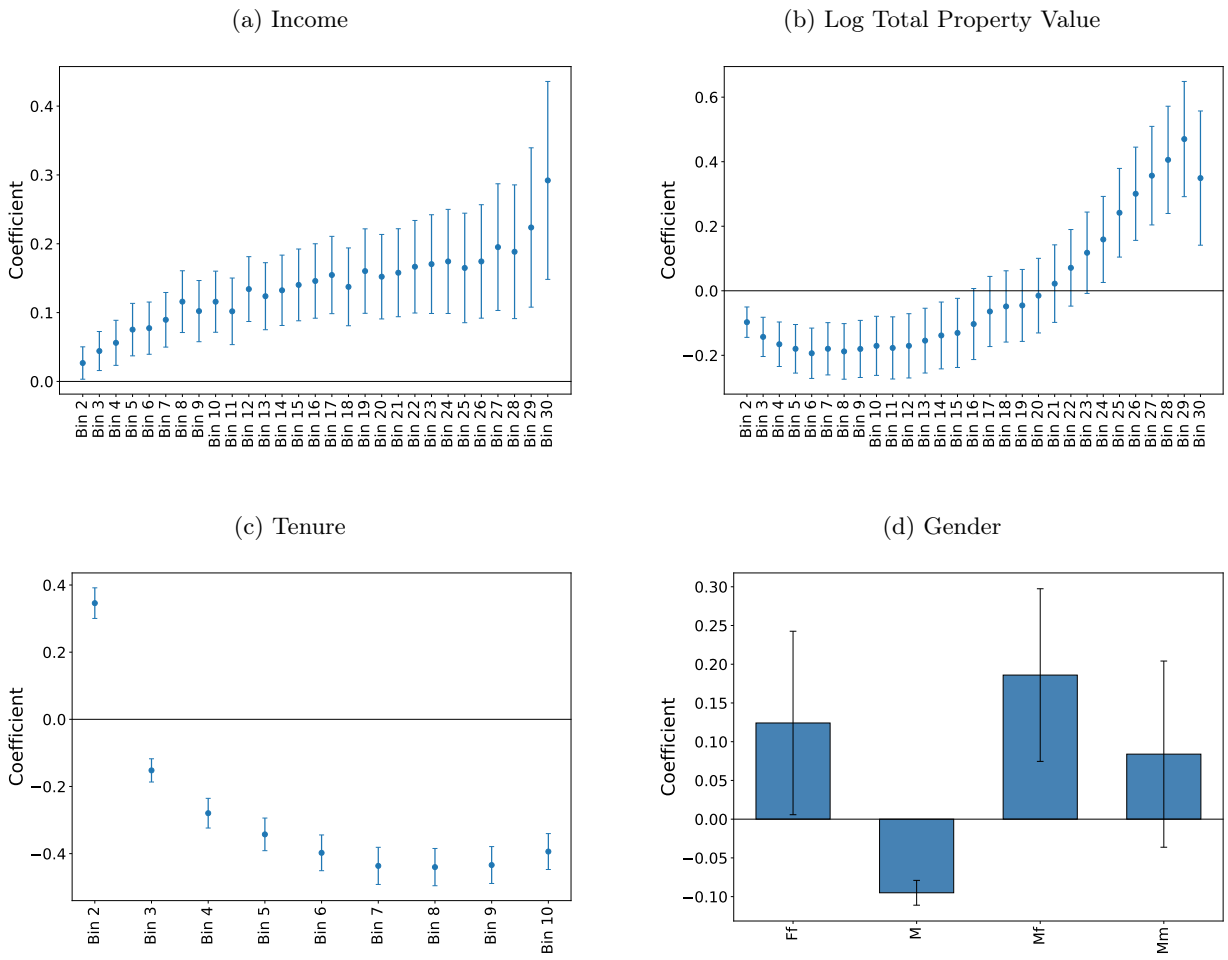
Among these concerns, the possibility that Republicans and Democrats may systematically buy different properties that in turn require different types of investments is addressed by specification (3) of the table, which includes property fixed effects. This specification is particularly powerful because it allows us 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 differences in the properties themselves.

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 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 Republicans are simply less likely to do the kind of investments that require permits in general, and, as a mechanical sort of 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

Figure 2: 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 (0.75 percentage points). The omitted categories are the lowest income decile, the lowest property-value decile, the shortest tenure group, and single female, respectively.

views on climate adaptation investment.

3.3 Magnitudes

The estimated gap of 4–7% of the probability of filing a wind-adaptation permit between Democrats and Republicans may appear modest overall (given a baseline probability of 0.75 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 2a, 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 6.7% 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 9.5% less likely than single-female owners to file a wind-adaptation permit (Table B.5, panel B), 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 of the effects documented here.

3.4 Accounting for Permitting Activity

A natural 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 three panels, each of which shows the results of the different choice of fixed effects (zip code × year in panel A, block × year in panel B, and property and year fixed effects in panel C).

Column (1) of the three panels 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 (non-wind permits are 94% of the total). This isolates Republicans' propensity to engage in home-improvement activity that is unrelated to wind adaptation. The number here is much smaller, between −1.8% and −0.1% across specifications. Republicans do appear to be slightly less likely to file non-wind permits, but the magnitude of the difference is much smaller than the wind-permit gap; and it is insignificantly different from zero when adding property fixed effects.

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

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)	(4) Wind permit (% of baseline)
Republican	−0.067***	−0.018***	−0.045***	−0.035***
	(0.009)	(0.002)	(0.008)	(0.006)
Other	−0.013*	−0.005***	−0.008	−0.006
	(0.008)	(0.002)	(0.007)	(0.006)
Any permit control			Y	
Cond. on any permit				Y
Observations	66,194,785	66,194,785	66,194,785	8,261,489
R^2 (overall)	0.017	0.038	0.066	0.090
R^2 (within)	0.002	0.009	0.051	0.004

Panel B: Block × Year fixed effects

	(1) Wind permit (% of baseline)	(2) Non-wind permit (% of baseline)	(3) Wind permit (% of baseline)	(4) Wind permit (% of baseline)
Republican	−0.064***	−0.017***	−0.044***	−0.034***
	(0.008)	(0.002)	(0.007)	(0.005)
Other	−0.012*	−0.004***	−0.008	−0.006
	(0.007)	(0.002)	(0.007)	(0.005)
Any permit control			Y	
Cond. on any permit				Y
Observations	66,189,501	66,189,501	66,189,501	8,259,856
R^2 (overall)	0.021	0.046	0.069	0.105
R^2 (within)	0.002	0.008	0.051	0.004

Panel C: Property + Year fixed effects

	(1) Wind permit (% of baseline)	(2) Non-wind permit (% of baseline)	(3) Wind permit (% of baseline)	(4) Wind permit (% of baseline)
Republican	−0.038***	−0.001	−0.035***	−0.009
	(0.013)	(0.003)	(0.012)	(0.015)
Other	0.001	0.010***	−0.008	0.002
	(0.012)	(0.003)	(0.012)	(0.015)
Any permit control			Y	
Cond. on any permit				Y
Observations	66,120,781	66,120,781	66,120,781	6,538,147
R^2 (overall)	0.108	0.130	0.149	0.385
R^2 (within)	0.001	0.008	0.048	0.005

Note: The dependent variable in columns (1), (3), and (4) 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 in all columns are expressed as a fraction of the respective baseline probability: 0.75 percentage points for wind permits (columns 1 and 3), 11.7 percentage points for non-wind permits (column 2), and 6.01 percentage points for wind permits in the conditional-on-permitting sample (column 4). Column (4) restricts the sample to property-years with at least one building permit; 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. Fixed effects are as indicated by the panel heading. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

by inducing a different propensity to file permits more generally. The Republican gap declines only modestly, to 3.5%–4.5% across specifications. The bulk of the partisan difference in wind-adaptation permits cannot be attributed to general differences in home-improvement behavior.

Finally, for an even tighter test, column (4) restricts the sample to owner-property-years with at least one permit filed. This exercise shrinks the sample dramatically, from 66 million to between 6.5 and 8.3 million observations (depending on the specification). In other words, this test studies the propensity to file for wind-adaptation permits among property owners that are filing a permit in that year. The results are once again similar.[19]

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.

3.5 Robustness

This section reports a number of robustness checks on the baseline results. Table 5 presents three panels corresponding to the three fixed-effects specifications; I focus the discussion on Panel C (property + year fixed effects), but results are qualitatively similar across all panels. The baseline specification is reproduced in column (1) of each panel, whereas the remaining columns report the following robustness results.

Never previously adapted. Column (2) restricts 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 larger in absolute value than the baseline (-4.7% vs. -3.8% in Panel C). The result confirms that the partisan gap is not driven by differential rates of prior adaptation: even among households that had not yet invested in wind adaptation, Republicans are significantly less likely to do so.

Excluding new construction. Column (3) excludes 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 slightly larger than the baseline when new construction is excluded (e.g., -3.9% in Panel C), but the difference is small, consistent with the fact that this is a small fraction of the sample (and 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 (4) 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

[19]The specification in panel C with property fixed effects shows a smaller and insignificant gap of about 1%, but this is a specification in which the variation that remains after adding about 6 million fixed effects is small, and picks up a special sample of properties in which two different individuals have owned the properties in the 11 years of the sample, and *both* homeowners have filed permits during their tenure. Therefore, the results in these case are likely less informative about the general patterns. Nonetheless, the point estimate is not statistically significantly different from the -3.8% in the baseline specification.

that the mortgage is still active and therefore insurance is required. This reduces the sample to approximately 27.5 million observations in Panel C. In the cross-sectional specifications (Panels A and B), the partisan gap remains significant and similar in magnitude to the baseline (−6.1% and −5.9%, respectively). In the property fixed-effects specification (Panel C), the point estimate is −3.0% ($p = 0.07$), significant at the 10% level. Overall, the test suggests that the partisan gap is not primarily driven by omitted insurance variation.

Logit and discrete-time hazard specifications. Columns (5) and (6) replace the linear probability model with nonlinear alternatives. Column (5) 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. Column (6) 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:[20]

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

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 (0.75%), 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 Panels A and B, the Republican coefficient is −0.049 to −0.050 across the logit and hazard specifications ($p < 0.001$), implying approximately a 5% lower probability/hazard of adaptation—consistent with the linear probability model estimates of 6–7%. The hazard ratios are $\exp(-0.049) = 0.952$ in both Panels A and B.

Both nonlinear models require dropping observations in fixed-effect groups with no outcome variation (separation), which reduces the sample. This reduction is modest for Panels A and B (to 54 million and 42 million for logit; 52 million and 40 million for the hazard model) but substantial for Panel C (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 Republican coefficient remains significant in both specifications in Panel C: −0.035 ($p < 0.001$) for logit and −0.047 ($p = 0.002$) for the hazard model, implying 3.4–4.6% lower probability/hazard of adaptation.

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

[20]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.

differently on housing investments, and specifically on wind-adaptation projects, conditional on making them? We can 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 8.1 million permits). The average reported value is about $10,000.

Appendix Table B.4 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 six columns, corresponding to the three fixed-effect specifications for the two winsorization cases (10% both sides and 10% on the upper end only). Republicans spend slightly more on permits than Democrats—about $88–$112 more, or roughly 1% of the mean permit value. At the same time the Republican × wind interaction is negative, indicating that Republicans spend relatively *less* on wind-adaptation permits. The magnitude of this interaction (−$26 to −$44 across specifications) is between one-third and one-half of the Republican effect, though it is not statistically significant. From a quantitative standpoint, all the intensive margin effects of political orientation are small, 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—rather than climate—may be effective at closing it; if instead it reflects deeper differences in preferences or access to adaptation opportunities, different policy interventions would be needed.

Two broad channels could generate the observed patterns. First, Republicans may hold different beliefs about climate risk—perceiving hurricanes and extreme wind events as less likely or less severe—and therefore see less value in protective investment (*belief channel*). Second, Republicans and Democrats may differ along some other dimension, such as trust in government recom-

Table 5: Robustness Checks

Panel A: Zip code × Year fixed effects

	(1) Baseline (0.75%)	(2) Never adapted (0.61%)	(3) No new constr. (0.72%)	(4) Mortgage only (0.82%)	(5) Logit	(6) Hazard
Republican	−0.067***	−0.067***	−0.067***	−0.061***	−0.050***	−0.049***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.006)	(0.006)
Other/missing	−0.013*	−0.008	−0.015**	−0.032***	−0.015***	−0.014**
	(0.008)	(0.008)	(0.008)	(0.009)	(0.006)	(0.006)
Observations	66,194,785	61,459,379	63,314,853	32,602,685	54,034,878	52,474,433
R^2 (overall)	0.017	0.016	0.017	0.019		
R^2 (within)	0.002	0.002	0.002	0.002		

Panel B: Block × Year fixed effects

	(1) Baseline (0.75%)	(2) Never adapted (0.61%)	(3) No new constr. (0.72%)	(4) Mortgage only (0.82%)	(5) Logit	(6) Hazard
Republican	−0.064***	−0.065***	−0.064***	−0.059***	−0.049***	−0.049***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.005)	(0.006)
Other/missing	−0.012*	−0.008	−0.014*	−0.029***	−0.015***	−0.014**
	(0.007)	(0.008)	(0.007)	(0.007)	(0.005)	(0.006)
Observations	66,189,501	61,454,163	63,310,158	32,600,946	41,953,965	40,360,183
R^2 (overall)	0.021	0.020	0.020	0.023		
R^2 (within)	0.002	0.001	0.001	0.002		

Panel C: Property + Year fixed effects

	(1) Baseline (0.75%)	(2) Never adapted (0.61%)	(3) No new constr. (0.72%)	(4) Mortgage only (0.82%)	(5) Logit	(6) Hazard
Republican	−0.038***	−0.047**	−0.039***	−0.030*	−0.035***	−0.047***
	(0.012)	(0.021)	(0.014)	(0.016)	(0.010)	(0.015)
Other/missing	0.001	−0.020	0.003	−0.021	0.001	−0.007
	(0.012)	(0.016)	(0.013)	(0.015)	(0.010)	(0.015)
Observations	66,120,781	61,361,347	63,217,272	27,468,600	5,121,829	3,606,559
R^2 (overall)	0.108	0.175	0.107	0.138		
R^2 (within)	0.001	0.009	0.002	0.001		

Note: The dependent variable is an indicator for filing at least one wind-related permit in a given year. Columns (1)–(4) report linear probability model (LPM) estimates; coefficients are expressed as a fraction of the respective sample baseline filing probability, shown in parentheses below each column heading. Column (5) reports logit coefficients (log-odds ratios) and column (6) 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. Column (1) reproduces the baseline specification. Column (2) restricts to property-years where the property had not previously filed any wind-adaptation permit. Column (3) excludes property-years flagged as new construction (permit keyword or within two years of year built). Column (4) restricts to properties purchased with a mortgage. Column (5) estimates a logit model; observations in fixed-effect groups with no outcome variation (separation) are dropped. Column (6) 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.

mendations, responsiveness to regulatory signals, or attitudes toward precautionary spending, that incidentally correlates with wind-adaptation behavior (*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 where wind hardening is purely voluntary, an examination of how the gap varies with local climate attention, and an analysis of the time path of the partisan gap. To be clear, perfectly distinguishing pure beliefs and some non-beliefs channels is impossible (and to a certain extent the distinction gets into philosophical territory), so the more limited goal of this section is to show that these additional results are consistent with the belief channel, and rule out at least some of the non-beliefs channels.

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. The omitted category is Democrat donor—the group with the strongest revealed attachment to Democratic politics.

Table 6 reports the results. 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 20.5% lower than that of Democrat donors in the zip×year specification (column 1), and 15.6% lower in the property fixed-effects specification (column 3). Republican non-donors show a smaller gap of 9.4% (column 1) and 10.4% (column 3). Democrat non-donors fall in between, with a statistically insignificant gap of 3.7–7.3% relative to Democrat donors.

Two features of these results are worth highlighting. First, the gap between Republican donors and Republican non-donors (roughly 11 percentage points in column 1) is large and precisely estimated, indicating that within the Republican party, stronger political engagement is associated with less climate adaptation. Second, 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 3 displays the geographic distribution of properties in the sample, distinguishing mandate areas (blue) from no-mandate areas

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

	Dep. var.: Wind permit (% of baseline)		
	(1)	(2)	(3)
Republican, FEC donor	−0.205***	−0.194***	−0.156***
	(0.034)	(0.031)	(0.058)
Republican, non-donor	−0.094**	−0.102***	−0.104
	(0.037)	(0.036)	(0.068)
Democrat, non-donor	−0.037	−0.048	−0.073
	(0.035)	(0.035)	(0.067)
Controls	Y	Y	Y
Fixed effects	Zip × Year	Block × Year	Property + Year
Clustering	Zip	Zip	Zip
Observations	66,194,785	66,189,501	66,120,781
R^2 (overall)	0.017	0.021	0.108
R^2 (within)	0.002	0.002	0.001

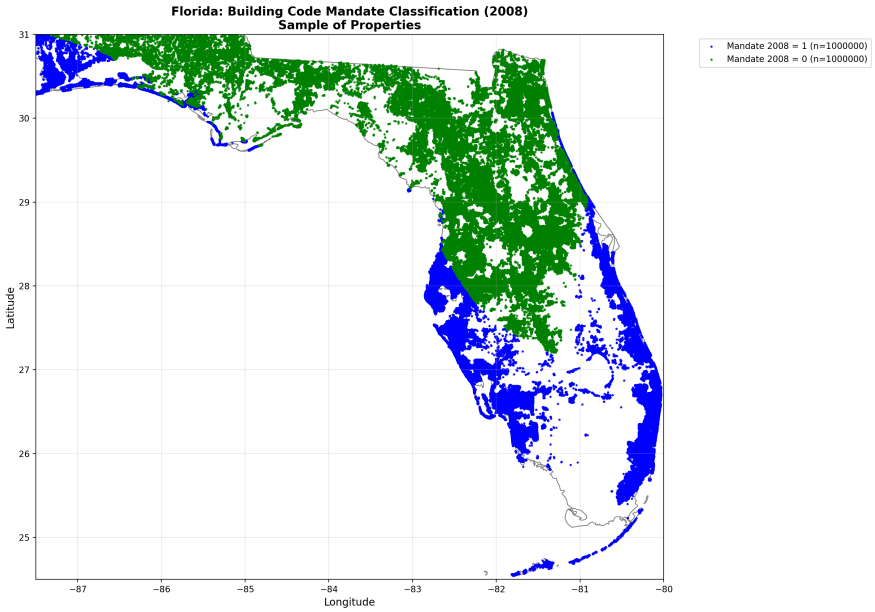
Note: Table reports results of a regression of wind-permit filing on party affiliation interacted with FEC donor status. The omitted category is Democrat FEC donor. Coefficients are expressed as a fraction of the baseline probability of filing a wind-related permit (0.75 percentage points). An indicator 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). 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.

(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 4 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 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 splits the sample at the 2008 mandate boundary (using property + year fixed effects; results are similar in the block and zip code specifications). Column (1) reproduces the full-sample estimate: Republicans are 3.8% less likely than Democrats to file a wind-adaptation permit relative to the baseline rate of 0.75%. 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. The Republican coefficient in mandate areas is −0.041, indicating that Republicans have a probability that is 4.1%

Figure 3: Florida building code mandate areas



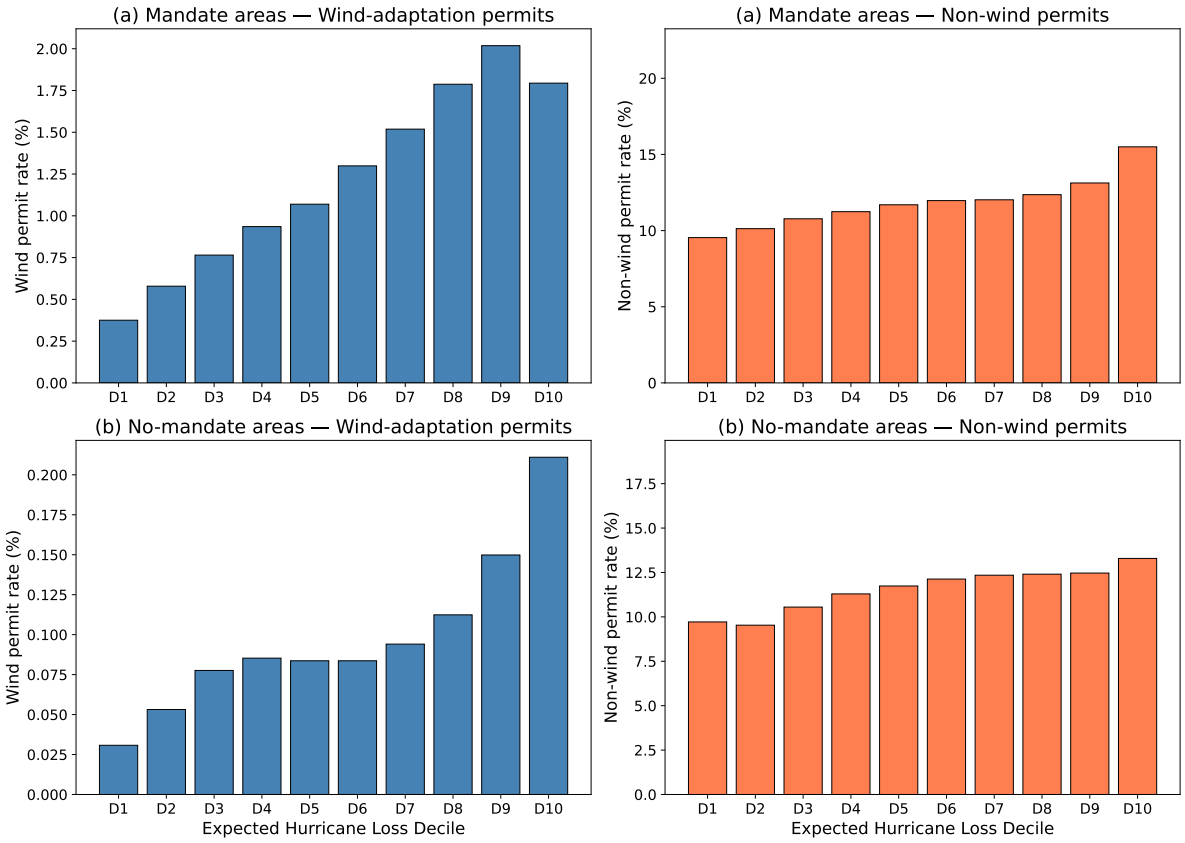
Note: The figure maps properties in the sample by their location relative to the 2008 Florida Building Code wind-protection mandate boundary. Blue points denote properties in the mandate area, where the code requires wind-adaptation measures such as hurricane straps, impact-resistant windows, and reinforced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

of the baseline lower than Democrats to file a wind permit. In no-mandate areas, the Republican coefficient is -0.092 ($p < 0.05$): Republicans have a probability of adapting that is a significant 9.2% of the baseline lower than Democrats to adapt. The "other/missing" party category shows no significant effect in either subsample, confirming that the pattern is specific to Republican affiliation.

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 and significant partisan gap in this subsample (where, it is useful to keep in mind, risk is significantly lower) helps rule out explanations rooted in supply-side or institutional differences between Republican and Democratic homeowners. If the gap were driven by differential access to contractors, different information from insurers or lenders, or differences in the types of renovations undertaken that mechanically trigger code-compliant upgrades, these channels would not generate a partisan gap in an environment where the decision to harden a home against wind rests entirely on the homeowner's own assessment of whether the investment is worthwhile.

Note that the mandate boundary simultaneously varies regulatory constraint and objective risk—mandate areas are designated precisely because they face higher wind exposure—so a direct comparison of coefficient magnitudes across the two subsamples does not cleanly isolate a single channel. Nevertheless, the evidence from the no-mandate subsample narrows the set of candidate explanations to channels that operate through the homeowner's own judgment about the value of adaptation,

Figure 4: 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.

Table 7: Heterogeneity in the Partisan Gap: Mandate Areas and Climate Attention

Panel A: Mandate vs. No-Mandate Areas

	(1) Full sample (0.75%)	(2) Mandate (1.2%)	(3) No mandate (0.10%)
Republican	−0.038***	−0.041***	−0.092**
	(0.012)	(0.012)	(0.041)
Other/missing	0.001	−0.008	−0.000
	(0.012)	(0.012)	(0.051)
Observations	66,120,781	38,650,720	27,470,038
R^2 (within)	0.001	0.002	0.000

Panel B: Above vs. Below Median Climate Attention (0.75%)

	(1) No party × time/geo	(2) + year × party	(3) + year × party + CBSA × party
R (baseline)	−0.082***		
	(0.024)		
R × above median	0.077**	0.129**	0.145***
	(0.036)	(0.054)	(0.054)
Implied R gap: below	−8.2%		
Implied R gap: above	−0.5%		
Observations		50,878,087	
R^2 (within)	0.002	0.002	0.002

Note: The dependent variable is an indicator for filing at least one wind-related permit in a given year. All specifications use property + year fixed effects (Specification 3 in Table 3). Coefficients are scaled by the baseline filing probability and expressed as a fraction thereof; e.g., −0.082 means Republicans are 8.2% less likely to file relative to baseline. The omitted party category is Democrat. **Panel A** splits the sample by whether the property is in a Florida Building Code wind-protection mandate area. Baseline filing rates are shown in parentheses below column headings. **Panel B** interacts party affiliation with an indicator for above-median local climate attention, measured as the share of climate-related articles in local newspapers at the CBSA×year level (Kostovetsky, Peng, Rauh, and Yönaç, 2024). "R (baseline)" is the Republican effect in below-median attention periods; "R × above median" is the additional Republican effect when attention is above the median. The sample in Panel B is restricted to CBSA×year observations with available newspaper data (2014–2022, 77% of the full sample). In columns (2)–(3) of Panel B, party main effects are absorbed by party×year and party×CBSA interactions. Standard errors clustered at the zip-code level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

which is consistent with—though not uniquely identified as—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 property and year fixed effects (column 3 of Table 3). Each coefficient measures the Republican effect in a given year relative to Democrats, expressed as a percentage of the 0.75% baseline filing rate.

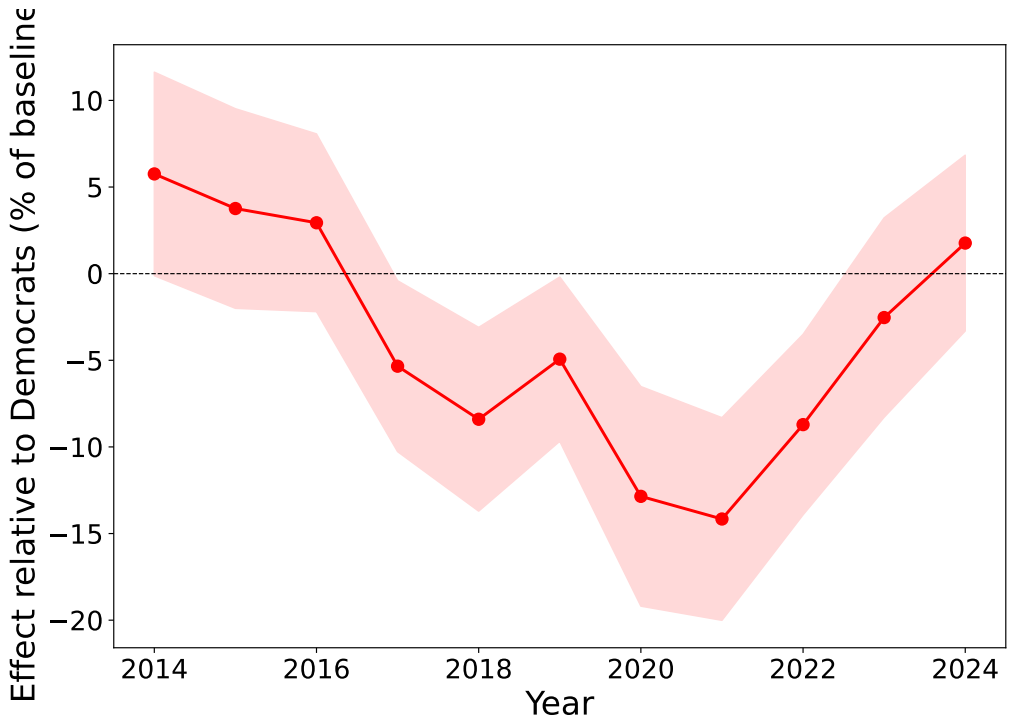
Figure 5 plots the results. Three distinct phases emerge. First, in 2014–2016—the final years of the Obama administration—the Republican coefficient hovers near zero (roughly +3% to +6% of the baseline) and is not statistically distinguishable from the Democrat rate. The partisan gap in wind-adaptation 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 to approximately −5% in 2017, −8% in 2018, −5% in 2019, and reaches its trough at roughly −13% in 2020 and −14% in 2021. 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 2017–2020, driven by a combination of increased Democratic urgency and decreased Republican concern (Dunlap et al., 2016). 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. The Republican coefficient rises from −14% in 2021 to roughly −9% in 2022, and then returns to approximately zero in 2023 (−2.5%, not significant) and +2% in 2024. 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 direct evidence for a belief channel. The supply-side and in-

Figure 5: Republican effect on wind-adaptation permits over time



Note: Each point plots the estimated coefficient on a Republican × year interaction from a property fixed-effects regression (column 3 of Table 3) with clip fixed effects and standard errors clustered at the zip-code level. Coefficients are expressed as a percentage of the baseline wind-adaptation filing rate (0.75 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.

stitutional factors ruled out by the no-mandate analysis do not vary sharply at the boundaries of presidential administrations. The channels that *do* track this timing are precisely those related to the political salience of climate change and the identity valence of climate-related investment. When climate became sharply partisan during 2017–2021, the Republican gap in adaptation investment widened; when a financially framed subsidy program reduced the identity valence of the same investment, the gap closed.

4.4 Climate Attention and the Partisan Gap

Panel B of Table 7 explores a more direct test of the belief channel by examining whether the partisan gap in wind-adaptation investment varies with local exposure to climate-related information. The exercise is motivated by Giglio et al. (2021b), who show that the discount on properties exposed to sea-level rise fluctuates with local attention to climate change—widening when attention is high and narrowing when attention fades. An analogous logic applies here: if the Republican adaptation gap reflects beliefs shaped by political identity, the gap should narrow in periods when climate risks are locally salient and harder to dismiss, and widen when attention recedes and the default

identity-driven prior reasserts itself.

To measure local climate attention, I draw on the newspaper-based index constructed by Kostovetsky et al. (2024). Their measure captures the share of articles mentioning climate-related keywords in over 5,000 U.S. newspapers, aggregated to the Core Based Statistical Area (CBSA) by quarter. I match this data to the permits panel by mapping each Florida county (FIPS code) to its corresponding CBSA using the Census Bureau crosswalk, and then averaging the quarterly attention measure to the annual level to align with the permit data. The resulting match covers 20 Florida CBSAs spanning approximately 77% of the property-year observations in the main sample (the remaining observations fall in rural counties outside any CBSA or in years beyond the attention data's 2022 endpoint). Within the matched sample, the attention measure varies both across metro areas—reflecting differences in local media markets, hurricane exposure, and editorial emphasis—and over time within the same metro area, as coverage responds to hurricanes, policy events, and national climate discourse.

I split observations at the median of the climate attention distribution and interact the Republican indicator with a dummy for above-median attention. Because the attention measure varies at the CBSA×year level—a coarser level than the property fixed effects—the main effect of attention is absorbed by the fixed effects, and identification comes from how the *partisan gap* differs between high- and low-attention periods within the same property.

A natural concern is that periods of high climate attention may coincide with other factors that independently affect the partisan gap. As Figure 5 documents, the gap widens during the Trump administration and narrows thereafter—a pattern that could correlate with aggregate trends in climate coverage. Similarly, metro areas with chronically high attention may differ from low-attention areas in ways that affect partisan behavior. To address these confounds, I estimate three progressively demanding specifications. Column (1) of Panel B includes only the baseline demographic and property controls. Column (2) adds year×party interactions, which absorb any aggregate time trend in the partisan gap—ensuring that the attention interaction is not simply picking up the Trump-era widening documented above. Column (3) further adds CBSA×party interactions, which absorb permanent differences in the partisan gap across metro areas, so that identification relies entirely on within-metro, within-property temporal variation in climate attention.

The results are once again consistent with the belief channel. In column (1), the baseline Republican effect in low-attention periods is -8.2% of the filing rate, but the interaction with above-median attention is $+7.7\%$ ($p < 0.05$), nearly fully offsetting the gap. The implied Republican gap is -8.2% when attention is below the median but only -0.5%—statistically indistinguishable from zero—when attention is above the median. Rather than attenuating with additional controls, the interaction coefficient *strengthens*: to $+12.9\%$ ($p < 0.05$) with year×party controls in column (2), and to $+14.5\%$ ($p < 0.01$) when CBSA×party interactions are also included in column (3) (note that we don't have a baseline Republican effect for comparison as in column (1) because specifications (2) and (3) interact the party group dummies with years and/or CBSAs). The fact that the effect survives and grows with these demanding controls indicates that it is not driven by the aggregate time trends

documented in the preceding subsection or by permanent cross-sectional differences across metro areas, but rather by within-metro temporal variation in climate salience.

The interpretation is consistent with the belief channel: in periods when climate risks are locally prominent—following a hurricane, during heightened media coverage, or in the wake of a major climate event—the informational environment makes it harder for any homeowner, regardless of political identity, to discount the value of wind adaptation. Republicans close the gap not because their political identity changes, but because the salience of objective risk temporarily overcomes the identity-driven prior against climate-related investment. When attention subsides, the default partisan gap reasserts itself.

Together, the four pieces of evidence in this section—political intensity, the mandate/no-mandate split, time variation, and climate attention—point toward a mechanism rooted in how political identity shapes homeowners' subjective assessments of climate risk. The partisan gap responds to the strength of partisan engagement, to the broader political environment, and to the local salience of climate information, consistent with a belief channel that operates through discretionary judgment rather than institutional or supply-side frictions.

5 Conclusion

This paper shows that political orientation affects household investment in climate adaptation. Using a novel property–owner–year panel of 66 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 6.7% lower than that of Democrats, conditional on income, property characteristics, and a rich set of demographic controls. The gap is robust to progressively tighter identification strategies: 6.4% with census-block-by-year fixed effects and 3.8% with property fixed effects exploiting ownership transitions within the same dwelling. 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 present both in areas where renovations are subject to an adaptation mandate (thus partially constraining homeowners in their choice) and in areas with no mandate (where wind adaptation is fully voluntary); the gap narrows sharply in periods of high local climate news coverage and widens when attention fades; and the gap widens sharply in 2017 with the start of the Trump administration, deepens to roughly -13% to -14% by 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).

These findings have important economic implications because climate damages are 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, the finding that financially framed subsidy programs appear to narrow the partisan gap suggests scope for policy design that depoliticizes adaptation by emphasizing private returns – insurance savings and property value protection – rather than climate framing.

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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 CoreLogic property identifier (clip).

2. From the separate permit *status* file, I extract the earliest status record and earliest date for each permit ID, and flag permits whose status is suspended, withdrawn, rejected, canceled, or revoked.

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, coordinates, and year built per clip; a *dynamic* property file with annual assessed value, square footage, bedrooms, bathrooms, and effective year built; 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 up to five 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, net worth, 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, 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.

B Additional Tables

Table B.1: 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.2: 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 CoreLogic permit record. The keyword classification searches across all text fields in the permit record (description, project name, permit type). Some entries combine information from multiple fields, separated by dashes.

Table B.3: Waterfall: Progressive Addition of Controls

Panel A: Zip code × Year fixed effects

	Republican	SE	Observations	R^2
Party only	0.084**	(0.040)	66,194,915	0.000
+ Geo x Year FE	0.053***	(0.011)	66,194,785	0.016
+ Property	−0.024**	(0.009)	66,194,785	0.017
+ Demographics	−0.059***	(0.009)	66,194,785	0.017
+ Socioeconomic	−0.066***	(0.009)	66,194,785	0.017

Panel B: Block × Year fixed effects

	Republican	SE	Observations	R^2
Party only	0.084**	(0.040)	66,194,915	0.000
+ Geo x Year FE	0.023**	(0.009)	66,189,501	0.020
+ Property	−0.029***	(0.008)	66,189,501	0.020
+ Demographics	−0.058***	(0.008)	66,189,501	0.021
+ Socioeconomic	−0.064***	(0.008)	66,189,501	0.021

Panel C: Property + Year fixed effects

	Republican	SE	Observations	R^2
Party only	0.084**	(0.040)	66,194,915	0.000
+ Property FE	0.009	(0.014)	66,120,781	0.107
+ Property chars	−0.013	(0.014)	66,120,781	0.107
+ Demographics	−0.039***	(0.013)	66,120,781	0.107
+ Socioeconomic	−0.038***	(0.012)	66,120,781	0.108

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 (0.75 percentage points); the omitted category is Democrat. "Party only" includes only the party indicators with no controls or fixed effects. "+ Geo × Year FE" (Panels A and B) or "+ Property FE" (Panel C) adds the fixed effects indicated by the panel heading. "+ Property" adds property characteristics: assessed value, years since last renovation, tenure at the property, and multiple-owner indicator; in Panels A and B, year built and square footage are also included as controls, while in Panel C these are time-invariant and absorbed by the property fixed effects. "+ Demographics" adds gender, ethnicity, age, and presence of children. "+ Socioeconomic" adds income, net worth, education, charitable and political contribution indicators, and FEC donor status. 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.4: Permit Value: Party × Wind Interactions (Permit-Level)

	W10% Both Sides			W10% Upper Only		
	(1)	(2)	(3)	(4)	(5)	(6)
	Zip × Year	Block × Year	Property	Zip × Year	Block × Year	Property
Republican	111***	95***	88**	112***	95***	89**
	(19)	(17)	(35)	(19)	(18)	(35)
Other/missing	64***	56***	82***	64***	56***	84***
	(16)	(15)	(32)	(16)	(15)	(32)
Wind permit	730***	778***	1,285***	761***	808***	1,312***
	(126)	(124)	(135)	(126)	(125)	(135)
R × Wind	−27	−26	−40	−31	−30	−44
	(97)	(95)	(111)	(97)	(95)	(111)
Other × Wind	12	6	−27	9	3	−30
	(82)	(77)	(93)	(83)	(78)	(93)
Controls	Y	Y	Y	Y	Y	Y
Fixed effects	Zip × Yr	Block × Yr	Prop. + Yr	Zip × Yr	Block × Yr	Prop. + Yr
Clustering	Zip	Zip	Zip	Zip	Zip	Zip
Observations	8,135,967	8,133,953	6,950,611	8,135,967	8,133,953	6,950,611
Mean (dep. var.)	$10,559	$10,559	$10,559	$10,503	$10,503	$10,503

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. 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.5: Full Coefficient Estimates — Part I

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Party affiliation (excluded: Democrat)			
Republican	−0.050***	−0.048***	−0.028***
	(0.007)	(0.006)	(0.009)
Other/missing	−0.010*	−0.009*	0.001
	(0.006)	(0.005)	(0.009)
Gender (excluded: Female)			
Female–Female (FF)	0.093**	0.081*	−0.048
	(0.045)	(0.045)	(0.095)
Male (M)	−0.071***	−0.068***	−0.036***
	(0.006)	(0.006)	(0.009)
Male–Female (MF)	0.140***	0.127***	0.135
	(0.043)	(0.042)	(0.093)
Male–Male (MM)	0.063	0.060	−0.016
	(0.046)	(0.046)	(0.095)
No gender info	−0.218***	−0.206***	−0.142
	(0.044)	(0.042)	(0.094)
Owner age, owner 1 (excluded: 30–40)			
Owner 1: <30	−0.109***	−0.108***	−0.135***
	(0.010)	(0.010)	(0.013)
Owner 1: 40–50	0.027***	0.029***	0.041***
	(0.009)	(0.008)	(0.010)
Owner 1: 50–60	0.082***	0.080***	0.093***
	(0.013)	(0.012)	(0.016)
Owner 1: 60–70	0.239***	0.228***	0.187***
	(0.022)	(0.020)	(0.024)
Owner 1: >70	0.087***	0.072***	0.062**
	(0.022)	(0.019)	(0.024)
Owner 1: Age unknown	0.028	0.020	−0.062
	(0.045)	(0.044)	(0.097)

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: 0.75%). Column (1) includes zip code × year fixed effects; column (2) census block × year fixed effects; column (3) property fixed effects with year indicators. 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.6: Full Coefficient Estimates — Part II

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Owner age, owner 2 (excluded: 30–40)			
Owner 2: <30	−0.090***	−0.089***	−0.117***
	(0.014)	(0.013)	(0.016)
Owner 2: 40–50	0.032***	0.032***	0.042***
	(0.010)	(0.010)	(0.013)
Owner 2: 50–60	0.128***	0.123***	0.132***
	(0.017)	(0.016)	(0.021)
Owner 2: 60–70	0.323***	0.311***	0.287***
	(0.029)	(0.027)	(0.029)
Owner 2: >70	0.172***	0.160***	0.206***
	(0.026)	(0.023)	(0.027)
Owner 2: Age unknown	0.054	0.043	−0.052
	(0.046)	(0.046)	(0.095)
Ethnicity, owner 1 (excluded: Black)			
Hispanic	−0.025**	−0.023**	0.037**
	(0.012)	(0.009)	(0.018)
White	0.051***	0.048***	0.039*
	(0.013)	(0.011)	(0.022)
Other	−0.004	−0.006	0.016
	(0.013)	(0.011)	(0.022)
Missing	0.075***	0.069***	0.083***
	(0.017)	(0.015)	(0.027)
Ethnicity, owner 2 (excluded: Black)			
Hispanic	0.033**	0.032***	0.045*
	(0.013)	(0.011)	(0.023)
White	0.073***	0.071***	0.051**
	(0.013)	(0.013)	(0.025)
Other	0.021	0.019	0.031
	(0.014)	(0.014)	(0.027)
Missing	0.098***	0.089***	0.094***
	(0.018)	(0.017)	(0.031)

Table B.7: Full Coefficient Estimates — Part III

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Net worth, owner 1 (excluded: $0)			
$1-4999	−0.005	−0.003	0.030
	(0.024)	(0.024)	(0.050)
$10,000 - $24,999	0.056**	0.059**	0.055
	(0.026)	(0.026)	(0.053)
$100,000 - $249,999	0.101***	0.105***	0.232***
	(0.021)	(0.021)	(0.046)
$10000-24999	−0.020	−0.006	−0.019
	(0.021)	(0.021)	(0.046)
$100000-249999	0.009	0.011	0.012
	(0.022)	(0.021)	(0.043)
$25,000 - $49,999	0.039	0.044*	0.124**
	(0.024)	(0.024)	(0.049)
$250,000 - $499,999	0.171***	0.169***	0.314***
	(0.024)	(0.024)	(0.054)
$25000-49999	−0.015	−0.004	0.049
	(0.021)	(0.020)	(0.044)
$250000-499999	−0.052**	−0.052**	−0.189***
	(0.023)	(0.022)	(0.047)
$499999+	−0.140***	−0.173***	−0.525***
	(0.030)	(0.029)	(0.070)
$5,000 - $9,999	0.030	0.034	0.088
	(0.034)	(0.034)	(0.081)
$50,000 - $99,999	0.068***	0.074***	0.163***
	(0.022)	(0.022)	(0.049)
$5000-9999	0.020	0.035	0.088*
	(0.024)	(0.024)	(0.050)
$50000-99999	−0.063***	−0.046**	0.016
	(0.021)	(0.021)	(0.046)
Greater than $499,999	0.309***	0.292***	0.493***
	(0.029)	(0.029)	(0.061)
Less than $1	0.036*	0.040*	0.087**
	(0.021)	(0.021)	(0.044)
missing	0.027	0.027	0.116***
	(0.019)	(0.019)	(0.041)

Table B.8: Full Coefficient Estimates — Part IV

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Net worth, owner 2 (excluded: $0)			
$1-4999	0.049	0.042	0.028
	(0.032)	(0.032)	(0.066)
$10,000 - $24,999	0.092***	0.087**	0.114
	(0.035)	(0.036)	(0.078)
$100,000 - $249,999	0.135***	0.132***	0.224***
	(0.031)	(0.030)	(0.065)
$10000-24999	−0.022	−0.018	−0.008
	(0.030)	(0.030)	(0.068)
$100000-249999	0.025	0.026	0.073
	(0.028)	(0.028)	(0.062)
$25,000 - $49,999	0.053	0.052	0.075
	(0.034)	(0.034)	(0.071)
$250,000 - $499,999	0.225***	0.220***	0.403***
	(0.033)	(0.032)	(0.068)
$25000-49999	0.015	0.019	0.069
	(0.026)	(0.026)	(0.062)
$250000-499999	0.012	0.014	−0.048
	(0.030)	(0.029)	(0.067)
$499999+	0.067*	0.044	−0.144**
	(0.037)	(0.036)	(0.073)
$5,000 - $9,999	0.125**	0.122**	0.153
	(0.049)	(0.049)	(0.099)
$50,000 - $99,999	0.103***	0.101***	0.163**
	(0.032)	(0.032)	(0.070)
$5000-9999	0.018	0.021	−0.013
	(0.035)	(0.035)	(0.079)
$50000-99999	−0.036	−0.026	0.020
	(0.029)	(0.028)	(0.065)
Greater than $499,999	0.429***	0.409***	0.631***
	(0.039)	(0.038)	(0.076)
Less than $1	0.063**	0.060**	0.098
	(0.029)	(0.029)	(0.062)
missing	0.115***	0.104***	0.149**
	(0.027)	(0.027)	(0.061)

Table B.9: Full Coefficient Estimates — Part V

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Education, owner 1 (excluded: Attended Vocational/Technical Extremely Likely)			
Attended Vocational/Technical School Likely	0.074	0.082	0.013
	(0.132)	(0.132)	(0.229)
Bach Degree - Extremely Likely	0.095*	0.102**	0.070
	(0.050)	(0.050)	(0.082)
Bach Degree - Likely	0.090*	0.098*	0.089
	(0.051)	(0.052)	(0.084)
Completed College Likely	0.184***	0.189***	0.232***
	(0.053)	(0.053)	(0.086)
Completed Graduate School Likely	0.314***	0.309***	0.373***
	(0.063)	(0.063)	(0.098)
Completed High School Likely	0.174***	0.177***	0.244***
	(0.053)	(0.053)	(0.087)
Did Not Complete High School Likely	0.017	0.025	0.040
	(0.091)	(0.090)	(0.132)
Grad Degree - Extremely Likely	0.145***	0.150***	0.053
	(0.050)	(0.050)	(0.083)
Grad Degree - Likely	0.111**	0.113**	0.099
	(0.051)	(0.051)	(0.082)
HS Diploma - Extremely Likely	0.029	0.035	0.045
	(0.051)	(0.051)	(0.082)
HS Diploma - Likely	0.047	0.052	0.069
	(0.051)	(0.051)	(0.082)
Less than HS Diploma - Ex Like	0.245**	0.247**	0.355
	(0.124)	(0.124)	(0.229)
Less than HS Diploma - Likely	0.014	0.024	0.037
	(0.051)	(0.051)	(0.083)
missing	0.083	0.085*	0.057
	(0.051)	(0.051)	(0.082)
Some College - Likely	0.080	0.086*	0.081
	(0.050)	(0.050)	(0.082)
Some College -Extremely Likely	0.146***	0.150***	0.112
	(0.051)	(0.052)	(0.084)
Vocational Technical Degree - Extremely Likely	0.124*	0.133**	0.009
	(0.064)	(0.065)	(0.113)

Table B.10: Full Coefficient Estimates — Part VI

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Education, owner 2 (excluded: Attended Vocational/Technical Extremely Likely)			
Attended Vocational/Technical School Likely	−0.424***	−0.419***	−0.363*
	(0.143)	(0.142)	(0.215)
Bach Degree - Extremely Likely	−0.145*	−0.145*	−0.222*
	(0.083)	(0.082)	(0.118)
Bach Degree - Likely	−0.142*	−0.141*	−0.195*
	(0.083)	(0.082)	(0.117)
Completed College Likely	−0.065	−0.064	−0.061
	(0.081)	(0.081)	(0.115)
Completed Graduate School Likely	0.071	0.071	0.037
	(0.093)	(0.092)	(0.141)
Completed High School Likely	−0.077	−0.079	−0.131
	(0.086)	(0.086)	(0.122)
Did Not Complete High School Likely	−0.113	−0.116	−0.138
	(0.161)	(0.162)	(0.261)
Grad Degree - Extremely Likely	−0.137*	−0.135	−0.221*
	(0.083)	(0.082)	(0.120)
Grad Degree - Likely	−0.139*	−0.141*	−0.192
	(0.083)	(0.083)	(0.118)
HS Diploma - Extremely Likely	−0.201**	−0.200**	−0.234**
	(0.083)	(0.082)	(0.117)
HS Diploma - Likely	−0.166**	−0.167**	−0.189
	(0.082)	(0.081)	(0.116)
Less than HS Diploma - Ex Like	−0.112	−0.103	−0.173
	(0.177)	(0.176)	(0.301)
Less than HS Diploma - Likely	−0.212**	−0.204**	−0.234**
	(0.084)	(0.083)	(0.118)
missing	−0.109	−0.113	−0.148
	(0.082)	(0.081)	(0.115)
Some College - Likely	−0.155*	−0.153*	−0.202*
	(0.083)	(0.082)	(0.117)
Some College -Extremely Likely	−0.125	−0.123	−0.171
	(0.082)	(0.081)	(0.115)
Vocational Technical Degree - Extremely Likely	−0.168*	−0.168*	−0.232
	(0.096)	(0.095)	(0.154)

Table B.11: Full Coefficient Estimates — Part VII

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Charitable contributions (excluded: No)			
Owner 1: Unknown	0.075***	0.074***	0.096***
	(0.011)	(0.010)	(0.017)
Owner 1: Yes	0.070***	0.068***	0.045**
	(0.011)	(0.010)	(0.017)
Owner 2: Unknown	0.042***	0.035**	0.060***
	(0.014)	(0.014)	(0.022)
Owner 2: Yes	0.032**	0.023	0.033
	(0.015)	(0.014)	(0.022)
Years since last renovation (excluded: Decile 1)			
Decile 2	0.005	0.010	0.139***
	(0.025)	(0.021)	(0.042)
Decile 3	−0.031	−0.021	0.236***
	(0.026)	(0.022)	(0.060)
Decile 4	−0.067**	−0.049**	0.312***
	(0.027)	(0.022)	(0.062)
Decile 5	−0.092***	−0.076***	0.395***
	(0.028)	(0.023)	(0.063)
Decile 6	−0.110***	−0.109***	0.486***
	(0.030)	(0.025)	(0.066)
Decile 7	−0.146***	−0.148***	0.544***
	(0.032)	(0.027)	(0.067)
Decile 8	−0.183***	−0.193***	0.567***
	(0.033)	(0.028)	(0.068)
Decile 9	−0.166***	−0.190***	0.558***
	(0.035)	(0.029)	(0.071)
Decile 10	−0.135***	−0.158***	0.492***
	(0.036)	(0.030)	(0.071)
Other controls			
Has children	−0.019***	−0.012**	−0.005
	(0.007)	(0.005)	(0.007)
Multiple owners	0.027***	0.023***	0.023***
	(0.007)	(0.005)	(0.008)
FEC donor	0.248***	0.250***	0.339***
	(0.017)	(0.016)	(0.029)

Table B.12: Full Coefficient Estimates — Part VIII

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Year built, bins 2–16 (excluded: Bin 1)			
Bin 2	0.046**	0.024**	
	(0.023)	(0.012)	
Bin 3	0.043**	0.035***	
	(0.019)	(0.012)	
Bin 4	0.032	0.038***	
	(0.020)	(0.013)	
Bin 5	0.043*	0.038***	
	(0.023)	(0.013)	
Bin 6	0.077***	0.078***	
	(0.021)	(0.014)	
Bin 7	0.099***	0.096***	
	(0.025)	(0.015)	
Bin 8	0.123***	0.108***	
	(0.023)	(0.015)	
Bin 9	0.152***	0.126***	
	(0.024)	(0.017)	
Bin 10	0.179***	0.144***	
	(0.025)	(0.018)	
Bin 11	0.179***	0.142***	
	(0.026)	(0.019)	
Bin 12	0.162***	0.130***	
	(0.026)	(0.020)	
Bin 13	0.161***	0.140***	
	(0.024)	(0.019)	
Bin 14	0.185***	0.153***	
	(0.028)	(0.021)	
Bin 15	0.199***	0.169***	
	(0.027)	(0.022)	
Bin 16	0.204***	0.172***	
	(0.029)	(0.024)	

Table B.13: Full Coefficient Estimates — Part IX

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Year built, bins 17–30 (excluded: Bin 1)			
Bin 17	0.182***	0.141***	
	(0.033)	(0.023)	
Bin 18	0.153***	0.098***	
	(0.039)	(0.024)	
Bin 19	0.063*	0.029	
	(0.032)	(0.022)	
Bin 20	0.007	−0.017	
	(0.029)	(0.020)	
Bin 21	−0.037	−0.049**	
	(0.031)	(0.022)	
Bin 22	−0.074**	−0.087***	
	(0.031)	(0.021)	
Bin 23	−0.161***	−0.177***	
	(0.032)	(0.022)	
Bin 24	−0.215***	−0.259***	
	(0.031)	(0.024)	
Bin 25	−0.268***	−0.319***	
	(0.033)	(0.025)	
Bin 26	−0.348***	−0.389***	
	(0.036)	(0.030)	
Bin 27	−0.401***	−0.452***	
	(0.040)	(0.035)	
Bin 28	−0.420***	−0.498***	
	(0.057)	(0.044)	
Bin 29	−0.500***	−0.568***	
	(0.059)	(0.047)	
Bin 30	−0.547***	−0.603***	
	(0.063)	(0.051)	
Missing	0.117	0.120	
	(0.139)	(0.122)	

Table B.14: Full Coefficient Estimates — Part X

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Log property value, bins 2–16 (excluded: Bin 1)			
Bin 2	−0.073***	−0.070***	−0.131***
	(0.018)	(0.016)	(0.028)
Bin 3	−0.107***	−0.105***	−0.208***
	(0.023)	(0.021)	(0.038)
Bin 4	−0.124***	−0.120***	−0.264***
	(0.026)	(0.024)	(0.044)
Bin 5	−0.135***	−0.126***	−0.303***
	(0.029)	(0.027)	(0.049)
Bin 6	−0.145***	−0.137***	−0.340***
	(0.030)	(0.028)	(0.053)
Bin 7	−0.135***	−0.129***	−0.356***
	(0.031)	(0.029)	(0.056)
Bin 8	−0.141***	−0.135***	−0.379***
	(0.033)	(0.031)	(0.059)
Bin 9	−0.135***	−0.131***	−0.393***
	(0.034)	(0.032)	(0.062)
Bin 10	−0.128***	−0.126***	−0.401***
	(0.035)	(0.033)	(0.064)
Bin 11	−0.133***	−0.132***	−0.424***
	(0.037)	(0.035)	(0.067)
Bin 12	−0.128***	−0.128***	−0.428***
	(0.038)	(0.036)	(0.070)
Bin 13	−0.116***	−0.119***	−0.430***
	(0.038)	(0.037)	(0.072)
Bin 14	−0.104***	−0.108***	−0.440***
	(0.040)	(0.038)	(0.074)
Bin 15	−0.098**	−0.102**	−0.444***
	(0.041)	(0.040)	(0.078)
Bin 16	−0.077*	−0.083**	−0.437***
	(0.042)	(0.040)	(0.080)

Table B.15: Full Coefficient Estimates — Part XI

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Log property value, bins 17–30 (excluded: Bin 1)			
Bin 17	−0.048	−0.057	−0.420***
	(0.042)	(0.039)	(0.080)
Bin 18	−0.036	−0.046	−0.426***
	(0.042)	(0.040)	(0.082)
Bin 19	−0.034	−0.046	−0.444***
	(0.043)	(0.041)	(0.084)
Bin 20	−0.011	−0.029	−0.440***
	(0.044)	(0.042)	(0.086)
Bin 21	0.017	−0.010	−0.437***
	(0.046)	(0.043)	(0.088)
Bin 22	0.053	0.014	−0.434***
	(0.045)	(0.042)	(0.089)
Bin 23	0.088*	0.045	−0.425***
	(0.048)	(0.045)	(0.093)
Bin 24	0.119**	0.073	−0.421***
	(0.051)	(0.047)	(0.096)
Bin 25	0.181***	0.129***	−0.411***
	(0.053)	(0.048)	(0.098)
Bin 26	0.226***	0.173***	−0.412***
	(0.055)	(0.051)	(0.102)
Bin 27	0.268***	0.210***	−0.451***
	(0.058)	(0.053)	(0.107)
Bin 28	0.304***	0.261***	−0.517***
	(0.064)	(0.055)	(0.113)
Bin 29	0.353***	0.317***	−0.617***
	(0.068)	(0.057)	(0.123)
Bin 30	0.262***	0.206***	−0.912***
	(0.080)	(0.065)	(0.159)
Missing	0.341***	0.358***	0.139
	(0.081)	(0.099)	(0.128)

Table B.16: Full Coefficient Estimates — Part XII

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Household income, bins 2–16 (excluded: Bin 1)			
Bin 2	0.020**	0.012*	0.030***
	(0.009)	(0.007)	(0.010)
Bin 3	0.033***	0.021***	0.038***
	(0.011)	(0.008)	(0.012)
Bin 4	0.042***	0.028***	0.045***
	(0.013)	(0.008)	(0.014)
Bin 5	0.056***	0.039***	0.056***
	(0.015)	(0.009)	(0.014)
Bin 6	0.058***	0.036***	0.053***
	(0.015)	(0.009)	(0.013)
Bin 7	0.067***	0.044***	0.058***
	(0.015)	(0.009)	(0.014)
Bin 8	0.087***	0.064***	0.074***
	(0.017)	(0.011)	(0.016)
Bin 9	0.077***	0.053***	0.060***
	(0.017)	(0.011)	(0.016)
Bin 10	0.087***	0.063***	0.063***
	(0.017)	(0.011)	(0.016)
Bin 11	0.076***	0.052***	0.036**
	(0.019)	(0.011)	(0.015)
Bin 12	0.101***	0.076***	0.066***
	(0.018)	(0.012)	(0.016)
Bin 13	0.093***	0.067***	0.052***
	(0.019)	(0.012)	(0.016)
Bin 14	0.099***	0.074***	0.057***
	(0.020)	(0.013)	(0.016)
Bin 15	0.105***	0.080***	0.043***
	(0.020)	(0.012)	(0.016)
Bin 16	0.109***	0.082***	0.051***
	(0.021)	(0.013)	(0.016)

Table B.17: Full Coefficient Estimates — Part XIII

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Household income, bins 17–30 (excluded: Bin 1)			
Bin 17	0.116***	0.090***	0.043***
	(0.021)	(0.013)	(0.015)
Bin 18	0.103***	0.076***	0.017
	(0.022)	(0.013)	(0.016)
Bin 19	0.120***	0.092***	0.034*
	(0.023)	(0.015)	(0.018)
Bin 20	0.114***	0.086***	0.032*
	(0.023)	(0.014)	(0.017)
Bin 21	0.118***	0.087***	0.025
	(0.024)	(0.014)	(0.017)
Bin 22	0.125***	0.092***	0.022
	(0.026)	(0.015)	(0.017)
Bin 23	0.128***	0.094***	0.025
	(0.027)	(0.016)	(0.018)
Bin 24	0.131***	0.094***	0.029
	(0.029)	(0.016)	(0.018)
Bin 25	0.124***	0.086***	0.006
	(0.030)	(0.016)	(0.020)
Bin 26	0.131***	0.092***	0.015
	(0.032)	(0.017)	(0.019)
Bin 27	0.146***	0.097***	0.016
	(0.035)	(0.020)	(0.021)
Bin 28	0.141***	0.093***	0.008
	(0.037)	(0.020)	(0.023)
Bin 29	0.168***	0.115***	0.024
	(0.044)	(0.026)	(0.029)
Bin 30	0.219***	0.160***	0.028
	(0.055)	(0.036)	(0.042)
Missing	0.056***	0.025***	−0.025*
	(0.020)	(0.008)	(0.014)

Table B.18: Full Coefficient Estimates — Part XIV

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Square footage (excluded: missing)			
Bin 1	0.020	0.018	
	(0.078)	(0.077)	
Bin 2	0.066	0.049	
	(0.080)	(0.078)	
Bin 3	0.089	0.075	
	(0.080)	(0.079)	
Bin 4	0.126	0.100	
	(0.081)	(0.079)	
Bin 5	0.144*	0.119	
	(0.082)	(0.079)	
Bin 6	0.158*	0.133*	
	(0.082)	(0.080)	
Bin 7	0.197**	0.159*	
	(0.084)	(0.081)	
Bin 8	0.215**	0.181**	
	(0.085)	(0.082)	
Bin 9	0.219**	0.186**	
	(0.087)	(0.083)	
Bin 10	0.159*	0.139	
	(0.091)	(0.086)	
Ownership tenure (excluded: Decile 1)			
Decile 2	0.260***	0.262***	0.280***
	(0.017)	(0.017)	(0.018)
Decile 3	−0.114***	−0.111***	−0.101***
	(0.013)	(0.012)	(0.012)
Decile 4	−0.210***	−0.207***	−0.209***
	(0.017)	(0.016)	(0.017)
Decile 5	−0.257***	−0.252***	−0.277***
	(0.019)	(0.018)	(0.020)
Decile 6	−0.298***	−0.292***	−0.345***
	(0.020)	(0.020)	(0.023)
Decile 7	−0.327***	−0.322***	−0.397***
	(0.021)	(0.020)	(0.025)
Decile 8	−0.330***	−0.327***	−0.428***
	(0.021)	(0.021)	(0.026)
Decile 9	−0.326***	−0.322***	−0.440***
	(0.021)	(0.021)	(0.026)
Decile 10	−0.295***	−0.294***	−0.378***
	(0.020)	(0.020)	(0.028)

Table B.19: Full Coefficient Estimates — Part XV

	Dep. var.: Wind permit (%)		
	(1)	(2)	(3)
	Zip × Year	Block × Year	Property + Year
Year effects (excluded: 2014)			
2015			0.011
			(0.009)
2016			0.080***
			(0.014)
2017			0.235***
			(0.024)
2018			0.426***
			(0.035)
2019			0.347***
			(0.034)
2020			0.473***
			(0.045)
2021			0.441***
			(0.043)
2022			0.289***
			(0.044)
2023			0.402***
			(0.049)
2024			0.458***
			(0.050)
Fixed effects	Zip × Year	Block × Year	Property + Year
Clustering	Zip	Zip	Zip
Observations	66,194,785	66,189,501	66,120,781
R^2 (overall)	0.017	0.021	0.108
R^2 (within)	0.002	0.002	0.001
RMSE	8.555	8.542	8.539