Household Adaptation and Climate Beliefs: Evidence from Building Permits*

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Abstract

I study how beliefs about climate change shape households' climate adaptation decisions. Parsing the textual description of 152 million building permits for single-family residential housing, I identify which ones are intended to protect the house against three major climate-related hazards: wildfires, hurricanes, and floods. These three types of permits directly reflect households' adaptation to these risks. I validate these measures of adaptation by showing that, in the cross-section of U.S. counties for the period 2000-2023, they strongly correlate with the local exposures to these risks: for example, wildfire-related permits are significantly more frequent in wildfire-exposed areas, and especially so in the riskiest areas. The main result of the paper focuses on the link with climate change beliefs, which is related to *long-term* exposure to these hazards: I show that, controlling for the current exposure to these hazards, wildfire and hurricane-related permits are more frequent precisely where people are more worried about climate change (which makes expected future risks higher); the role of climate beliefs in driving adaptation becomes stronger in more exposed areas. Flood adaptation is less well measured by permitting activity and does not show a clear link with climate beliefs. This analysis suggests that where households are more aware about climate risks and its link to future risks of wildfire and hurricanes, they respond by actively taking individual adaptation measures.

Key words: Climate adaptation, individual investment, flood, hurricane, wildfire, wind, beliefs.

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1 Introduction

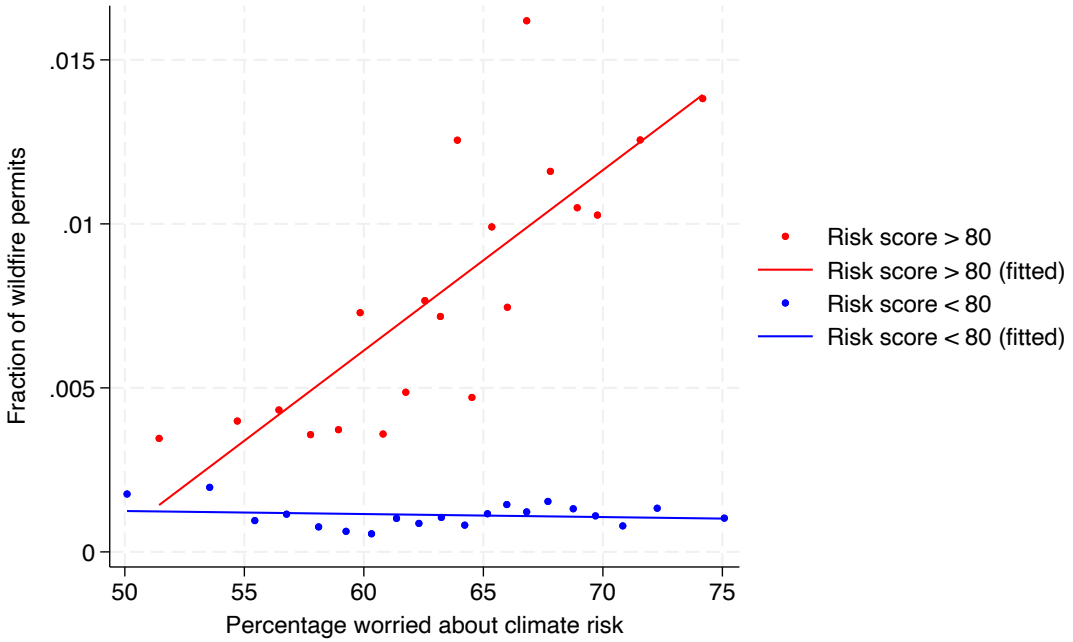
Climate change is an important source of risk for human societies and economic activity all around the globe. For several decades, economists and policymakers have worked to understand how a sustainable path can be forged that achieves economic growth while limiting the human-induced change in the climate, which is expected to have potentially devastating losses in the coming decades. Climate change mitigation, i.e. the effort to reduce the likelihood and severity of climate change, has been (and still remains) the main pillar of society's response to climate change. Unfortunately, the success of mitigation efforts has been limited, partly due to the lack of political will and cooperation incentives from many countries that are responsible for a large fraction of emissions.

If mitigation is only partially successful, then *adaptation* – that is, the effort to make the economic system more resilient to climate damages, when they will occur – becomes crucial to protect societies from future climate damages. Yet, much less work has focused on climate adaptation, its effectiveness and its determinants, compared to mitigation. Part of the reason is that adaptation investments are very specific to the different types of climate-related damage (e.g., adaptation to hurricanes is very different than adaptation to wildfires), and different adaptation measures can be taken by different subjects (e.g., governments and households can both invest in flood resilience, but in very different ways), making it difficult to study it systematically. Measurement is also an issue, as it is difficult to directly observe granular information about adaptation investments, and, even harder, to identify those that are aimed specifically at *climate* adaptation.

In this paper, I propose a novel approach to measure individual adaptation investments taken in the housing market, based on a comprehensive textual analysis of nationwide building permit data. In particular, I exploit a new dataset from Corelogic that reports 152 million residential permits, covering about 80% of the U.S. real estate market over the last two decades, and includes textual descriptions of the work performed in the permit. The language in these permits is typically standardized, which allows me to identify keywords that specifically refer to adaptation investments for three major hazards that have been linked to climate change: *wildfires, hurricanes and floods*. To make their houses more resilient to these risks, households can undertake a number of investments, like installing fire-resistant roofs and sidings, impact-resistant windows, storm shutters, backflow prevention valves, sump pumps, and so on. These interventions typically require a building permit, and I can therefore identify them from the permit descriptions.

I use this dataset to explore a key question about the determinants of household adaptation: to what extent are their adaptation investments driven by their *beliefs about climate change*? Of course, households in areas currently exposed to wildfires, hurricanes, or floods have an incentive to protect their houses against these hazards, even if they do not understand or believe in the link between climate change and the future severity of those hazards. But if households are worried about climate change, and understand that climate change will worsen their *future* exposures to those hazards, this should induce them to invest more in adaptation, even controlling for their immediate risk exposure, and especially so in exposed areas that climate change will make riskier. Whether that is true empirically is the focus of this paper. This is an important question because

Figure 1: Wildfire permits and climate beliefs



Note: This figure shows the binscatter of the fraction of wildfire-related permits for each U.S. county-year as a function of the climate beliefs (percentage of the population worried about climate risk), separately for areas at high wildfire risk (FEMA score >80, red), and areas with low wildfire risk (FEMA score <80, blue). Observations are weighted by population size, and the graph controls for the number of permits per capita in each county, as well as state fixed effects.

climate change is likely to significantly worsen these risks over time, and building resilience requires agents (both governments and households) to prepare to face future risks, not just the current ones. The key empirical result of the paper is that, in areas exposed to these hazards, there is indeed a strong relationship between climate beliefs and adaptation with respect to both wildfire and hurricane risks; flood-related adaptation measures built from permit data are noisier, and do not display a statistically clear relation with climate beliefs. Therefore, for wildfires and hurricanes, for which adaptation investments are observed more precisely, climate beliefs appear to be an important determinant of household adaptation decisions.

Figure 1 summarizes the key results of the paper for the case of wildfire adaptation investments. The figure shows a binscatter plot where the Y axis represents the fraction of building permits in a county and year that are classified as wildfire-related (e.g., fire-resistant roofs), and the X axis shows the percentage of households in a county and year that are worried about climate risk (as measured by a granular nationwide survey by the Yale Program on Climate Change Communication). The plot controls for state fixed effects, so it studies variation across counties within each state, to control for state-level unobservables like permit regulations. The blue dots correspond to low-wildfire-risk counties. In those counties, there is (not surprisingly) little investment in wildfire adaptation, and there is no link to climate beliefs (the blue line is flat). The red dots correspond to counties classified by FEMA as high wildfire risk. For these counties, a significant fraction of permits (up

to 2%) are devoted to wildfire resilience. The fact that permits classified as wildfire-related seem to concentrate in areas with higher wildfire risk (that is, the red dots are above the blue dots) provides validation that indeed the textual analysis of permits is capturing meaningful resilience investments. Most interestingly, there is positive and significant variation of wildfire adaptation investments with climate beliefs in high-wildfire-risk counties: wildfire adaptation is stronger in counties where households are more worried about climate risk, suggesting that households that are more worried about climate risk understand that it will induce more extreme wildfires in the future, and take action today by improving their houses.

The methodological foundation of my analysis is the classification of building permits as pertaining to one of those three hazards: wildfires, hurricanes (wind), and floods. To do so, I proceed as follows. I start from three documents by FEMA meant to explain to households what measures they can take to make their houses more resilient. I generate a set of keywords from these documents (with the help of GPT-4o). The keywords from this list are often not sufficiently specific to isolate investments that are clearly about mitigating those hazards: for example, finding "flood" in a permit might refer to the installation of floodlights. Therefore, I examine manually several thousand permit descriptions to identify, for each keyword, a set of "complementary" and "exclusion" words that clearly indicate that the permit specifically relates to hazard mitigation, or clearly indicate that it does not, respectively. The highly stylized nature of permit description makes this keyword approach efficient; I validate it by manually examining several thousands permits that were automatically classified in this way.

What are the kind of investments that individual households can make to protect themselves against wildfires, hurricanes, and floods? While the list obtained from the FEMA documents is relatively varied, a few measures seem to be most relevant in practice. The vast majority is captured by the building permits. For wildfires, the most important measures are clearing the vegetation surrounding the house, and installing fire-resistant roofs, sidings, windows, and vents that prevent embers from entering the house and make it harder for the fire to spread to the house. Except for the vegetation clearing measures, the other ones all appear in the permit data. For floods, while governments are responsible for managing the flow of waters (e.g., floodplain management), individuals can make sure that the outside and basement of the houses are waterproof, and they can install barriers, trenches, and sump pumps (to remove the water that does enter). Elevation of the house is one type of residential adaptation that is particularly effective (see Hovekamp and Wagner (2023)), but it is extremely costly to apply it to existing homes, so it is rarely seen except for new construction (and also, as I describe in greater detail below, it is difficult to identify it in the permit data). Finally, hurricanes are an interesting hazard when thinking about adaptation, because they feature strong winds together with potential floods (due to the storm surge). Whereas government are most effective in dealing with the flood-related component, by managing the flow of water in the city, the protection against strong winds falls almost entirely on individual households. FEMA suggests a variety of measures to strengthen the house against high winds: straps and bracings to tie down the house to the foundation, as well as the roof to the house, and also impact windows

and doors as well as storm shutters to prevent debris and wind to break into the house. All of these appear in the permit data.

In the paper, I focus my analysis on the period 2000-2023, since before then the availability of permit data is less broad; in addition, general awareness of climate risks (the focus of this paper) was low before the early 2000s, as often discussed in the literature (see for example Acharya et al. (2022)). During this period, I observe at least 2 million permits per year across the US, and I see significant variation over time, following the housing cycle: a peak around 2005-2006, a trough in 2008, another peak before the global pandemic of 2020, and finally a more moderate drop during Covid. Permits are also not uniformly distributed across states: for example, Florida has a substantially higher average number of permits per property than most other states. Some of this cross-sectional variation reflects differences in the laws that regulate the use of permits for residential construction, though major investments require permits everywhere. Some of the cross-sectional differences reflect other differences among the local housing markets (e.g., the average wealth in different states). Because of these large differences across states, my analysis will focus of within-state variation, across counties and years (and I also verify the results by studying variation within counties over time).

Among this universe of permits, the permits identified as wildfire, hurricane and flood related represent a small but significant fraction. Specifically, I identify close to 500,000 wildfire-related permits, 780,000 wind-related permits, and 700,000 flood-related permits. While these numbers are small relative to the total number of permits, they are for the most part concentrated in at-risk counties, so that in those counties they represent a relatively high fraction of permits issued.

One potential concern with this approach to measure adaptation investment is measurement error. Climate permits are the independent variable in my analysis, and therefore random measurement error will not bias the results; however, misclassification of permits will result in loss of power. To address this concern, the first empirical exercise in the paper is devoted to showing that indeed these hazard-related permits (identified from the textual description) tend to be meaningfully higher in areas where the corresponding risks, as classified by FEMA, are higher: for example, as evidenced by the average difference between blue and red dots in figure 1, wildfire-related permits are essentially absent in areas with low wildfire risk, while they are much higher in areas exposed to wildfire risk. The more detailed analysis reported in the paper shows that, indeed, wildfire and hurricane permits very strongly associate with wildfire and hurricane-prone areas, suggesting that resilience measures against these two hazards are measured well in the data. The same is not true for floods, most likely because the kind of resilience measures we can detect in permits may be adopted even in areas that are not at risk of severe flooding (the kind of flooding that is commonly associated with climate change). That is, the data is consistent with more measurement error for flood adaptation measures.

Armed with the classification of permits into the various hazard types, I move to the core of the economic analysis: the relation between *climate beliefs* and adaptation investments, controlling for measures of current hazard exposure from FEMA. The measure of climate beliefs I employ

comes from the Yale Program for Climate Change Communication. It provides a survey (provided at the county-year level) of more than 22,000 households on various aspects of their beliefs about climate change: how worried they are, whether they experienced its consequences, and so on. In this paper, the main variable I use is the fraction of households that say they are somewhat or very worried about climate change, in a given county-year: this question is available for the longest sample (going back to 2014), and captures directly a core aspect of climate change beliefs. I also explore the robustness with respect to other questions of the survey, finding similar results.

The main empirical analysis studies separately the three hazards – wildfire, hurricane and flood, and, given the fact that beliefs are observed at the county-year level, is estimated with permit data aggregated at the county-year level. For each of the three hazard, I regress the fraction of wildfire, hurricane, or flood-related permits in a county and year on state fixed effects, year fixed effects, the number of permits per capita in that county-year (which controls for other county-year-level variation that affects generally building and renovation activity), as well as on the FEMA hazard risk score, the climate beliefs, and, last but not least, their interaction. The key term of interest is the interaction. In low-risk areas, we would not expect to see much of a relation between climate beliefs and hazard-related permits: while in theory some currently-not-exposed areas could become exposed in the future, the first-order effect of climate change is to worsen the current risks in the future decades. In areas that are currently exposed to a risk, we might then see a relation between adaptation and climate beliefs, *if* households understand the link between climate and future worsening of wildfires, winds and floods. This interaction term, in the specification of Figure 1, corresponds to the observation that the red line has a strong positive slope (while the blue line does not). The formal statistical test of that result shows that indeed that difference in slopes is both statistically and economically significant.

Similar results hold when looking at hurricanes (though statistical significance is slightly weaker), and they also hold when studying a variety of other specifications, including discrete and continuous risk classification, using county fixed effects (and therefore identifying the slope from time variation of climate belief within county, in risky areas), studying only areas that received little to no direct damages from the hazards over the last 20 years, and several other variations.

In the case of floods, instead, I find no significant relation between adaptation measures and climate beliefs. This is consistent with the issue, mentioned above, that permit-based flood adaptation measures appear to be noisier – even the relation between flood adaptation and current flood risk is much weaker. This suggests that additional refinements will be required to better understand households flood adaptation. I still present the full set of results, however, both for completeness and also to highlight how the strong results for wildfire and wind adaptation do not appear to arise mechanically.

A final caveat is that the analysis is subject to potential endogeneity concerns. I do not have an instrument, or a quasi-random shock, for climate beliefs, and therefore the analysis establishes causality only insofar as the controls (which are overall permitting activity and a variety of state, year, state x year, or county fixed effects) capture confounders. That said, while the relation I

document is not causal, it still shows a strong association between households' *actions* and their *beliefs* about climate change (and therefore future risks), similar to a recent literature linking beliefs on investors and their actions (for example, Giglio et al. (2021), which also documents a non-causal association).

The paper builds on a very large literature on climate economics and climate finance. This literature is vast and reviewed in detail in Giglio et al. (2021), and I refer the interested reader to that review. One important thing to point out is that a large part of that literature has focused on *mitigation* rather than adaptation to climate change. The paper also builds on a much smaller, recent literature trying to understand the incentives and determinants of individual and government climate beliefs and adaptation. Hovekamp and Wagner (2023) study the effectiveness of house elevation imposed by regulation mandates in reducing damages due to floods (therefore, focusing in a sense on the *government* adaptation decision – through regulation – instead of the household-level decision). Bakkensen and Barrage (2022) study, using a survey, flood risk beliefs, and link them to house prices. Meyer et al. (2014) document, via a survey, hurricane risk perception and preparedness of individual households. Bellon et al. (2024) study the uptake of clean-energy government-sponsored loans (PACE loans) by households in Florida and study their effect on property prices, the mortgage market and local fiscal outcomes. They also use the text of permit data to validate that the PACE loans are indeed used for green investing – that is, they belong to the types of projects covered by the PACE program (impact windows, roofing repairs/reinforcements, HVAC, solar panels, and others). Relative to these papers, my focus is on systematically identifying climate-adaptation investments for the different types of climate risks described above, and study their determinants (and particularly the role of climate beliefs). A few studies, like Lu and Nakhmurina (2024) and Gandhi et al. (2022), focus instead of government-level adaptation to climate change, which tend to be very different from the kind of investments that individuals do.

2 Housing permits: institutional setting and data

In this section I review the institutional setting of housing permits, and describe the main dataset used in this paper, from Corelogic. The discussion in this section refers to permits in general; section 3 below describes how I identify the permits that specifically relate to adaptation for climate-related hazards (wildfires, hurricanes, and floods). Finally, the other datasets used in the analysis (most importantly, the climate beliefs data) will be introduced in section 5.

2.1 Building permits in the U.S.

Building permits in the U.S. operate within a multi-level regulatory framework, involving federal guidelines, state building codes, and municipal regulations. In practice, state and local governments adopt and enforce building codes (often based on model codes like the International Building Code (IBC) for commercial buildings and International Residential Code (IRC) for residential buildings)

to ensure that construction meets minimum safety standards.[1]

The federal government itself plays a limited direct role in private building regulation – it sets standards for federal buildings, military facilities, and manufactured homes, but does not impose a national building code for general construction. Nonetheless, federal agencies such as FEMA influence local building practices by providing model guidelines and incentives for hazard mitigation (for example, FEMA's floodplain regulations under the National Flood Insurance Program (NFIP) require communities to adopt certain building permit restrictions in flood-prone areas).[2]

At the state level, building codes are typically established through state law or building commissions, often mandating the use of 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.[3] Key institutions include the International Code Council (ICC), which publishes the IBC and IRC, and FEMA, which publishes guidance such as FEMA's "Building Codes Save" study. At the local level, city or county building departments are responsible for issuing permits and conducting inspections. These local authorities review building plans, verify compliance with all applicable codes, and ensure projects conform to zoning ordinances.[4]

Building permits are the enforcement mechanism that ensures code compliance. A permit is an official approval required before construction or substantial renovation can begin, indicating that the proposed work plans adhere to building codes and local regulations. Obtaining a permit typically involves submitting architectural or engineering plans to the local building department for review and paying any required fees. By law, most new construction, major alterations, or repairs affecting structural elements, life-safety systems, or occupancy changes must go through the permit process.[5]

Once a permit is issued, the project must undergo inspections at key stages (e.g., foundation, framing, electrical, plumbing, and final inspections), where certified inspectors verify that the work on-site complies with the approved plans and code requirements.[6] A project that passes all inspections is granted a certificate of occupancy or final approval, signifying the building is safe and code-compliant.[7]

In summary, the institutional framework for building permits involves model codes (IBC/IRC) promulgated at the national level, adopted (and sometimes modified) by states, and enforced locally through permits and inspections—a system designed to ensure structural safety and lawful land use in every construction project.[8]

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

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

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

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

[5] Connecticut State Building Code. "Building Regulations and Permit Process." `https://portal.ct.gov/das/services-for-agencies-and-municipalities/safety-codes-and-inspections`

[6] Akitabox. "Code Enforcement and Inspections in Construction." `https://home.akitabox.com/blog/code-enforcement/`

[7] Procore. "Understanding the Certificate of Occupancy." `https://www.procore.com/library/certificate-of-occupancy`

[8] Connecticut State Building Code & Office of the State Building Inspector. "Model Codes and Local Enforcement." `https://portal.ct.gov/das/services-for-agencies-and-municipalities/safety-codes-and-inspections`

2.2 The Corelogic permit data

Corelogic provides a number of housing-related datasets, with a nationwide geographic coverage, aggregating, cleaning, linking, and normalizing information collected from county tax assessors, city building departments, and multiple listing services. Corelogic's datasets include property characteristics, ownership details, tax assessments, sales records, and also building permits. In this paper, I exploit the less widely used dataset on building permits. The permits dataset contains information about individual building permit applications submitted to local building department in the U.S.. Each application contains information about the property (e.g: the address, type of property: commercial or residential), information about the permit (e.g: description of the project, the permit effective and expiration date, the permit status, and in some cases the dollar value of the project), and information about the contractor (e.g: contractor's name, address and contractor ID).

The entire dataset contains 330 million of permits across the entire U.S.. 152 million of those relate to single-family residential permits, which are the focus of this paper. Not all localities are covered by the dataset, which has better coverage for the largest municipalities. Time coverage varies by location: for some cities, permit information goes back to the 1970s and 80s, but coverage clearly improves over time. In this paper I will be focusing on the period 2000 to 2023, given the improved coverage over the last two decades.

Two limitations of the data are noteworthy. First, as mentioned above, the data doesn't cover every municipality: smaller localities tend to be less likely to have building permit data collected by CoreLogic. Limited coverage could lead to an underestimation of climate change adaptation efforts if certain high-risk regions (e.g., coastal areas prone to hurricanes or wildfire-prone zones) are not as widely covered, and might bias the results if the lack of coverage correlates with climate beliefs and natural hazard risk in a way that the controls do not account for. That said, as discussed in greater detail below (section 3), counties with no permit data account for only about 9% of the population, suggesting that the coverage is overall quite broad.[9]

A second limitation is that not all housing investments and projects require a permit: typically, permits are required only for relatively major interventions (the details of which vary across localities); typically, minor repairs are excluded. An important question, therefore, will be whether the kind of climate adaptation investments I am studying in this paper indeed require a permit. The answer is that for the most part they do, and indeed, I do find a large number of these permits in the data across the U.S.; see a more extensive discussion in section 3.

Finally, it is worth emphasizing that despite some limitations, permit data presents a key advantage for understanding household response to climate risk, compared to other data sources like pricing information: while in general, housing decisions remain invisible in price data until a property is sold, permits are recorded as they are obtained. They allow us to track climate adaptation investments in real time, providing a more immediate and dynamic measure of resilience efforts.

[9]Relatedly, Brummet (2016) compared Consumer Expenditure data with the CoreLogic dataset for 2014 and found that single-family residential homes matched in approximately 83% of cases between the two datasets.

3 Identifying climate adaptation investments from permit data

The focus of this paper is households' decision to invest in climate adaptation, as reflected in the building permits they request to mitigate wildfire, hurricane, and flood risk. In this section I first describe the main ways in which households can protect their houses against these risks, and discuss to what extent they are subject to permitting requirements. Then, I detail the procedure I follow to identify adaptation permits in the universe of 152 million single family residential permits in the Corelogic data. I conclude with some summary statistics on the dataset.

3.1 Wildfire, Hurricane, and Flood-related Permits: Institutional Setting

A wide range of weather phenomena and hazards are associated with climate change; which ones are most relevant for households depends crucially on the geographic region. For example, the Atlantic coast is especially exposed to hurricanes, whereas a variety of areas both near the coast and inland are exposed to wildfire risk. In this paper, I focus on adaptation to three major hazards that are both a) relevant for a large number of US households, and b) related to climate change—in the sense that climate change is predicted to increase the severity and frequency of these hazards: they are wildfires, hurricanes, and floods. These are three of the five main weather-related hazards highlighted by FEMA that pose the highest risks in the U.S..[10] The other two mentioned by FEMA are droughts and heat. I do not include droughts in the analysis because they tend to be less directly relevant for most households (as opposed to, for example, for agricultural production). I also exclude extreme heat: while in theory I could measure adaptation investments in the permit data (most importantly, installing air conditioning), HVAC installations are not specific to adaptation to extreme heat, so it would be difficult to distinguish which permits relate to "standard" HVAC installations and which are motivated by the desire of specifically building resilience to *extreme* heat.

The three climate-related hazards I consider can impose potentially very large damages on properties. While households alone cannot entirely eliminate their risk exposures on their own, they can make modifications to their houses to protect them from these hazards. A variety of documents is available that describes the adaptation measures households can take. In this paper, I start from three documents issued by FEMA, aimed precisely at informing households about the best way they can reduce their exposure. They are called, respectively, "Protect your property from wildfires", "Protect your property from severe winds", and "Protect your property from flooding". As I describe below, I use these documents as starting points to identify a set of keywords useful to classify permits. Here, however, I first briefly summarize the main actions households can take.

For wildfire risk, the among the most important house modifications, we find: installing fire-rated ("class-A") roofs and sidings; installing impact-resistant or fire-resistant windows, covering vents, and sealing gaps, to prevent embers from entering the house; and clearing the vegetation surrounding the house. Many of these interventions (like re-roofing and sidings, and installing

[10] See https://web.archive.org/web/20250201000719/https://www.fema.gov/sites/default/files/documents/fema_climate-adaptation-planning-guide_2024.pdf.

tempered or fire-resistant windows) generally require a permit, as the building code requires them to meet code-specified standards.

For wind/hurricane risk, the main modifications are: replacing doors and windows with impact-resistant ones, installing storm shutters, reinforcing doors, reinforcing the roof (with straps). These are all typically covered by permitting requirements, and indeed I find them all in the permit data. Minor retrofits that don't alter the structure – for instance, clipping on temporary storm shutter panels – may be exempt from permits, but anything that becomes a permanent part of the building (windows, doors, roofs, etc.) is covered by permit requirements to ensure code compliance.

Finally, for flood risk, the most effective action households can take is to elevate an existing house on a new foundation, or build a new elevated foundation (which always requires a building permit, since it changes the structural system and site conditions). Unfortunately, we see little of this in the data given its prohibitive cost. Other actions are possible too, like installing flood vents in foundation walls, anchoring fuel tanks, or installing backflow prevention valves. These typically also need permits, to verify that the installations conform to building standards (for example, flood vents must be of a certain size and placed in accordance with code).

Overall, the vast majority of the kind of interventions that households can use to mitigate wildfire, hurricane, and flood risk tend to be subject to permitting requirements in most jurisdictions. Importantly, we can also look directly at the permit dataset to verify that indeed these interventions are subject to such requirements. If an area did not require permitting for, for example, installing backflow prevention valves, there would be no reason to actually find permits in the data describing this intervention. As the next section shows, I actually find large numbers of permits for all of the main interventions described above, with wide geographic coverage, suggesting that permit data can give us useful (if not perfect) insights about climate-adaptation investments.

One additional institutional feature which is important to discuss is the fact that local regulations sometimes *mandate* that some construction be built according to specific standards, which can also include wildfire, hurricane, or flood resilience. For instance, a code may stipulate that in a "Wind-Borne Debris Region" (an area prone to hurricanes), whenever windows are installed or replaced, they must be either impact-resistant or protected by approved shutters.[11] The reason this institutional feature is important for my analysis is not that these modifications wouldn't be covered by the data (they would be, because permits would be required), but rather that the decision of installing impact-resistant windows would then not fully be attributable to the *individual household*'s decision to adapt.

There is, however, an important consideration that allows us to still interpret the investments observed in the permit data as reflecting the individual households' choice, even in areas where standards are mandated by code. It is the fact that in general, existing buildings are not required to be brought up to code, and can instead be left in violation of code, unless work is made: in that case, the modification must comply with the code. That is, the existing buildings are generally

[11] International Code Council, *International Building Code*, Section 1609.2, 2018 Edition. `https://codes.iccsafe.org/s/IBC2018/chapter-16-structural-design/IBC2018-Ch16-Sec1609.2`

grandfathered in.[12] For example, a house in a "Wind-Borne Debris Region" might have windows that are not impact-resistant, but an owner would not be required to bring existing windows to code *unless* the owner decided to install new windows. Therefore, households retain substantial latitude to decide *when* and *whether* to make improvements like replacing the roof or windows, or keep using the existing ones; or to install additional components like a sump pump or a backflow prevention valve. Therefore, even in areas where the code requires that upgrades and modifications satisfy some resilience requirements, the ultimate decision of whether to engage in these projects is still left to the individual household.

3.2 Identifying Climate Adaptation Permits in the Data

To identify which permits relate to wildfire, hurricane, or flood-adaptation measures, I parse the textual description of each of 152 million single family residential permits from the Corelogic data, and use a keyword-based approach to classify them. I begin by creating a set of keywords that are associated with the three types of investments in the three FEMA documents mentioned above. I uploaded each of the three document to chatGPT-4o and prompted it to provide a list of keywords, based on those files, that could be used to identify these types of investments from permit descriptions. The list returned by GPT was extensive, and included both words that were clearly very specific to adaptation measures (e.g., *backflow, sump pump, Class A*, *impact window*) and words that were not sufficiently specific (e.g., "flood", which could identify for example flood lights, naturally unrelated to flood risk, or "fire", that could identify fire alarms).

To refine the list and exclude unrelated permits, for each keyword I manually reviewed 1,000 randomly selected permits (or as many as available, if less than that) that contained that keyword. I then compiled – separately for each keyword – a list of words that clearly identify a permit as related to one or more hazards, which I refer to as "complementary" words, and a list of words that clearly excluded a permit as referring to those hazards, which I refer to as "exclusion" words. Some examples: if the keyword *backflow* appears in a permit description, it almost always indicates a backflow prevention valve, which is clearly flood mitigation – but not if it is associated with *irrigation*, as it would then relate to the irrigation system. Therefore, *irrigation* would be included in the "exclusion words". Similarly, the word *barrier* could relate to hurricane protection, and certainly so if the words *wind* or *hurricane* also appear in the permit description (so *wind* and *hurricane* would be in the "complementary" words list for that keyword); but it could also refer to vapor or moisture barriers, which are not clearly related to these kind of adaptation investments: therefore, *vapor* and *moisture* would belong to the "exclusion" words list. As a final example, the word *wind* appears to clearly identify hurricane-adaptation investments when it appears alongside terms like *impact, storm, debris, bracing, anchor*, or *tempered* (all included in the "complementary" words list). However, it clearly does not relate to hurricane risk when it appears together with *turbine* or

[12] Typically, the requirement to bring the *entire* structure to code only triggers if a renovation covers more than 50% of the building in the first place, see Federal Emergency Management Agency, *Substantial Improvement/Substantial Damage Desk Reference*, FEMA P-758, May 2010. `https://www.fema.gov/sites/default/files/2020-07/fema_p-758_complete_r3.pdf`. The investments described here do not typically qualify.

generator, which would then belong to the "exclusion" words list. This extensive, manually-curated lists of "complementary" and "exclusion" words for each keyword helps sharpen the classification of permits into adaptation-related and non-adaptation-related ones. Finally, I also manually construct an additional set of general exclusion words that eliminate some additional ambiguity, and are applied to all permits: a permit is never classified as related to one of the three hazards if it contains any of these words.[13] To sum up, a permit is only flagged as related to, e.g., wind adaptation if 1) it contains one of the wind-related keywords, 2) it contains at least one of the words that are "complementary" to that keyword, 3) it contains none of the exclusion keywords (the general list and the keyword-specific list).

The entire list of keywords, together with their "complement" and "exclusion" words, is reported in Appendix tables 11, 12, and 13 separately for wildfire, wind, and flood permits. While these tables show that we consider a large variety of possible keyword combinations to identify climate adaptation, the very stylized language typically used in permit descriptions implies that a small number of combinations end up identifying the vast majority of those permits in practice. Tables 2, 1 and 3 show the pairs of words (one keyword and one complementary word, reported in alphabetical order for readability) and the frequency with which they appear in the permits that are ultimately identified as wildfire, hurricane, and flood-related.[14] The tables only report the 20 most frequent pairs for each type, which account for more than 96% of permits in all cases.

Specifically, table 1 shows the frequencies among the 493,510 permits identified as wildfire-related. There are two main types of investments that are identified in the permit data: fire-resistant (class-A) roofs, and impact windows (which help prevent embers from entering the house and therefore spreading the fire inside).

Table 2 shows the frequencies of keyword and complementary word pairs among the 773,825 permit identified as wind-related. The main types of adaptation investments in this case relate to impact windows, storm shutters, and wind barriers. Note that, as highlighted above, impact windows are also useful to protect from wildfires. Therefore, a permit that mentions impact windows is classified as *both* relating to wind adaptation and to wildfire adaptation. While this assignment might misclassify one type of adaptation for the other, this is a minor issue in practice, because our analysis in the next sections takes into account the different levels of risk of hurricane, wildfire, and flood in different areas: so in a wildfire-prone area, impact windows are most likely to refer to wildfire adaptation, whereas in hurricane-prone areas, they are most likely to refer to hurricane adaptation.

Finally, table 3 shows the main keywords and complement words that identify flood-related

[13]The entire 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 elevators, and has nothing to do with stilts. Earthquakes can also bring significant damages to the house, but are not climate-related.

[14]The alphabetical order means that the cases where *impact* is the keyword and *window* is the complementary word are grouped together, in this table, with those where *window* is the keyword and *impact* is the complementary word. Some words are so specific to the kind of investments we study that no complement is required to identify them as related to that hazard, though exclusion words still exist. For example, *backflow* on its own is sufficient to identify flood-related investment, but, as Appendix table 11 shows, if the word *irrigation* is also included, the permit is still not identified as flood-related.

Table 1: Keyword Frequency for wildfire

Climate Pair	Frequency	Cumulative Probability
Impact window	260,293	0.53
ClassA	146,304	0.83
Fire roof	39,467	0.91
Impact resistant	18,604	0.94
ClassA fire	8,924	0.96
Fire resist	5,577	0.97
Fire firerated	4,256	0.98
Fire firewall	3,705	0.99
Impact mitigation	2,713	0.99
Combustible noncombustible	719	1.00
Fire retar	488	1.00
Fire firestone	367	1.00
Clips hurricane	331	1.00
Defensible	270	1.00
Fire fireproof	254	1.00
Mitigation vegetation	241	1.00
Fire noncombustible	83	1.00
Fireresistant resistant	38	1.00
Fire wildfiremitigation	23	1.00
Fire tempered	16	1.00

Note: The table shows the frequency of pairs of keywords with complementary word that identified permits as widlfire-related. Spaces and dashes are ignored.

investments. The main ones, among the 700,281 identified, are backflow prevention valves, sump pumps, seawalls and waterproofing. As also noted by Hovekamp and Wagner (2023), the most effective intervention households can make against floods is to elevate the property with stilts. That is, however, extremely expensive to retrofit, which means that it only occurs when new construction is built, which is much less frequent.[15]

A few final notes on the procedure are important. First, an alternative procedure to this keyword-based approach would be to ask a large language model like GPT to classify each permit. Beyond the large scale of the problem (152 million permits for single family residential), an additional issue is that permit description is typically very short (ranging from 10 to 30 words), which gives the LLM little context to distinguish which permits clearly relate to flood, wind, or wildfire adaptation and which do not. In a sample of permits used for validation, this approach yielded significantly more errors than manual classification.

An alternative approach that also makes more extensive use of LLMs would be to use the keywords extracted by my extensive manual inspection (and described in Appendix tables 11, 12, and 13), to train/fine tune an LLM, and then use the trained LLM to classify all the universe of

[15]Since permits in the dataset include both existing buildings and new construction, in theory it would be possible to identify new construction that involves stilts. Unfortunately, manual inspection of the permit description shows that many times, contractors would mention in the permit description the fact that a house is on stilts even when referring to completely unrelated work (e.g., "installation of electrical panel in house on stilts"), making it much harder to identify work that directly involves the construction of stilts. The only keyword that seemed to reliably identify this kind of work is "elevate", which I do include but occurs in a very small number of permits.

Table 2: Keyword Frequency for wind

Climate Pair	Frequency	Cumulative Probability
Impact window	260,293	0.34
Shutter wind	123,418	0.50
Hurricane shutters	84,291	0.61
Anchor	39,589	0.66
Shutter storm	31,215	0.70
Storm stormpanel	29,233	0.74
Barrier wind	26,758	0.77
Storm stormshelter	22,130	0.80
Highwind wind	20,855	0.83
Impact resistant	18,604	0.85
Door impact	17,718	0.87
Roll shutter	15,824	0.89
Tempered wind	10,534	0.91
Wind windload	8,723	0.92
Barrier secondary	6,717	0.93
Hurricane protection	5,167	0.93
Impact shutter	4,944	0.94
Stormprot wind	4,044	0.95
Hurricane panels	3,514	0.95
Aluminum shutter	3,483	0.96

Note: Same as table 1, but for wind.

permits. Given the fact that the text of the permits tends to be highly standardized (as evidenced by the fact that a few pairs of words tend to repeat a large number of times), this is unlikely to give significantly different results than the current keyword-based approach, and I leave it to future research to explore this avenue.

A second point that is worth remarking is that of course, this approach will be somewhat noisy. Certainly there will be some misclassification of permits, in one way or the other. In the next section, I'll show direct evidence that these permits are indeed more frequent in riskier areas – wind-related permits, as identified with this procedure, do tend to occur in hurricane-prone areas, and so on for wildfires and floods. The section will also show that there appears to be less noise in identifying some types of permits (wildfires and wind) than others (flood), which is probably attributable to heterogeneity in the ability to identify permits of different types using the keywords I used, but also in the kind of interventions available to households (for example, fire-resistant roofs are very specific to wildfire risk, whereas storm drains may be useful even in areas that are not directly exposed to severe floods).

Finally, I note that I can also try to identify permits that relate to new construction (if they contain the text "new const") or if they indicate that they are repairs for existing damage (keywords "damage", "dmg", "repair"). I will use this additional information in robustness tests in section 5.1.

Table 3: Keyword Frequency for flood

Keywords	Count	Cumulative Frequency
Backflow	284,764	0.41
Pump sump	70,402	0.51
Seawall	60,900	0.60
Waterproof	53,078	0.68
Control erosion	43,543	0.74
Drain draintile	34,812	0.79
Storm stormpanel	29,233	0.83
Drain stormwater	16,936	0.86
Bulkhead	14,215	0.88
Drain stormdrain	11,169	0.89
Drainage grading	8,820	0.91
Barrier water	7,370	0.92
Storm stormsewer	7,297	0.93
Barrier secondary	6,717	0.94
Drain frenchdrain	4,750	0.95
Flood sewer	4,532	0.95
Control flood	4,189	0.96
Drainage flood	3,928	0.96
Elevate	3,619	0.97
Drain interiordrain	2,725	0.97

Note: Same as table 1, but for flood.

3.3 Sample preparation and summary statistics

I close this section by discussing how I prepare the sample for the analysis, specifically by applying some filters to the data and by aggregating permits to the county and year level. Finally, I provide some summary statistic on the final sample.

First, given that the core results of the paper in the next sections will exploit variation at the county-year level, I aggregate the permit information at that level. To do so, in addition to keeping track of the *total* and *per-capita* number of permits in a county and year (that is, overall permitting activity), I construct the *fraction of wildfire, wind,* and *flood permits* in each county and year. These three statistics will be the independent variables that my analysis will aim to explain (by relating them to the corresponding risks in each area, as well as beliefs about climate change).

My sample therefore starts with a total of 3,142 US counties, observed yearly since 2000. Not all this data can be used for the analysis, however. For 1,308 counties, there is no permit data at all over the entire sample period. These counties tend to be significantly smaller than the average in terms of population, and are more likely not to be covered at all by Corelogic. They account for about 9% of the total U.S. population. These counties will be excluded from my analysis.

Of the remaining 1,834 counties, about half of them (919) do not have *any* permit related to wind, flood, or wildfire during the entire period. These are counties that are most likely to not be affected by any hazard of the ones we consider, or where permitting regulations or Corelogic

data collection prevent us from seeing this type of permits. These are also relatively small counties, accounting for a total of 12% of the population all together. I exclude these set of counties from my analysis as well.

The remaining 915 counties, which form the focus of my analysis, account for about 79% of the U.S. population. Panel (a) of figure 2 shows the geographic distribution of total permits across US counties, aggregated over the period 2000-2023. The map distinguishes counties with no permit data, those for which we have permit data but none of the three hazard-related permits, and the remaining counties. Not surprisingly, permits tend to concentrate in more populated areas. Panel (b) of the figure reports instead the total permits per capita. Per-capita permits vary significantly in the cross-section of counties. Some of this variation relates to the physical environment, and some to the regulatory environment regarding permitting (there are clear discontinuities along some state borders).

For the 915 counties in the final sample, Table 4 reports various statistics at the county level, aggregated over the period 2000-2023. The average county has a total of 106,346 total permits over this period, or 0.28 per person, and a population of 282,200.[16] The average county sees 0.8% of permits related to flood, 0.4% related to wind, and 0.2% related to wildfires. While these numbers appear small, they still correspond to 500,000 to 700,000 permits in the entire dataset, which provides sufficient variation for the empirical analysis below. The table also shows that the climate-related permits are highly concentrated in a small fraction of the 915 counties in the sample, many of which are highly populated. Note that to reflect the heterogeneity in population by county, all the statistical analysis in the next sections will weight the observations by population size.

Table 4: Summary Statistics

	Mean	SD	Min	p10	p25	p50	p75	p90	Max
Wildfire (fraction)	0.002	0.013	0.000	0.000	0.000	0.000	0.001	0.002	0.333
Wind (fraction)	0.004	0.019	0.000	0.000	0.000	0.000	0.001	0.003	0.333
Flood (fraction)	0.008	0.025	0.000	0.000	0.000	0.002	0.007	0.021	0.562
# Permits	106,346	258,601	3	533	3,138	14,543	85,033	278,243	2,973,589
Permits per Capita	0.282	0.329	0.000	0.013	0.057	0.168	0.382	0.712	2.304
Population (000s)	282.2	570.5	1.1	17.9	41.5	110.9	291.8	706.7	10,039.1

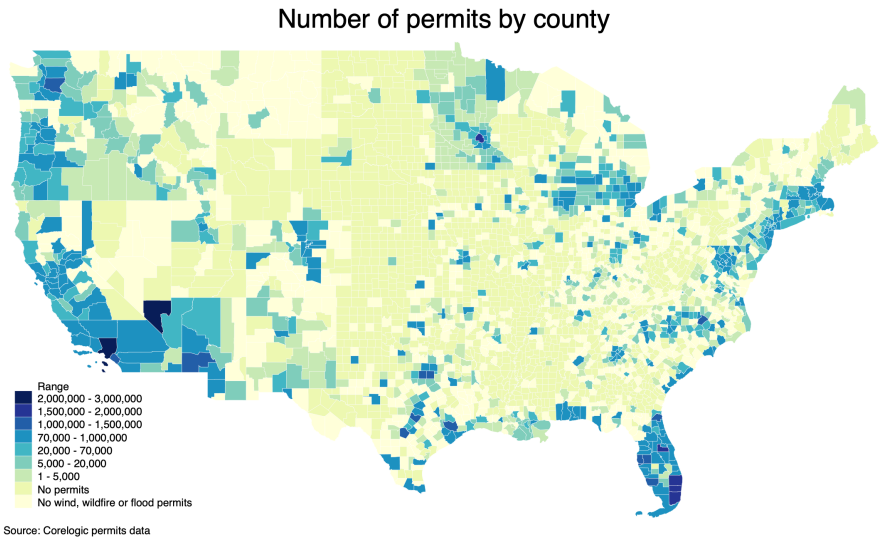
Note: The table shows the summary statistics of permit and population data, at the county level. The sample is all U.S. counties for which, over the entire sample 2000-2023, there has been at least one permit classified as either wildfire-related, wind-related, or flood related. The total number of counties is 915.

The next figure, figure 3, shows the fraction of wildfire, wind, and flood permits by county over the entire time period in the three subplots. All three types of permits appear along the coasts and in lesser measure inland. While there is some overlap between the use of different types of permits (partly because some areas are exposed to multiple perils, and partly because some adaptation measures can help with many hazards), there are many differences in the degree to which counties

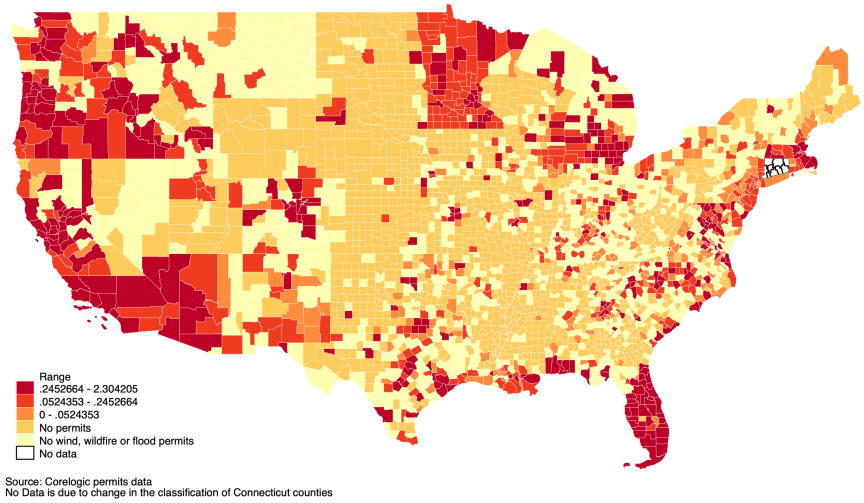
[16] These numbers do not map into each other because the 0.28 is the average of the county-level permits per capita, as opposed to the total permits over the total population.

Figure 2: Permits by county

(a) Total permits



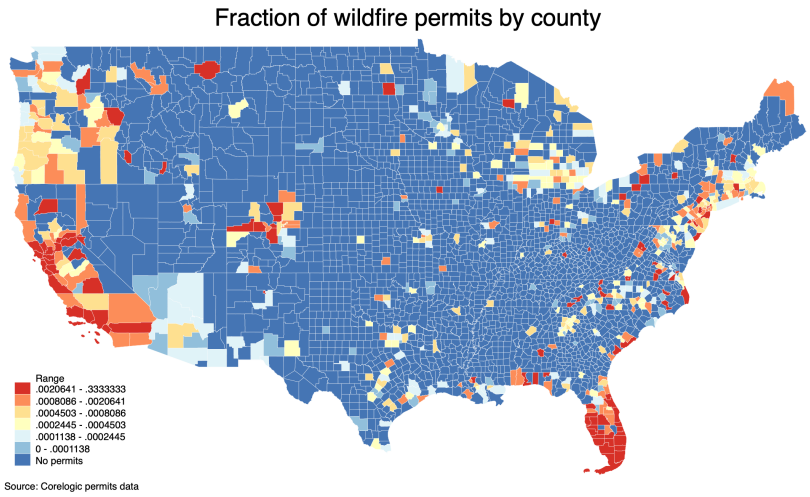
(b) Permits per capita



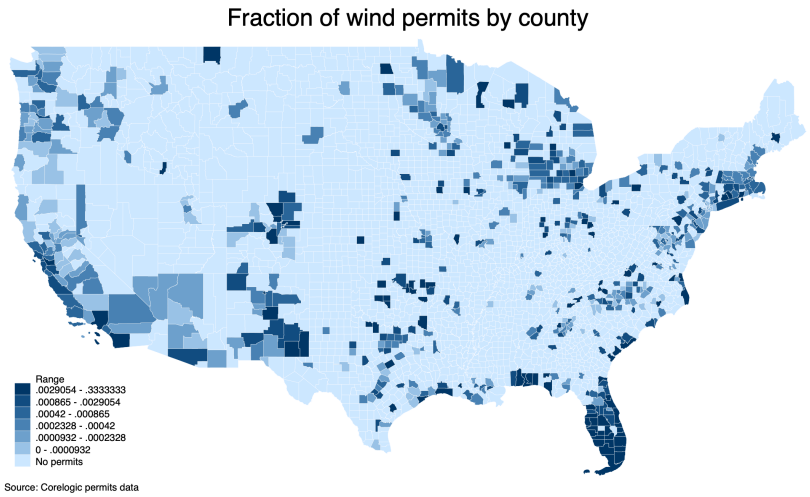
Note: This figure shows, for each county, the total number of permits (panel a) and permits per capita (panel b) in the dataset, over the period 2000-2023.

Figure 3: Fraction of hazard-related permits by county

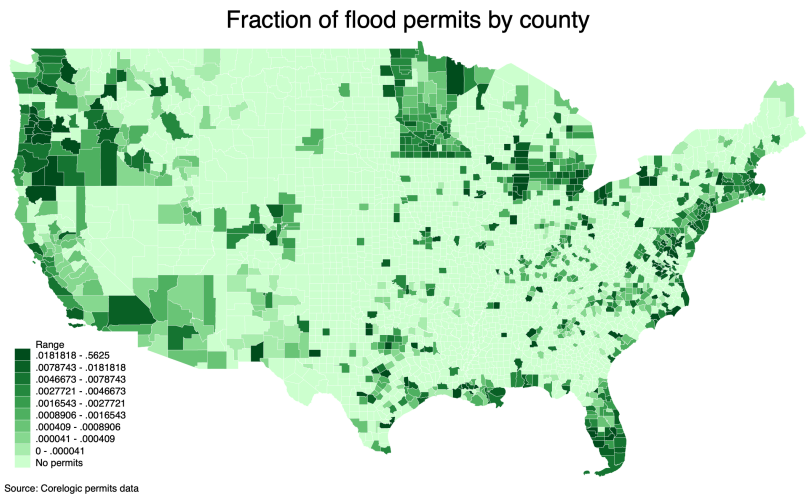
(a) Fraction of wildfire permits



(b) Fraction of wind-related permits



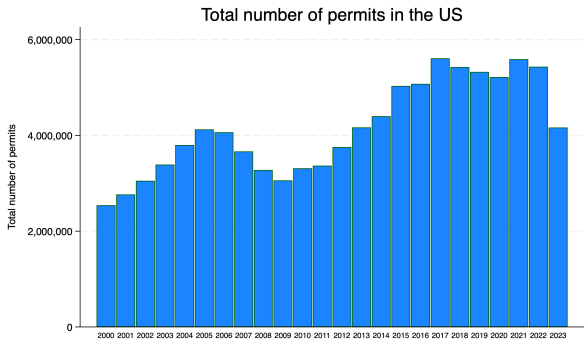
(c) Fraction of flood-related permits



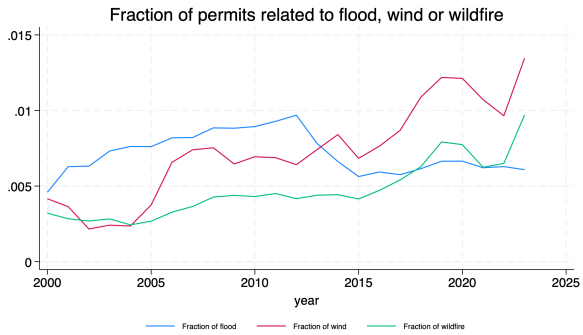
Note: This figure shows, for each county, the fraction of wildfire (panel a), wind (panel b) and flood (panel c) permits, over the period 2000-2023.

Figure 4: Time-series of wildfire, wind and flood permits

(a) Aggregate time series



(b) Fraction of permits by type



Note: This figure shows the binscatter of the fraction of wildfire-related permits (panel a), wind-related permits (panel b) and flood-related permits (panel c) for each U.S. county-year as a function of the FEMA score risk for each type of hazard (wildfire risk in panel a, wind risk in panel b, flood risk in panel c). Observations are weighted by population size, and the graph controls for the number of permits per capita in each county. 80 is the level above which a county is considered at high risk by FEMA.

use different adaptation measures. In the cross-section of countries in our sample, the correlation between the fraction of wind and wildfire permits is 0.57, whereas the correlation between wind and flood, and wildfire and flood, are less than 1%.

Panel (a) of figure 4 shows the time-series behavior of total permits. Every year in our sample I see more than 2 million permits, with significant time variation (the biggest decline occurred after the financial crisis, whereas there was less of a decline due to the Covid pandemic). Panel (b) shows the aggregate time series of the fraction of wildfire, wind and flood permits. Flood-related permits are stable over this time period, whereas wildfire and wind permits show an upward trend, with a downturn after Covid followed by a recovery. The empirical analysis in the next sections will exploit variation both across counties (within states) as well as over time.

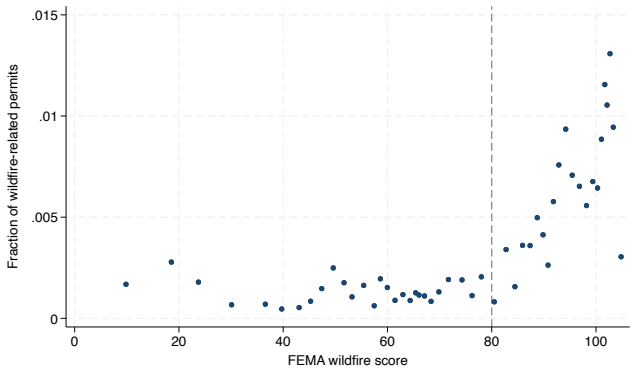
4 Weather risk and adaptation investment

In this section I show that the permit-based measures of hazard adaptation investment (against wildfire, hurricane, and flood risk) strongly correlate with the current exposures to those risks. That is, I show that in the data we find more wildfire-related permits in areas at higher risk of wildfires, and more wind-related permits in areas at risk of hurricanes. The relation also holds for flood risk, but it appears somewhat more noisy. Note that this analysis doesn't tell us (nor does it assume) anything about climate change (which will instead be explored in Section 5). It simply is a *validation* that the methodology to classify permit types can indeed detect resilience investments that we would expect households to make given their current exposure as measured by FEMA.

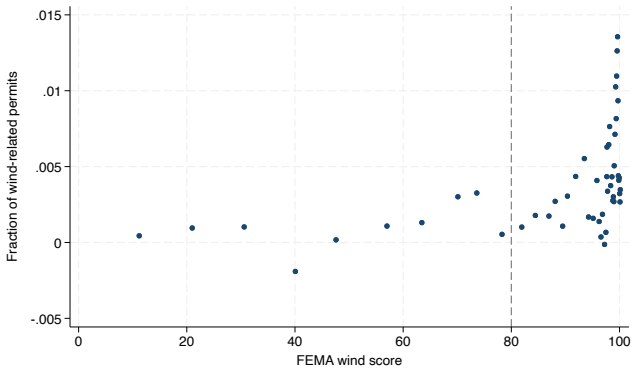
I measure exposure to weather hazards using the FEMA National Risk Index (NRI), which provides, for each type of hazard, a county-level score normalized to range between 0 and 100, that

Figure 5: Wildfire, wind and flood permits vs. local risk

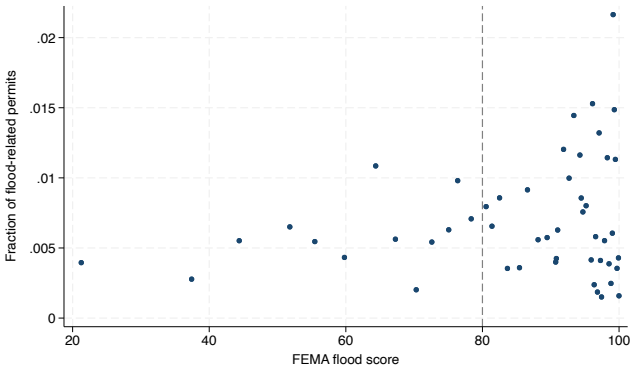
(a) Wildfire permits and wildfire risk



(b) Wind permits and wind risk



(c) Flood permits and flood risk



Note: This figure shows the binscatter of the fraction of wildfire-related permits (panel a), wind-related permits (panel b) and flood-related permits (panel c) for each U.S. county-year as a function of the FEMA score risk for each type of hazard (wildfire risk in panel a, wind risk in panel b, flood risk in panel c). Observations are weighted by population size, and the graph controls for the number of permits per capita in each county. 80 is the level above which a county is considered at high risk by FEMA.

indicates that county's current exposure to the hazard.[17] The hazards covered by the NRI are: Avalanche, Coastal Flooding, Cold Wave, Drought, Earthquake, Hail, Heat Wave, Hurricane, Ice Storm, Landslide, Lightning, Riverine Flooding, Strong Wind, Tornado, Tsunami, Volcanic Activity, Wildfire, and Winter Weather. For each county, I use the Wildfire score to capture wildfire risk exposure, the maximum among Tornado, Hurricane and Strong Wind scores to capture wind risk, and the maximum among Coastal Flooding, Riverine Flooding, and Tsunami risk to capture flood exposure (I take the maximum so that a county is considered at risk if it's exposed to at least one of those risks). For the remainder of the paper, I will refer to these aggregated risk scores as "wildfire risk", "wind risk" (or "hurricane risk"), and "flood risk".

If the measure of hazard-related adaptation investment from permits is able to properly capture

[17]Specifically, the index is constructed combining three variables: the expected annual loss each community faces from natural hazards, how vulnerable a community is regarding to natural disasters and the resilience the community is facing to natural hazards. The normalization corresponds to percentile ranks across U.S. counties.

households' response to the underlying risks, we would expect to see this kind of permitting activity more in areas that are at higher risk. I study this in figure 5. Each panel corresponds to a different hazard: wildfire, wind, and flood. Each panel presents a binscatter plot of the fraction of permits attributed to adaptation to one of the three hazards, against the FEMA risk score for that hazard, for each county-year in the sample. The vertical bar shows the threshold for the "high-risk" classification by FEMA. To make sure the results are not mechanically driven by variation in the number of permits in each county and year, the figures control for permits per capita.[18]

The three figures show that, indeed, there appears to be a relation between risk exposure and adaptation investment, and the relation is nonlinear. As long as the risk is not very large, investment in resilience and adaptation is close to zero. It rises above zero strongly only in counties that are sufficiently risky. Note that some measures are noisier than others. Whereas for wildfires and wind risk it appears that the link between adaptation and risk is less noisy, it is substantially noisier for floods, with less of a difference, on average, between more and less exposed counties. This could indicate one of two things. First, that perhaps my measure of flood-related permits isn't as accurate as for the other types of hazard. Second, that perhaps there's simply less that households can do about floods, which leads to less "signal" in our measure relative to the "noise". Indeed, we will find below weaker results for floods throughout the analysis, consistent with these preliminary validation tests. In the next section I will present a set of formal tests of the relation between adaptation investment, the risks of these natural hazards, and beliefs about the climate.

5 Beliefs and climate adaptation

The previous section showed that, as one would expect, households tend to make improvements to their house that can help prevent the damages from specific hazards when they are exposed to those hazards. This, per se, tells us nothing about their perceptions of climate change, even if climate change is likely to be a key determinant of the increase in the frequency and severity of those hazards in the future. It simply tells us that households respond to the current risks they face.

In this section, I study to what extent adaptation investments against those hazards are linked to *climate beliefs*, above and beyond the direct hazard exposures: i.e. whether beliefs about climate change are an important driver of adaptation measures by households. For that to be the case, households need to 1. be aware of climate change, 2. understand that climate change makes future wildfire, hurricane, and flood risks more frequent and severe, and 3. act on those beliefs by engaging in adaptation investments in their houses. This section shows evidence that climate beliefs indeed appear to play an important role in determining household adaptation, controlling for current risk exposure. Specifically, I show that, among households located in areas exposed to these hazards, those that are more worried about climate risk tend to invest more in adaptation (whereas there is no relation in areas that are not exposed). In other words, climate beliefs appear to be a significant

[18]The figures are very similar without the controls. The presence of the control in the binscatter is the reason the FEMA risk goes slightly above 100 in some situations, and the fractions are sometimes negative.

driver of adaptation investment. These results, obtained by studying variation at the county-year level, hold controlling for relatively fine sources of local variation, by including state and year fixed effects, different granularity of measures of current risk, and even hold when including county-specific fixed effects (thus exploiting only the county-level time series variation in climate beliefs and adaptation investment). The results are economically and statistically significant for wildfires and hurricanes, whereas they appear weak and insignificant for floods (which, as discussed above, is measured less well).

To measure climate beliefs, I use the Yale Climate Opinion Survey. Based on a survey conducted twice a year by the Yale Project on Climate Change Communication (YPCCC) and the George Mason University Center for Climate Change Communication[19], with over 22,000 responses over the years from all over the U.S., the dataset provides county-by-year aggregated answers to a variety of questions that relate to the perception of climate change risk.[20] The variable we focus on in this paper is the percentage of people in a county that respond that they are "somewhat worried" or "very worried" to the question "How worried are you about global warming?". This question is available since 2014 (with two years missing in between). We also explore for robustness using other measures, including the fraction that "thinks that global warming is happening", whether they "have experienced effects of global warming", or whether they "think that global warming is affecting the weather in the US".[21]

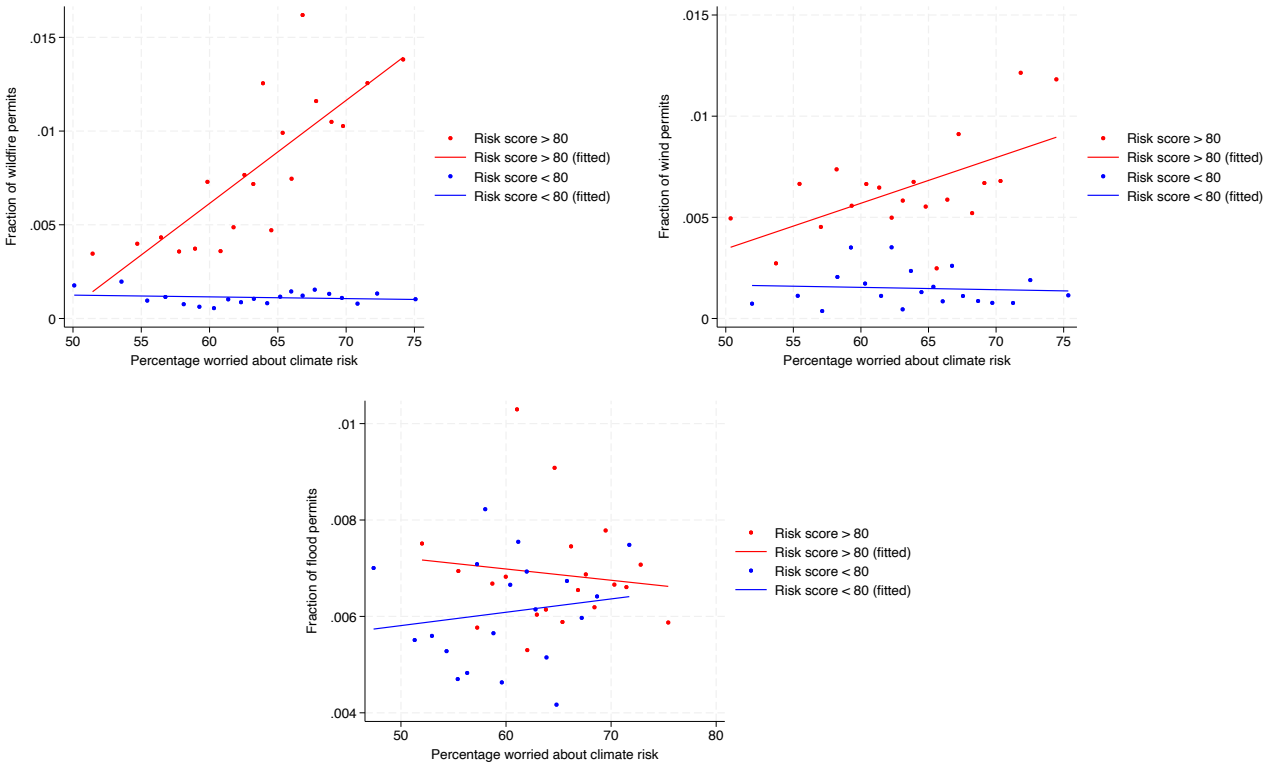
We explore the relation between adaptation and climate beliefs in Figure 6 and Tables 5, 6 and 7. The three panels in the figure show the main result, for wildfire, wind, and flood adaptation respectively, and the three tables show the formal tests and a set of variations in the specification. Each panel in figure 6 overlays two binscatter plots. The blue binscatter plots the fraction of permits that relate to wildfire, wind, or flood adaptation (respectively) against the climate change beliefs, in areas that are not currently at high risk (FEMA wildfire, wind, or flood risk score <80). The red binscatter plots the same relation in high-risk areas (FEMA risk score >80). The unit of analysis is the county-year, for the period 2014-2023 for which belief data is available, and the binscatter plot is controlling for the number of permits per capita as well as state fixed effects.

For wildfires, the blue binscatter shows that in lower-risk areas, there is little relation between climate beliefs and adaptation, and, generally, the level of wildfire-related permitting is low. The red binscatter shows that, in high-risk areas, there is a strong relation between wildfire permits and climate beliefs. In counties and years where only 50% of the population is worried about climate risk, only about 0.5% of permits are devoted to wildfire adaptation, whereas in counties and years where 70% of the population is worried about climate risk, the fraction of wildfire permits doubles or even triples, rising to 1.5% on average in the most worried places. This figure shows that, controlling for state fixed effects, as well as the permitting activity in that area (which will capture certain confounders), there is a strong relation between climate beliefs and weather hazard adaptation.

The remaining panels of figure 6 repeat the exercise for hurricane risk and flood risk, respectively.

[19] https://climatecommunication.yale.edu/visualizations-data/americans-climate-views/ .
[20] https://climatecommunication.yale.edu/about/projects/yale-climate-opinion-maps/ .
[21] The latter two are only available over a shorter time period.

Figure 6: Wildfire permits and climate beliefs



Note: This figure shows the binscatter of the fraction of wildfire-related permits (top left), wind-related permits (top right) and flood related permits (bottom) for each U.S. county-year as a function of the climate beliefs (percentage of the population worried about climate risk), separately for areas at high hazard risk (FEMA score >80, red), and areas with low hazard risk (FEMA score <80, blue). Observations are weighted by population size, and the graph controls for the number of permits per capita in each county, as well as state fixed effects.

For hurricane (wind) risk, the patterns are very similar to the case of wildfire, again showing a strong relationship between climate beliefs and investments in adaptation. For floods, however, there appear to be no significant relation. This could be due to several reasons, as mentioned above. First, it could be that the our measure of flood-related adaptation is too noisy – for example, it may pick up residential investments that may occur for reasons, not related to the floods associated with climate change. Support in favor of this hypothesis (beyond that described in the previous section) can be also seen in the fact that the blue dots and the red dots are not significantly different on average: flood adaptation measures don't appear to vary significantly between high-flood-risk and low-flood-risk areas. Second, households may believe that for the case of floods, the most important source of adaptation is the government, not individual adaptation, and thus respond little at the individual level. While the results for flood adaptation appear much weaker than those for wildfires and hurricane risks, I show them for completeness and to validate that the other sets of results are not generated mechanically.

Tables 5, 6 and 7 explore this relationship and its robustness to different specifications. As before, I describe in detail the results for wildfire adaptation first. In the table, the dependent

Table 5: Wildfire adaptation and climate beliefs

	(1) % Wildf. permits	(2) % Wildf. permits	(3) % Wildf. permits	(4) % Wildf. permits	(5) % Wildf. permits	(6) % Wildf. permits	(7) % Wildf. permits	(8) Wildf. perm. per capita
Wildfire risk	0.10	0.14	0.21	0.15			*(dummies)*	−0.08
	(0.63)	(0.52)	(0.31)	(0.52)				(0.34)
Climate beliefs	3.05**	2.49**	3.47**	2.84**	−1.75	0.38	0.32	0.39
	(0.02)	(0.03)	(0.03)	(0.01)	(0.11)	(0.48)	(0.54)	(0.45)
Wildf. risk x Cl. beliefs	8.11***	8.00***	10.67***	7.96***	4.46*			1.88**
	(0.00)	(0.01)	(0.01)	(0.00)	(0.09)			(0.04)
Permits per capita	−2.19	−2.66	−1.87	−4.33	−3.03	−1.65	−1.39	6.23**
	(0.59)	(0.53)	(0.67)	(0.39)	(0.36)	(0.67)	(0.67)	(0.04)
High risk dummy						0.22		
						(0.24)		
High risk x Cl. beliefs						5.48***	5.06***	
						(0.00)	(0.00)	
Climate beliefs	Worr.	Happen.	Exper.	Aff. Weath.	Worr.	Worr.	Worr.	Worr.
State fixed effects	Y	Y	Y	Y		Y	Y	Y
County fixed effects					Y			
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Clustering of stderrs	County	County	County	County	County	County	County	County
R-squared	0.285	0.277	0.373	0.288	0.745	0.288	0.300	0.357
Observations	6,892	6,892	2,571	5,193	6,887	6,892	6,892	6,892

Note: The table reports the results of regressions of household wildfire adaptation on wildfire risk and climate beliefs. All regressions are at the county-year observation level, and use data from 2014-2023, with some missing data due to unavailability of climate beliefs data in some years. The dependent variable in columns (1)-(6) is the fraction of permits attributed to adaptation to wildfire risk, whereas in column (7) it is the number of such adaptation permits per capita. All columns except (5) include state and year fixed effects, while column (5) includes county and year fixed effects. The baseline climate belief measure is the percentage of households worried about climate risk (columns (1), (5), (6), and (7)). Column (2) uses the percentage of households that believe global warming is happening, column (3) uses the percentage of households that report having experienced effects of global warming, and column (4) uses the percentage of households that believe global warming is affecting the weather in the US. Column (6) uses, a as a measure of risk of natural hazard, a dummy variable for whether the FEMA risk is above 80, instead of the continuous score. Column (7) uses as controls for risk dummy variables for the following seven groups of FEMA risk: ≤60; >60 and ≤80; >80 and ≤90; >90 and ≤95; >95 and ≤98; >98 and <100; 100. Parenthesis report p-values, and stars indicate significance at the 10% level (*), 5% level (**) and 1% level (***) respectively.

variable is the fraction of permits attributed to wildfire adaptation (except for column 8, in which we use wildfire permits per capita for robustness). For readability, the wildfire risk and climate beliefs measures are normalized relative to the national mean (so that a value of 0 for wildfire risk and climate beliefs denotes the average county). The regression is at the county-year level, for the period 2014-2023. All regressions are population-weighted, include geographical unit and year fixed effects (reported in the table as well), and have standard errors clustered at the county level (thus allowing for arbitrary correlation of the errors within the same county over time).[22]

The first column of the table presents the baseline specification. It regresses the fraction of wildfire adaptation permits in a county and year on the FEMA wildfire risk score, the measure of climate beliefs (the percentage of households that are somewhat worried or very worried about

[22]Ideally, one could also cluster by year to allow for correlation of the errors across counties within the same year, but the number of clusters would be too small for these standard errors to be valid.

Table 6: Wind adaptation and climate beliefs

	(1) % Wind permits	(2) % Wind permits	(3) % Wind permits	(4) % Wind permits	(5) % Wind permits	(6) % Wind permits	(7) % Wind permits	(8) Wind perm. per capita
Wind risk	0.26	0.31*	−0.10	0.28			*(dummies)*	0.06
	(0.16)	(0.11)	(0.54)	(0.13)				(0.36)
Climate beliefs	1.60	2.18	3.47	1.72	0.27	−0.21	−1.04	−0.14
	(0.35)	(0.22)	(0.14)	(0.31)	(0.91)	(0.85)	(0.36)	(0.85)
Wind risk x Cl. beliefs	4.70*	6.36**	7.77**	4.75	4.15*			1.62*
	(0.06)	(0.05)	(0.03)	(0.10)	(0.09)			(0.09)
Permits per capita	2.98	2.45	4.70	2.27	2.26	3.21	2.59	13.44***
	(0.63)	(0.70)	(0.50)	(0.76)	(0.55)	(0.60)	(0.66)	(0.01)
High risk dummy						0.22		
						(0.24)		
High risk x Cl. beliefs						2.51*	2.59*	
						(0.05)	(0.05)	
Climate beliefs	Worr.	Happen.	Exper.	Aff. Weath.	Worr.	Worr.	Worr.	Worr.
State fixed effects	Y	Y	Y	Y		Y	Y	Y
County fixed effects					Y			
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Clustering of stderrs	County	County	County	County	County	County	County	County
R-squared	0.231	0.232	0.348	0.272	0.699	0.231	0.235	0.364
Observations	6,892	6,892	2,571	5,193	6,887	6,892	6,892	6,892

Note: Same as table 5, but for wind adaptation investments.

climate risk), and the interaction of the two, in addition to the permits per capita. It has state and year fixed effects to control for other confounders that may vary at the state or the year level. The positive, but small and insignificant, coefficient on the wildfire risk variable shows that, for the *average* county, there is little effect of increases in the FEMA risk score on wildfire adaptation. This is perhaps not surprising in light of the result from the previous section – that adaptation measures seem to be concentrated in the highest-risk counties only. The climate beliefs measure enters positively, indicating that on average, controlling for the wildfire risk of a county, counties and years where households are more worried about climate risk tend to invest more in hazard adaptation. Finally, the interaction between wildfire risk and climate beliefs is positive and significant. This tells us that the relationship between climate beliefs and adaptation investment is especially strong for counties with high wildfire risk, suggesting that these counties are especially aware of the link between climate change and future natural hazard risks (this mirrors the positive slope among high risk counties in the figure).

The remaining columns of the table show that these results are robust to a number of variation in the specification. Columns (2), (3) and (4) vary the measure of climate beliefs from the YPCCC. Column (2) uses the percentage of households that believe global warming is happening, column (3) uses the percentage of households that report having experienced effects of global warming, and column (4) uses the percentage of households that believe global warming is affecting the weather in the US. The results are all very similar (which is perhaps not very surprising given that the measures are all relatively highly correlated).

Column (5) uses county fixed effects instead of state fixed effects (in addition to year fixed

Table 7: Flood adaptation and climate beliefs

	(1) % Flood permits	(2) % Flood permits	(3) % Flood permits	(4) % Flood permits	(5) % Flood permits	(6) % Flood permits	(7) % Flood permits	(8) Flood perm. per capita
Flood risk	0.68***	0.75***	0.62***	0.71***			*(dummies)*	0.05
	(0.00)	(0.00)	(0.01)	(0.00)				(0.34)
Climate beliefs	−0.41	0.17	−0.49	0.44	1.05	0.96	0.81	0.01
	(0.68)	(0.84)	(0.70)	(0.61)	(0.54)	(0.35)	(0.41)	(0.96)
Flood rsk. x Cl. beliefs	−2.34	0.84	−0.65	2.98	−2.68			−0.88**
	(0.27)	(0.73)	(0.90)	(0.27)	(0.25)			(0.04)
Permits per capita	2.36	2.61	2.71	3.25	−0.88	2.66	2.96	6.35***
	(0.26)	(0.22)	(0.31)	(0.17)	(0.65)	(0.22)	(0.19)	(0.00)
High risk dummy						0.15*		
						(0.08)		
High risk x Cl. beliefs						−1.41	−1.99**	
						(0.13)	(0.03)	
Climate beliefs	Worr.	Happen.	Exper.	Aff. Weath.	Worr.	Worr.	Worr.	Worr.
State fixed effects	Y	Y	Y	Y		Y	Y	Y
County fixed effects					Y			
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Clustering of stderrs	County	County	County	County	County	County	County	County
R-squared	0.079	0.079	0.103	0.092	0.373	0.078	0.088	0.295
Observations	6,892	6,892	2,571	5,193	6,887	6,892	6,892	6,892

Note: Same as table 5, but for flood adaptation investments.

effects). Therefore, rather than identifying the effects using variation across counties within states (and within year), it focuses on the time variation within county over time. This test is of course significantly more noisy, because we only have a short time series, yet the interaction term between risk exposure and climate beliefs is still positive and (marginally) significant: when counties become more worried about climate risks, they tend to increase their investment in climate adaptation, but only in those counties with high exposure to wildfires (in fact, the effect is marginally significantly negative for counties that are less affected by wildfire risk). One advantage of this test is that it fully, nonparametrically controls for the hazazrd exposure in a county (because the FEMA risk measure varies at the county level). Column (6) repeats the regression with a dummy variable indicating high risk (risk score >80) instead of the continuous variable. One potential concern with the analysis in the table is that it takes a (parametric) stand on the way that current risk enters the model: either as a continuous variable, or as a dummy for high vs. low risk. This may be problematic if the current risk has a nonlinear effect on adaptation, and is correlated with climate beliefs. To address this issue, column (7) controls for current risk exposure nonparametrically: by creating six bins of risk score: ≤60; >60 and ≤80; >80 and ≤90; >90 and ≤95; >95 and ≤98; >98 and <100; 100. The results are very similar to those of column (6), suggesting that climate beliefs are different from current exposure. Finally, column (8) uses as dependent variable the number of wildfire-related permits per capita (instead of the fraction of wildfire-related permits). Overall, the analysis in table 5 confirms, using statistical tests, the results from figure 6, showing a significant relation between adaptation investment and wildfire risk adaptation in areas that are currently exposed.

Table 8: Wildfire adaptation and climate beliefs - robustness

	(1) Baseline	(2) State-year FE	(3) Intens. Margin	(4) Low dmg.	(5) High dmg.	(6) No repairs, new const.
Wildfire risk	0.10	0.09	−0.35	0.11	−0.31	0.04
	(0.63)	(0.67)	(0.36)	(0.61)	(0.28)	(0.81)
Climate beliefs	3.05**	3.14**	3.24*	2.93**	3.48**	2.68**
	(0.02)	(0.02)	(0.08)	(0.02)	(0.03)	(0.04)
Wildf. risk x Cl. beliefs	8.11***	8.38***	15.13***	7.51***	11.53***	7.26***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Permits per capita	−2.19	−1.62	−1.80	−1.95	−1.26	2.60
	(0.59)	(0.70)	(0.77)	(0.63)	(0.84)	(0.56)
State fixed effects	Y	N	Y	Y	Y	Y
Year fixed effects	Y	N	Y	Y	Y	Y
State-year fixed effects	N	Y	N	N	N	N
Clustering of stderrs	County	County	County	County	County	County
R-squared	0.285	0.317	0.316	0.276	0.409	0.323
Observations	6,892	6,871	2,567	5,959	931	6,524

Note: The table reports the results of regressions similar to those of table 5, but with different specifications. Column (1) reports the baseline, and thus it's the same as column (1) of table 5. Column (2) uses state x year fixed effects. Column (3) focuses only on county-years where the fraction of wildfire permits is positive (thus studying the intensive margin). Columns (4) and (5) repeat the analysis separately on those counties where the total damages from wildfires over the entire period 2000-2023 was less tan $1 per capita (low damage) or more (high damage), respectively. Column (6) removes permits identified as repairs or new construction. Parenthesis report p-values, and stars indicate significance at the 10% level (*), 5% level (**) and 1% level (***) respectively.

Tables 6 and 7 repeat the analysis for wind and flood adaptation, respectively. Consistent with the results displayed in figure 6, the results for winds are very similar to those for wildfires, though more noisy. Most importantly, the interaction term between wind risk and climate beliefs is still positive and significant, indicating that in areas with high wind risk, there is a significant relation between climate beliefs and wind-related adaptation investment. Finally, consistent with figure 6, there seems to be no significant relation between climate beliefs and flood adaptation investment as captured by my permit-based measure (the only significant determinant of flood investment appears to be flood risk).

5.1 Robustness

This section studies the robustness of the results, and provides additional evidence on the mechanism driving them. Tables (8), (9), and (10) report the results for wildfire, wind, and flood adaptation investments. The first column in each table contains the baseline results from tables (5)-(7), for reference. The second column shows the results including state by year fixed effects, thus comparing counties within the same state *and* in the same year. The third column estimates the regression using only counties and years where the fraction of wildfire, wind, or flood permits (respectively) is strictly greater than zero. Therefore, this column focuses entirely on the intensive margin of investment in adaptation. All the results remain very similar across the first three columns (the

Table 9: Wind adaptation and climate beliefs - robustness

	(1) Baseline	(2) State-year FE	(3) Intens. Margin	(4) Low dmg.	(5) High dmg.	(6) No repairs, new const.
Wind risk	0.26	0.26	−0.19	0.34	−0.07	0.00
	(0.16)	(0.18)	(0.63)	(0.11)	(0.67)	(0.98)
Climate beliefs	1.60	1.68	1.82	1.40	2.28	1.87
	(0.35)	(0.34)	(0.52)	(0.41)	(0.24)	(0.30)
Wind risk x Cl. beliefs	4.70*	4.33	9.47*	4.10	6.44**	4.36
	(0.06)	(0.11)	(0.10)	(0.11)	(0.03)	(0.11)
Permits per capita	2.98	3.17	−0.17	1.85	6.57	10.18
	(0.63)	(0.64)	(0.99)	(0.78)	(0.39)	(0.18)
State fixed effects	Y	N	Y	Y	Y	Y
Year fixed effects	Y	N	Y	Y	Y	Y
State-year fixed effects	N	Y	N	N	N	N
Clustering of stderrs	County	County	County	County	County	County
R-squared	0.231	0.254	0.260	0.201	0.361	0.259
Observations	6,892	6,871	2,537	4,922	1,965	6,524

Note: Same as table 8, but for wind adaptation investments.

p-values for wind sometimes creep just above 0.10).

Columns (4) and (5) divide the sample in counties that have experienced low direct damages from the underlying hazard, and those that have experienced high damage. For example, for wildfire risk, I focus specifically on damage from wildfires, and similarly for wind and flood. The data for the damages at the county level comes from SHELDUS, which reports property damages per capita for each county and year. For this part of the analysis, I have summed up the SHELDUS damage data for each county the period 2000-2023. I denote as low-wildfire-damage counties all those counties where the sum of all wildfire-related damages for this period totals less than $1 per capita, and high-damage counties are those above that threshold (the exact threshold makes little difference for the quantitative results). The tables show that while the dependence of adaptation investment on climate beliefs is indeed higher in areas that have experienced more damage, the results hold also for areas where realized damages have historically been low. This indicates that households' choice to invest in adaptation is not (at the least not exclusively) a reaction to the realization of actual weather events, and suggests that instead it depends on the forward-looking component captured by climate beliefs.

Finally, column (6) repeats the analysis on a sample which removes all permits labeled as repair (about 6% of the sample) or new construction (about 15% of the sample). While we keep these in the main analysis to increase power, repairs and new construction may be less likely to be driven by adaptation preferences rather than other factors (e.g., some repairs are relatively urgent). Column (6) shows that results when excluding these kinds of permits remain very similar to the full sample.

Table 10: Flood adaptation and climate beliefs - robustness

	(1) Baseline	(2) State-year FE	(3) Intens. Margin	(4) Low dmg.	(5) High dmg.	(6) No repairs, new const.
Flood risk	0.68***	0.69***	0.47	0.58***	0.97***	0.57***
	(0.00)	(0.00)	(0.12)	(0.01)	(0.00)	(0.01)
Climate beliefs	−0.41	−0.49	−2.18*	−0.00	−1.72	−0.27
	(0.68)	(0.63)	(0.08)	(1.00)	(0.21)	(0.81)
Flood risk x Cl. beliefs	−2.34	−2.20	−1.49	−1.97	−3.62	−1.98
	(0.27)	(0.35)	(0.68)	(0.35)	(0.31)	(0.40)
Permits per capita	2.36	2.69	−3.28	2.73	0.69	3.65
	(0.26)	(0.24)	(0.26)	(0.19)	(0.86)	(0.15)
State fixed effects	Y	N	Y	Y	Y	Y
Year fixed effects	Y	N	Y	Y	Y	Y
State-year fixed effects	N	Y	N	N	N	N
Clustering of stderrs	County	County	County	County	County	County
R-squared	0.079	0.107	0.133	0.099	0.062	0.097
Observations	6,892	6,871	3,937	4,978	1,909	6,524

Note: Same as table 8, but for flood adaptation investments.

6 Conclusion

I propose a novel measure of household adaptation to climate-related hazards, based on textual analysis of 152 million single-family residential building permits. Using a keyword-based approach, I identify which permits relate to investments to protect the house against wildfire, hurricane, and flood risk. While the percentage of these permits is relatively low, I identify more than half a million permits of each type in the data. The data covers about 80% of the U.S. over the period 2000-2023. I show that wildfire-related permits indeed are more concentrated in wildfire-exposed areas, and similarly for wind- and flood-related permits (with less strong of a relation for the latter). This suggests that the measures are successfully capturing the response of households to the hazards they face.

Using this data, I study how, controlling for the direct risk exposures, *climate beliefs* (which are associated with future risks) affect the take-up of these adaptation measures. I show that for both wildfires and hurricane risks, there is a strong relation between how worried households are about climate change and how much they invest in adaptation, and especially so in risky areas. This suggests that those households that live in exposed areas and understand that climate change will increase the frequency and severity of those hazards are more inclined to make adaptation investments (at least for wildfire and hurricane hazards).

This new dataset on households adaptation investments can be applied to study a number of additional questions. For example, it can be used to understand how the availability of insurance affects households' decision to invest in adaptation. It also can be used to understand the role played by financial constraints in allowing household adapt to climate risk. More broadly, the data can be used to gather a fuller understanding of the determinants of individual household adaptation

to climate change.

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A Climate adaptation keywords

Table 11: Flood Keywords, Complements, and Exclusion Words

Keyword	Complements	Exclusion Words
Flood	control, dry proof, flood proof, floodproof, waterproof, flood vent, backflow, barrier, drainage, flow, storm drain, erosion, storm water, stormwater, prevent, floodwall, blockwall, runoff, raise, pilings, storm sewer, sewer, resistant	recovery, insp
Bioswale		
Elevate		
Barrier	water, flood	
Drain	draintile, drainage tile, perimeter drain, french drain, basement drain, interior drain, exterior drain, storm drain, storm sewer, stormwater	
Waterproof		
Sump	pump	
Pump	sump	fire
Backflow		irrigation
Mitigation	stormwater	earthquake, radon, insp
Resistant	flood resistant	
Storm	storm drain, storm sewer, stormwater drain, storm panel	
Retention Basin		
Detention Basin		
Seawall		
Bulkhead		
Revetment		
Erosion	control, prevent	
Grading	flood, drainage	upgrading

Table 12: Wind Keywords, Complements, and Exclusion Words

Keyword	Complements	Exclusion Words
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, high-wind, high wind, weather resistant, wind resistant	
Shutter	hurricane, impact, storm, wind, debris, pressure, heavy duty, reinforced, aluminum, roll, steel, polycarbonate, fiberglass	decorative
Storm	storm shutter, storm panel, storm shelter	
Impact	window, door	
Shelter	storm, hurricane	
Safe Room	safe room	

Table 13: Wildfire Keywords, Complements, and Exclusion Words

Keyword	Complements	Exclusion Words
Fire	wildfire mitigation, wildfire buffer, wildfire safety, wildfire retrofit, ember, class a, class-a, resist, retar, fire rated, fireproof, firewall, tempered, noncombustible, roof, firestone	destroy, recovery, control, alarm, system, insp, suppress, sprinkler, exting, fireplace, firepit
Mitigation	impact, vegetation	
Resistant	impact, fire resistant	
Combustible	noncombustible	
Class A		
Defensible		
Storm	storm panel	
Impact	window	