Article

Unpriced climate risk and the potential consequences of overvaluation in US housing markets

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Climate change impacts threaten the stability of the US housing market. In response to growing concerns that increasing costs of flooding are not fully captured in property values, we quantify the magnitude of unpriced flood risk in the housing market by comparing the empirical and economically efficient prices for properties at risk. We find that residential properties exposed to flood risk are overvalued by US$121–US$237 billion, depending on the discount rate. In general, highly overvalued properties are concentrated in counties along the coast with no flood risk disclosure laws and where there is less concern about climate change. Low-income households are at greater risk of losing home equity from price deflation, and municipalities that are heavily reliant on property taxes for revenue are vulnerable to budgetary shortfalls. The consequences of these financial risks will depend on policy choices that influence who bears the costs of climate change.

Climate change poses a range of financial and economic risks to households, communities and market sectors across the United States[1,2]. These risks stem not only from the physical impacts of climate change, but also from how property owners, private companies and public institutions respond to growing climate hazards. Adaptation responses will not only determine the magnitude of total costs, but also whether these costs become increasingly borne by American taxpayers, or alternatively become internalized by those who are directly exposed to physical climate impacts[3].

Among the natural hazards exacerbated by climate change, flooding is the deadliest, costliest and most widely experienced in the United States[4]. Currently, more than 14.6 million properties in the United States face at least a 1% annual probability of flooding[5], with expected annual damages to residential properties exceeding US$32 billion[6]. Increasing frequency and severity of flooding under climate change is predicted to increase the number of properties exposed to flooding
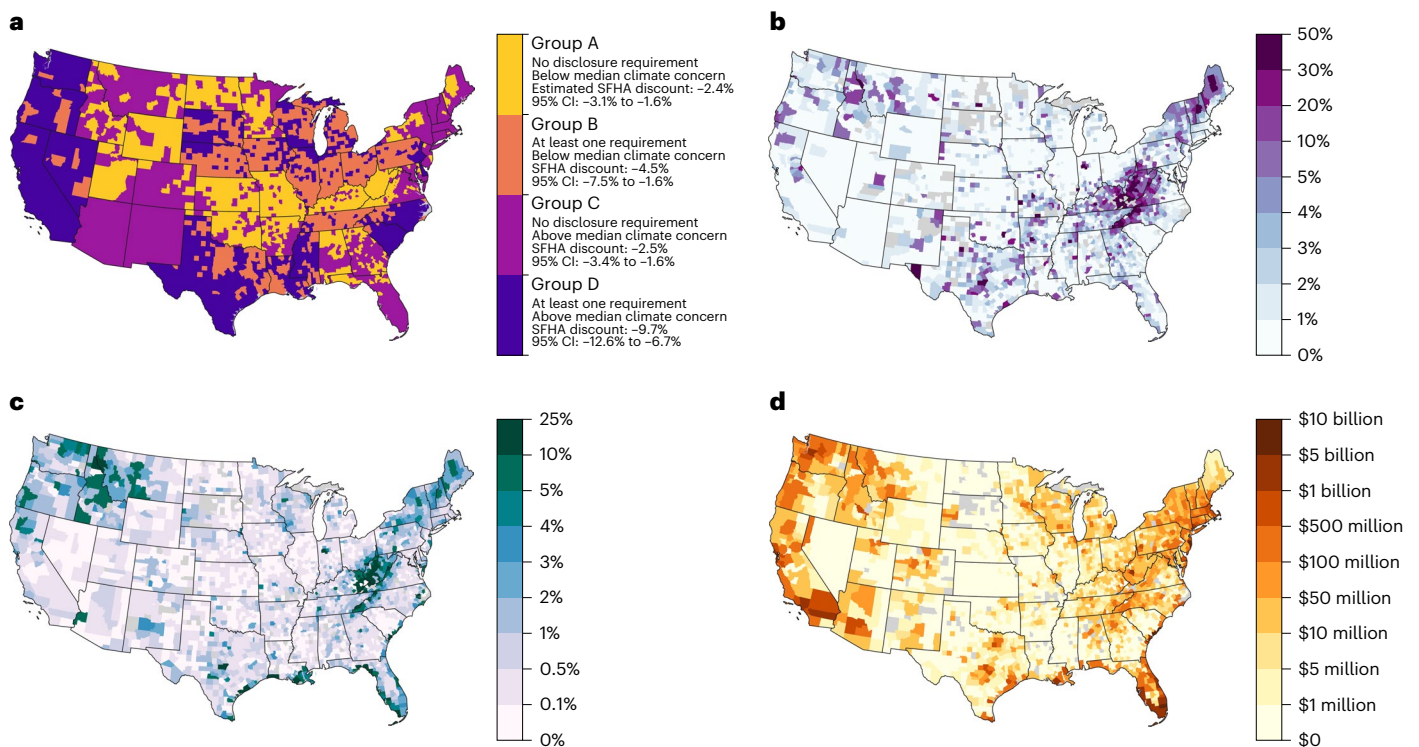
by 11% (ref. [5]) and average annual losses (AALs) by at least 26% by 2050 under Representative Concentration Pathway (RCP) 4.5[6], presenting substantial costs to property owners, insurers, mortgage lenders and the federal government.

The increasing burden of flooding under climate change has led to growing concerns that housing markets are mispricing these risks, thus causing a real estate bubble to develop[7–9]. While empirical studies have observed an average discount of 4.6% for properties located in the 100 yr flood zone[10], recent evidence suggests that this price discount does not fully capture the expected costs of flooding[7,11]. One study estimated that properties in the 100 yr flood zone could be overvalued by an average of 8.5% of their current value[9], not accounting for increasing damages from climate change. This unpriced flood risk could perpetuate perverse incentives for continued development in floodplains and underinvestment in hazard mitigation, further inflating the housing bubble. Despite these concerns, the magnitude, distribution and

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Group A
No disclosure requirement
Below median climate concern
Estimated SFHA discount: –2.4%
95% CI: –3.1% to –1.6%

Group B
At least one requirement
Below median climate concern
SFHA discount: –4.5%
95% CI: –7.5% to –1.6%

Group C
No disclosure requirement
Above median climate concern
SFHA discount: –2.5%
95% CI: –3.4% to –1.6%

Group D
At least one requirement
Above median climate concern
SFHA discount: –9.7%
95% CI: –12.6% to –6.7%

Fig. 1 | Flood risk capitalization and property overvaluation by county.
a, Estimated flood zone property price discount, differentiated by flood risk disclosure laws and attitudes towards climate change. **b**, Median property-level overvaluation, as a proportion of properties' current fair market value. **c**, Property overvaluation as a proportion of the total fair market value of all properties. **d**, Total overvaluation in dollars. The counties shapefile was downloaded from the US Census Bureau[45].

potential social and economic consequences of overvaluation in US housing markets remain uncertain.

Incomplete pricing of flood risk may be driven by lack of information about potential flood losses, cognitive biases in risk perceptions and/or socialization of flood-related costs (that is, transferred to taxpayers). In many cases, potential buyers may be unaware of a property's risk because of deficiencies in the Federal Emergency Management Agency (FEMA)'s flood insurance rate maps (FIRMs)[12], as well as inconsistent state-level flood risk disclosure laws[13]. Misperceptions of natural hazards and climate change further limit homebuyers' ability to rationally price flood risk, as a range of systemic biases may lead to underestimation of the probability and severity of being affected by flooding[14]. Additionally, subsidization of National Flood Insurance Program (NFIP) premiums and climate-agnostic mortgage lending practices have created distorted price signals by transferring flood-related costs away from property owners[15]. Only recently are these price signals starting to shift under the NFIP's new pricing methodology, Risk Rating 2.0, which determines premiums based on individual assessments of flood risk and rebuilding costs for each property[16], and as mortgage lenders begin to insulate themselves from credit risk associated with exposure to flood risk[17–20].

While efficient capitalization of flood risk in property prices may reduce the incentive to develop in floodplains, thus decreasing the total costs of flooding, it may also yield negative consequences for flood zone property owners and local governments. In the event of price deflation, many homeowners would be at risk of losing value in their largest asset–their home[21]. In turn, municipalities that are heavily reliant on property taxes for revenue would be vulnerable to budgetary shortfalls if the assessed values of flood zone properties decline[22,23]. These potential consequences of the flood risk housing bubble, the time horizon over which they occur, and their effect on the stability of the housing market will largely depend on how policymakers and the multiple players in the housing and mortgage markets respond to increasing flood hazards under climate change.

To better understand the scope and severity of these adaptation risks, we quantify the magnitude and distribution of unpriced flood risk and overvaluation in US housing markets. We further evaluate the potential loss of home equity among demographic groups in the United States and identify municipalities vulnerable to budgetary losses resulting from devaluation of flood zone properties. Finally, we consider possible changes in state and federal policy, as well as mortgage lending practices, that could internalize the costs of flooding among flood zone property owners and lead to widespread price deflation.

Results

We calculate overvaluation of properties exposed to flood risk based on the difference between our estimates of their empirical and economically efficient price discounts. In our efficient price estimates, we account for future damage costs to properties located both inside and outside of the Special Flood Hazard Area (SFHA; that is, the 100 yr flood zone as mapped by FEMA). Based on previous studies[9,10,24], we assume that only properties located within the SFHA currently capitalize exposure to flood risk, whereas properties outside of the SFHA do not. We describe two alternative analyses that test the sensitivity of this assumption in the Methods section 'Sensitivity and uncertainty analyses'.

Following best practices[25], we estimate the empirical flood zone price discount using a repeat sales panel model, which controls for time-invariant characteristics of individual properties. Similar to ref. [9], our approach identifies the effect of rezoning properties into the SFHA as the result of FIRM updates over time. To build the panel model, we employ an extensively processed version of the Zillow ZTRAX database[26], a comprehensive dataset of property transactions in the United
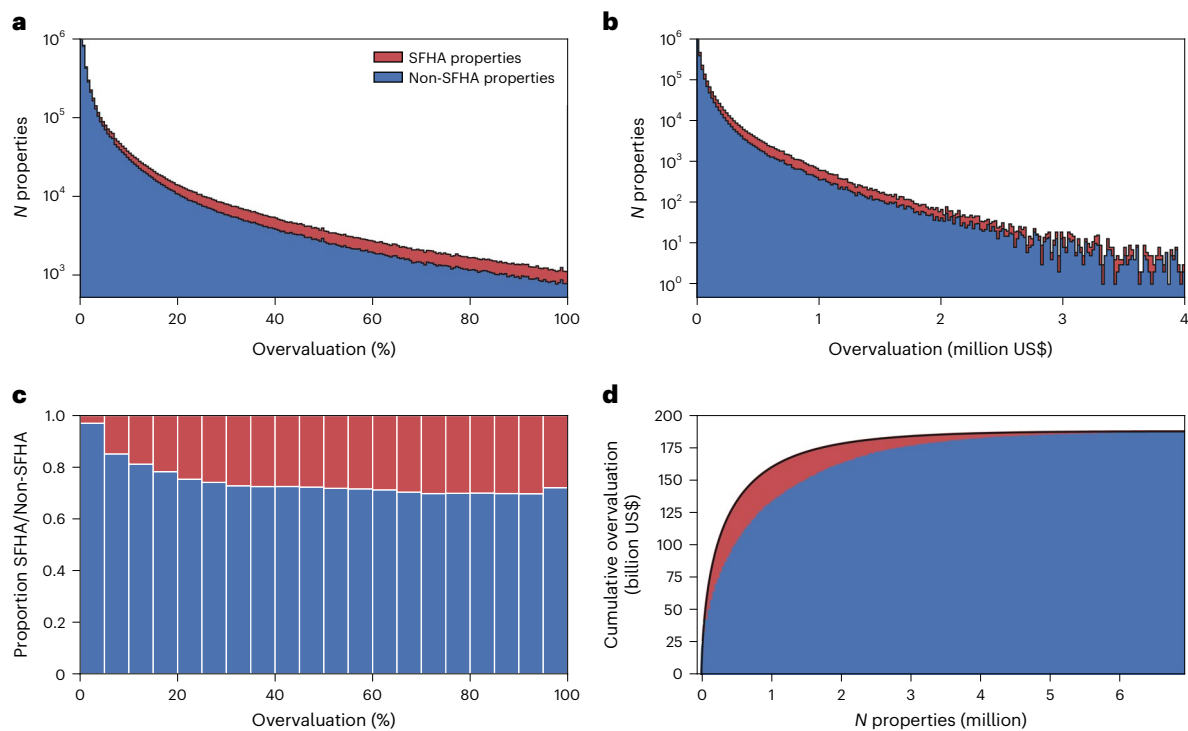
Fig. 2 | Distributions of overvaluation by property location. a, Histogram of overvaluation as a percentage of properties' values. **b**, Histogram of overvaluation in US$. **c**, Proportion of SFHA and non-SFHA properties for incremental levels of overvaluation. **d**, Cumulative overvaluation in US$, with properties sorted in descending order of overvaluation. In **a** and **b**, the *y* axis is on a log scale and the histogram for SFHA properties is stacked on the histogram for non-SFHA properties.

States over the last 30 yrs, joined with newly consolidated historical FIRM layers[27] (see Methods). We evaluate variation in the discount of flood zone property prices by accounting for state- and county-level differences in access to flood risk information and perceptions of climate risks. While there are many other factors that may drive heterogeneity in flood risk capitalization, we focused on these two because previous work has shown them to be particularly salient[7,9,13,28].

We define the efficient price of properties exposed to flooding as the difference between property values in the absence of flood risk and the net present value (NPV) of AALs from pluvial, fluvial and coastal flooding between 2020 and 2050, accounting for future impacts of climate change under RCP 4.5[6]. This approach leverages newly available national-scale flood inundation maps from the First Street Foundation under a range of recurrence intervals[29]. To estimate property-specific flood losses, we overlay these maps with the locations of property structures and apply depth-damage functions specified by the FEMA HAZUS model to calculate damage as a proportion of property value[30]. Unless stated otherwise, all overvaluation estimates are based on the NPV of AALs calculated using a 3% discount rate. Results based on other discount rates are shown in Supplementary Fig. 16.

Empirical flood zone discounts

Across all counties in the conterminous United States, we estimate that properties currently located in the SFHA are discounted by an average of −2.8%. However, flood risk capitalization varies according to differences in state-level flood risk disclosure laws and county-level perceptions of climate risk (Fig. 1a and Supplementary Fig. 7). In counties with no disclosure requirements (Groups A and C in Fig. 1a), we estimate a flood zone discount of −2.4 to −2.5%. In counties with at least one form of disclosure requirement, we estimate flood zone discounts of −9.7% (Group D) and −4.5% (Group B), depending on whether concerns about climate risk in a county are above or below the national median.

Magnitude and distribution of overvaluation

Our comparison of the empirical and efficient price discounts for all properties exposed to flood risk (that is, properties where the NPV of AALs is greater than zero) reveals that properties exposed to flood risk are overvalued by a total of US$121–US$237 billion, depending on the discount rate (Supplementary Fig. 16). Using a 3% discount rate, our preferred value[31], total overvaluation is US$187 billion. These estimates assume that properties outside the SFHA do not have a flood risk discount. Under alternative assumptions that properties outside the SFHA do capitalize some amount of their flood risk (see 'Sensitivity and uncertainty analyses' in Methods), total overvaluation decreases by 2–22% (Supplementary Figs. 11 and 12). We also show the sensitivity of these results to alternative discount rates and flood hazard scenarios in Supplementary Figs. 9 and 10.

We use several metrics to identify the regions of the United States where the financial and economic risks posed by overvaluation are greatest. Based on the median of property-level overvaluation, in terms of a proportion of properties' current fair market value, Appalachia and northern New England emerge as overvaluation hotspots (Fig. 1b). These regional trends reflect poor flood risk capitalization and relatively high AALs per property, but do not account for the number or value of properties at risk. When evaluated as a proportion of the total fair market value of all properties in a county, overvaluation remains high in Appalachia, yet is also high along the Gulf and Atlantic coasts (Fig. 1c). In some of these counties, overvaluation as a proportion of the total fair market value of all properties exceeds 10%. However, when evaluated in absolute dollar terms, overvaluation is greatest along the Gulf, Atlantic and Pacific coasts (Fig. 1d), which reflects regional differences in property prices (Supplementary Fig. 2). In particular, properties in Florida are overvalued by more than US$50 billion (Supplementary Fig. 17).

The distribution of overvaluation among properties exposed to flood risk is highly right skewed whereby relatively few properties
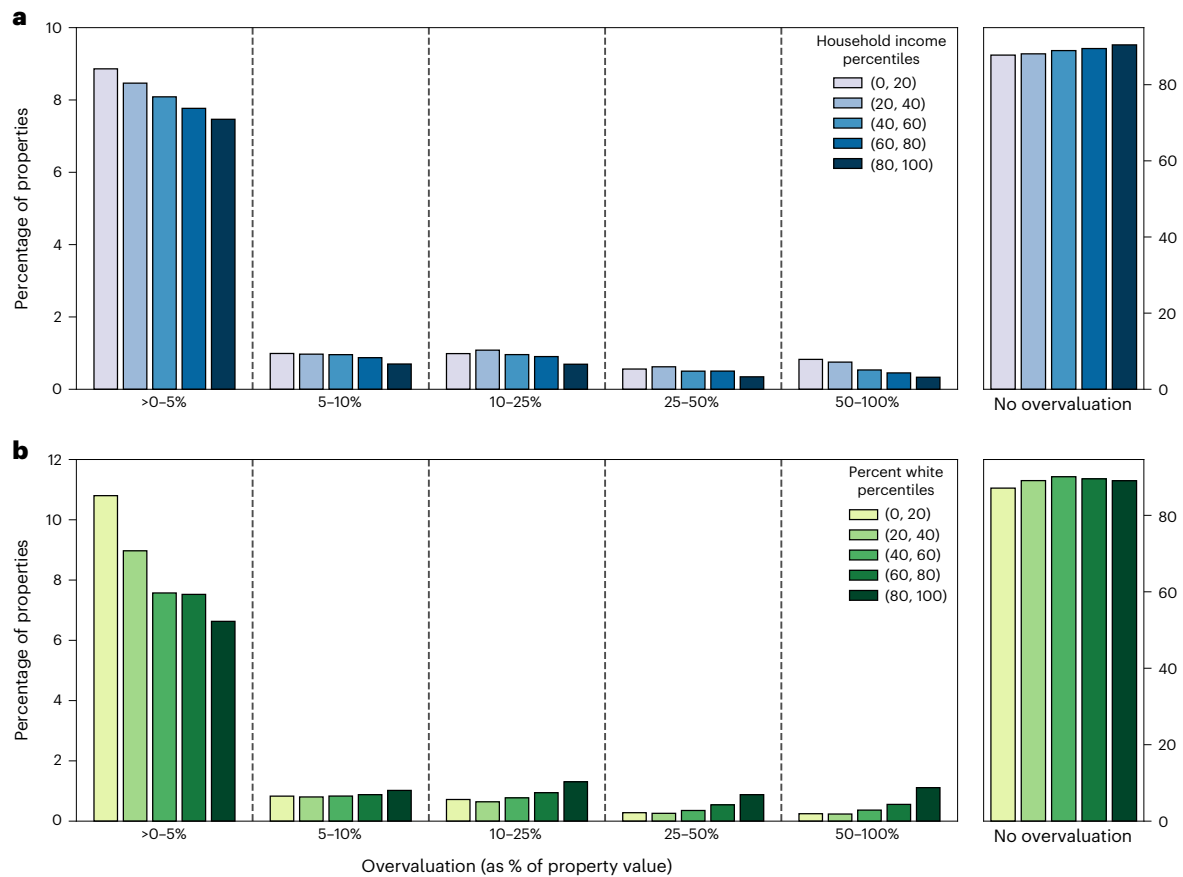
Fig. 3 | Distribution of property overvaluation among demographic groups. a,b, Census tracts are grouped by quintiles of median household income (**a**) and quintiles of the percentage of the population that is white (not Hispanic or Latino) (**b**). Within those groups, we evaluate the percentages of total properties that are overvalued by >0–5%, 5–10%, 10–25%, 25–50% and 50–100%. The 'No overvaluation' sub-plot includes properties that are not exposed to flood risk or for which the empirical price does not exceed the efficient price. Demographic data were derived from the 2019 American Community Survey, reported at the census tract level.

drive a large proportion of total overvaluation. In dollar terms, 11% of properties contribute 80% of total overvaluation and 19% contribute 90% of overvaluation (Fig. 2d). These acutely overvalued properties have higher average sales prices and are exposed to severe flood damages. In contrast, 55% of flood-exposed properties are overvalued by less than 1% of their value and 76% are overvalued by less than 5% (Fig. 2a). In dollar terms, 90% of flood-exposed properties are overvalued by less than US$50,000 and 94% are overvalued by less than US$100,000 (Fig. 2b).

A large portion of overvaluation is driven by properties located outside of the SFHA. These properties comprise 83% of all properties at risk of flooding and contribute 69% of total overvaluation in dollar terms (Fig. 2). Among properties in the highest decile of overvaluation in dollar terms, 69% are located outside of the SFHA; among properties in the second highest decile of overvaluation, 82% are located outside of the SFHA. While these properties are on average less overvalued (as a proportion of their value) than properties located in the SFHA (Fig. 2c), they still constitute a major source of the total unpriced flood risk in the United States due to their sheer number and less efficient capitalization of exposure to flooding. Under alternative assumptions that properties outside the SFHA do capitalize some amount of their flood risk (see 'Sensitivity and uncertainty analyses' in Methods), the portion of total overvaluation from non-SFHA properties decreases to 60–64% (Supplementary Figs. 11 and 12).

Potential impacts of overvaluation among demographic groups
Low-income property owners are at greater risk of losing home equity from property price deflation (Fig. 3a and Supplementary Fig. 13). These findings were derived by aggregating properties by census tract and grouping census tracts by household median income quintiles. Among census tracts in the lowest quintile of household median income, 9.0% of properties are overvalued by >0 to 5%. By contrast, 7.5% of properties in the highest quintile of household median income are overvalued by up to 5%. This trend holds for higher levels of overvaluation as well. For example, 0.8% of properties are overvalued by 50–100% in the lowest income quintile tracts, whereas 0.3% of properties are overvalued by 50–100% in the highest income tracts.

Modest overvaluation (that is, >0–5% of property value) is more widespread in census tracts with a higher percentage non-white population, but whiter tracts have a larger share of highly overvalued properties (that is, 5–100% of property value) (Fig. 3b and Supplementary Fig. 13). In census tracts with the lowest percent population white (not Hispanic or Latino), 11.0% of properties are overvalued by >0 to 5%. By contrast, in census tracts with the highest percentage of white population, 6.7% of properties are overvalued by >0 to 5%. This trend reverses at levels of overvaluation greater than 5%. In tracts in the lowest percent white quintile, 0.3% of properties are overvalued by 50–100%, whereas 1.1% of properties are overvalued by 50–100% in the highest percent white tracts. These demographic trends are less pronounced under the alternative assumptions regarding capitalization of exposure to flood
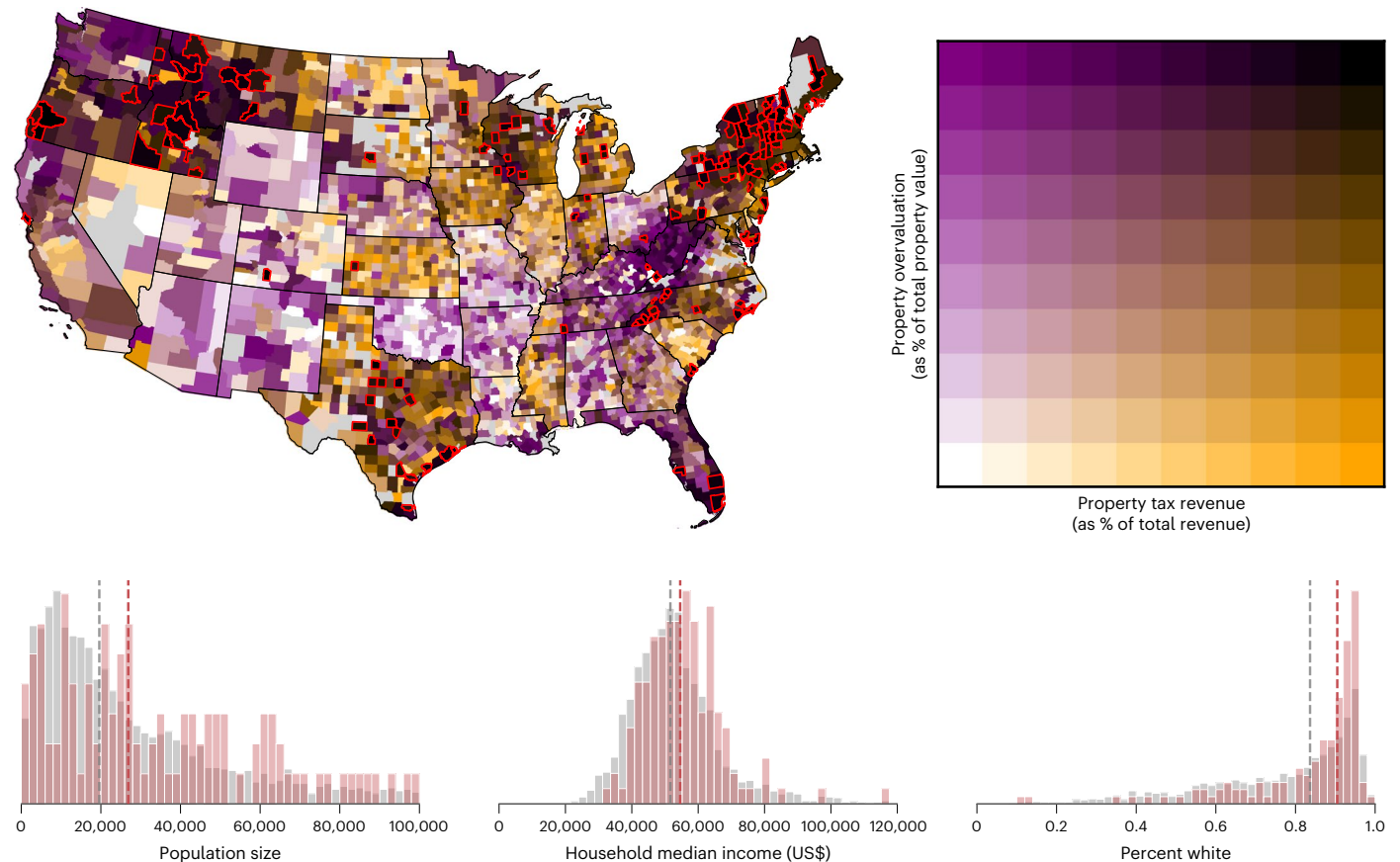
Fig. 4 | Local government vulnerability to loss of revenue due to property devaluation. Top: municipalities are grouped by county. Orange hues indicate the proportion of municipal revenue derived from property taxes and purple hues indicate property overvaluation as a proportion of total property value; colour breaks are by decile. Counties in black and outlined in red indicate municipalities that are both heavily reliant on property tax revenue and have high overvaluation. Bottom: histograms indicate distribution of municipal population characteristics, with all counties in grey and counties in the top quintile of both overvaluation and property tax revenue (outlined in red in map) in red. Vertical dashed lines indicate median values. Municipal tax revenue data were derived from the Government Finance Database[32]. The counties shapefile was downloaded from the US Census Bureau[45].

risk among properties located outside of the SFHA (see 'Sensitivity and uncertainty analyses' in Methods, and Supplementary Figs. 14 and 15).

Potential fiscal impacts of overvaluation

If housing markets were to fully capitalize exposure to flood risk, the corresponding price deflation could negatively impact the revenues of local governments that depend on property taxes. Across the United States, many municipalities are heavily reliant on property taxes for revenue, with some locales receiving over 50% of total revenue from property taxes[32]. We identify counties with relatively high property over-valuation and where local governments are heavily reliant on property taxes for revenue (Fig. 4 and Supplementary Table 1). The intersection of these two variables indicates municipalities that are most vulnerable to budgetary shortfalls if property price deflation were to occur. These municipalities are concentrated in coastal counties, as well as inland areas in northern New England, eastern Tennessee, central Texas, Wisconsin, Idaho and Montana. On average, the counties where these municipalities are located have larger populations, higher household incomes and are whiter compared with all other US counties (Fig. 4). Despite relatively high overvaluation, local governments in states such as Alabama, Louisiana and West Virginia are insulated from property devaluation because they are less reliant on property taxes for revenue.

Discussion

In this analysis, we quantify the magnitude of the housing bubble created by unpriced flood risk and evaluate the distribution of

overvaluation among property owners across the United States. Our results underscore the severity of the financial risks to current home-owners and municipalities posed by potentially widespread property price deflation. In general, highly overvalued properties are concentrated in counties along the coast, with no flood risk disclosure laws, and where there is less concern about climate change (Fig. 1). Within these counties, a large portion of total overvaluation is driven by properties located outside of the SFHA (Fig. 2), highlighting the deficiencies in communicating flood risk to residents in these areas.

Our results suggest that the housing market is more overvalued than previously established. We build on previous studies that alluded to the existence of climate housing bubbles, but which focused on local-ized markets and overlooked potential distributional consequences (see refs. [7,11]). Compared with the one other study that estimated over-valuation nationally[9], our central estimate of total overvaluation—US$187 billion, under a 3% discount rate—is more than double. The primary factor driving this difference is the benchmark for determining efficient property prices. We use the NPV of AALs between 2020 and 2050, accounting for climate change, whereas ref. [9] uses the NPV of NFIP premiums prior to Risk Rating 2.0. Our estimate more accurately captures future flood damages since historic NFIP premiums were not accurate measures of flood risk and were heavily subsidized. NFIP pre-miums also do not reflect future flood damages from climate change.

We also find that overvaluation is widespread among low-income households, putting them at risk of future price reductions and loss of home equity (Fig. 3). In the event of price deflation, these inequities

BOX 1

Future scenarios for adaptation responses mediating the magnitude and distribution of flood-related costs

These four scenarios illustrate how public and private actors could respond to increasing flood risk under climate change and the possible consequences of these adaptation strategies. The vertical axis of the figure indicates the magnitude of the long-term total costs of flood damages. The horizontal axis indicates the extent to which costs are socialized among the public versus internalized by flood zone property owners. Possible drivers and consequences for each scenario are illustrative, not comprehensive, and are not mutually exclusive.
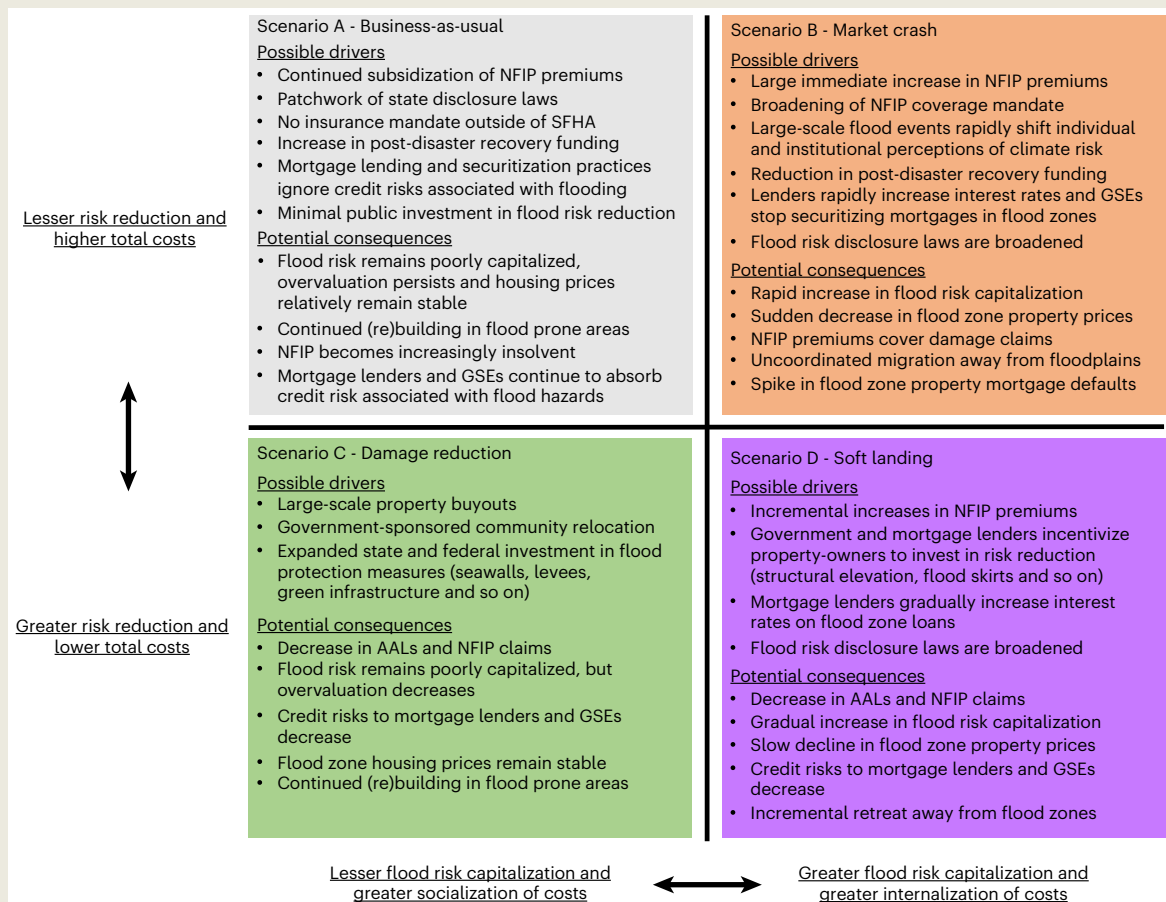
Under the 'Business-as-usual' scenario, increased socialization of flood losses will likely stabilize housing markets, at least in the near term, because homeowners are insulated from increasing costs, thus perpetuating overvaluation (Scenario A). This scenario also creates perverse incentives for development in flood-prone areas and local underinvestment in risk reduction activities, further increasing total costs from future floods.

Under the 'Damage reduction' scenario (Scenario C), flood costs are reduced through state and federal investment in an array of risk reduction interventions. These interventions may occur at the property level via buyouts or structure elevations, as well as the community level through seawalls, levees and various forms of green infrastructure. Such investments have the potential to decrease

overvaluation as efficient prices increase, providing financial protection to both homeowners and municipalities. However, under this scenario, perverse incentives for floodplain development remain, i.e. 'the levee effect'[46].

Alternatively, internalizing the costs of flooding among at-risk property owners will likely result in more efficient capitalization of flood risk[9,13], as shown in Scenarios B and D. Accurate capitalization of flood risk in property values has the potential to decrease total costs and improve social welfare by limiting development in flood-prone areas and possibly incentivizing local investments in risk reduction[47]. However, these shifts would also negatively impact current property owners and municipalities most directly exposed to flood hazards as flood zone properties decline in value.

Housing market responses to changes in policy and lending practices that internalize costs of flooding among property owners will likely depend on the time period over which these changes occur. Incremental shifts in these policies and practices over a longer period may allow for gradual adjustments in property prices (Scenario D 'Soft landing'). By contrast, abrupt changes over a shorter period of time may result in a 'Minsky moment'—a rapid decrease in asset prices leading to a market crash, followed by prolonged instability[48] (Scenario B 'Market crash').

	Scenario A - Business-as-usual	**Scenario B - Market crash**
	Possible drivers	Possible drivers
	• Continued subsidization of NFIP premiums	• Large immediate increase in NFIP premiums
	• Patchwork of state disclosure laws	• Broadening of NFIP coverage mandate
	• No insurance mandate outside of SFHA	• Large-scale flood events rapidly shift individual and institutional perceptions of climate risk
	• Increase in post-disaster recovery funding	• Reduction in post-disaster recovery funding
Lesser risk reduction and higher total costs	• Mortgage lending and securitization practices ignore credit risks associated with flooding	• Lenders rapidly increase interest rates and GSEs stop securitizing mortgages in flood zones
	• Minimal public investment in flood risk reduction	• Flood risk disclosure laws are broadened
	Potential consequences	Potential consequences
	• Flood risk remains poorly capitalized, overvaluation persists and housing prices relatively remain stable	• Rapid increase in flood risk capitalization
	• Continued (re)building in flood prone areas	• Sudden decrease in flood zone property prices
	• NFIP becomes increasingly insolvent	• NFIP premiums cover damage claims
	• Mortgage lenders and GSEs continue to absorb credit risk associated with flood hazards	• Uncoordinated migration away from floodplains
		• Spike in flood zone property mortgage defaults
	Scenario C - Damage reduction	**Scenario D - Soft landing**
	Possible drivers	Possible drivers
	• Large-scale property buyouts	• Incremental increases in NFIP premiums
	• Government-sponsored community relocation	• Government and mortgage lenders incentivize property-owners to invest in risk reduction (structural elevation, flood skirts and so on)
	• Expanded state and federal investment in flood protection measures (seawalls, levees, green infrastructure and so on)	• Mortgage lenders gradually increase interest rates on flood zone loans
Greater risk reduction and lower total costs	Potential consequences	• Flood risk disclosure laws are broadened
	• Decrease in AALs and NFIP claims	Potential consequences
	• Flood risk remains poorly capitalized, but overvaluation decreases	• Decrease in AALs and NFIP claims
	• Credit risks to mortgage lenders and GSEs decrease	• Gradual increase in flood risk capitalization
	• Flood zone housing prices remain stable	• Slow decline in flood zone property prices
	• Continued (re)building in flood prone areas	• Credit risks to mortgage lenders and GSEs decrease
		• Incremental retreat away from flood zones

Lesser flood risk capitalization and greater socialization of costs ⟷ Greater flood risk capitalization and greater internalization of costs

have the potential to exacerbate wealth gaps in the United States, as many households' most valuable asset is their home[21]. One explanation for such disparities is that low-income households tend to live in hazardous areas because of the lower property values in these places[33]. Another explanation is that lack of government investment in flood protection infrastructure in poorer neighbourhoods has increased flood losses compared with equally hazardous, yet better-protected wealthier neighbourhoods[34,35]. Parsing these underlying drivers is beyond the scope of this analysis but is an important area of future research.

If property price deflation occurs, municipalities with a large share of properties at risk of flooding and that are also heavily reliant on property taxes for revenue are vulnerable to fiscal losses. While the collapse of housing prices during the Great Recession had negligible impacts on local government property tax revenues[36,37], this non-effect has been attributed to time lags between market values and assessed values, coupled with the relatively rapid rebound in housing prices following the crash[38]. In contrast, declines in property values due to climate risk are unlikely to be temporary[39], particularly for properties affected by sea-level rise[40]. This implies that the insulating effect of lags in property assessment may be less relevant in this context. In the event that price deflation and declines in property tax revenues do occur, local governments may need to adapt their fiscal structure to continue to provide essential public goods and services, such as education, policing, parks and recreation, and public transit[22,23].

While the future dynamics of how unpriced flood risk is capitalized by the housing market are critical to homeowners, mortgage lenders and real estate investors, it remains uncertain if and when overvaluation will become realized and price deflation will occur. Among properties exposed to sea-level rise, ref. [11] identifies market trends consistent with dynamics at the peak of previous real estate bubbles, finding that the prices and sales volume of these properties are gradually declining. Despite these early warning signs, it is difficult to make predictions about the future of the flood zone housing market because these dynamics will depend on complex interactions between property owners, mortgage lenders and public institutions. In Box 1, we explore four future scenarios for how alternative climate adaptation responses by public and private actors could mediate the total economic costs of flooding, as well as the extent to which these costs are socialized by the public (that is, transferred to American taxpayers) versus internalized by flood zone property owners.

The pricing of NFIP premiums is a critical factor mediating the balance between flood risk capitalization and socialization. Historically, NFIP claims payments have far exceeded premiums, indebting the program to the US Treasury and effectively transferring costs of flooding to American taxpayers[15]. By increasing premium costs to reflect current risk, Congress could shift these costs away from the public and towards NFIP policyholders (Box 1, Scenarios B and D). In the spring of 2022, the NFIP began this process through a new pricing methodology called Risk Rating 2.0, which has modernized rate setting with premiums that more accurately reflect property-specific flood risk[16]. While it is too soon to evaluate the effect of Risk Rating 2.0 on property prices, in part because of an 18% annual cap on premium increases for existing policies, these adjustments have the potential to internalize flood costs and increase capitalization of risk[41].

Mortgage lenders could also play an important role in determining future capitalization of flood risk. Although borrowers are more likely to become delinquent or default on mortgage loans in the wake of disaster[42,43], lenders have several tools to protect against credit risk arising from flood events. Recent evidence suggests that lenders are increasingly transferring the credit risk associated with flooding to 'government-sponsored enterprises' (that is, Fannie Mae and Freddie Mac), whose debts are backed by taxpayers, and to capital markets through increased securitization of mortgages in flood-prone areas[18,19] (Box 1, Scenario A). Lenders could also mitigate this risk through tools

aimed at flood zone borrowers, which could include credit rationing through lower loan-to-value ratios, broadening and enforcing mandates to carry flood insurance, increasing interest rates and/or denying loans[17,20] (Box 1, Scenarios B and D). Together, these practices have the potential to send price signals to flood zone homeowners, potentially leading to greater capitalization of flood risk.

More accurate and accessible information on properties' flood risk would likely increase capitalization of flood risk in housing markets. To this end, the Infrastructure Investment and Jobs Act, passed by Congress in 2021, allocated an additional US$600 million to FEMA for improving its outdated flood maps. Non-governmental information on flood risk is also becoming more widely available to households. For example, the First Street Foundation has made its property-level flood risk estimates widely available on real estate websites, such as Redfin and Realtor.com. It is currently too soon to detect the effects of this new information on flood risk capitalization, although recent evidence suggests that access to these data has led homebuyers to bid on less risky properties[44]. Moreover, making disclosure of past flood damage and flood risk mandatory across all states would enable homebuyers to make more informed decisions and price flood risk more efficiently (Box 1, Scenarios B and D).

Together, our results illuminate the array of financial and economic risks associated with unpriced flood risk and overvaluation in the US housing market. As demonstrated through alternative future scenarios (Box 1), the realization of these risks depends on institutional, policy, and regulatory adaptation responses to increasing flood hazards, all of which must grapple with moral questions about who should bear the costs of climate-related disasters.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-023-01594-8.

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Methods

Property transaction data

We combine the Zillow ZTRAX database[49] and the PLACES database[50] to access property transactions, locations, and assessments for all states in the conterminous United States between 1996 and 2021. The ZTRAX database, provided to us by Zillow, contains property transaction and tax assessment data for approximately 150 million parcels in over 3,100 counties nationwide (Supplementary Fig. 1). To ensure consistency and accuracy of the data across the United States, we extensively processed the ZTRAX database based on the recommendations in ref. [26]. These data cleaning measures included identification of arms-length sales, geolocation of parcels and buildings, temporal linkages between transaction, assessor and parcel data, and the identification of property-types, such as single-family homes. More information on accessing the Zillow ZTRAX database can be found at www.zillow.com/ztrax.

The PLACES database uses assessor parcel numbers to link ZTRAX data to parcel boundaries using county- and town-specific string pattern matching and geographic quality controls. For approximately one third of United States counties, parcel polygon data in PLACES comes from open-access sources; for the remainder, parcel polygon data comes from Regrid through their 'Data with Purpose' program (https://regrid.com/purpose). The matching algorithm identifies over 1,000 unique combinations of syntaxes and links digital parcel boundaries from 2,951 counties to ZTRAX data with a median county-level success rate of 98.2% and a mean of 95.5% (measured as the percentage of the number of parcel boundaries matched to a tax assessor record). These linkages were used to identify the parcels and transactions in our statistical models.

Flood hazard data

We evaluated properties' exposure to fluvial, pluvial and coastal flood hazards in the years 2020 and 2050 using previously developed inundation maps[29]. These maps provide estimates of inundation depths at a 30 m spatial resolution under 5, 20, 100, 250 and 500 yr flood recurrence intervals in both years. The 2020 model outputs were validated by simulating historical flood events and comparing them to observed flood extents and depths, finding 87% similarity between the two[51]. Further validation of model outputs is described in the First Street Foundation technical documentation[52]. The 2050 estimates are based on downscaled Coupled Model Intercomparison Project 5 data under RCP 4.5. These data have been made available by the First Street Foundation and can be found on their website (www.floodfactor.com).

While uncertainty and disagreement remain across continental-scale flood models in terms of which areas are most exposed and the extent of future flooding[53], the outputs from ref. [29] provide the only peer-reviewed, publicly available, climate-adjusted, and historically validated US-scale flood model that has a high enough resolution to be property specific. Other high-resolution models do exist in the private sector, but are generally not made available for research purposes or are made available without transparent methods.

Calculating flood losses

We calculated expected annual flood losses to single-family homes in the United States using the methods described in ref. [54]. In brief, we overlaid the locations of residential structures derived from the ZTRAX and PLACES databases with the flood inundation maps and applied depth-damage functions recommended by FEMA[55]. These functions were developed through expert elicitation and are used to estimate the damage to inundated properties as a proportion of their value based on flood depth relative to first-floor elevation.

While depth-damage functions are widely used in flood risk assessments nationally, including FEMA's HAZUS-MH software, these functional relationships are highly uncertain and depend on numerous property-specific characteristics[56]. Unfortunately, many of these characteristics are not included in the ZTRAX data, such as first-floor elevations and structure types. To address the issue of missing first-floor elevations, which are crucial for translating inundation depths to depths relative to the first floor, we applied adjustments to inundation depths based on the recommendations in Sections 5.6.1–5.6.3 of the HAZUS Technical Methodology manual[57]. To overcome the limitation of incomplete structure records, we used the proportions of structure types found in the NFIP policies data, as described in ref. [54].

To calculate AALs for each property in 2020 and 2050, we integrated the estimated damages over the range of recurrence interval probabilities modelled in ref. [29] using trapezoidal Riemann sums[58]. In a given year, the probability p of one of these events occurring is $1/T$, where T equals the expected recurrence interval (for example, $p = 0.05$ for a 20 yr flood event). These probabilities are independent of each other, such that multiple flood events can occur in a single year. To estimate AALs for property i in year t between 2020 and 2050, we used a simple linear interpolation, where $t = 0$ is the year 2020 (equation 1).

$$\text{AAL}_{it} = \text{AAL}_{i2020} + t \times \frac{(\text{AAL}_{i2050} - \text{AAL}_{i2020})}{30} \tag{1}$$

We calculated the NPV of AALs for property i over a 30 yr time horizon (that is, the duration of a typical fixed-rate mortgage), where ρ is the discount rate (equation 2). All results are reported using a 3% discount rate, unless stated otherwise. The NPVs of AALs by county are shown in Supplementary Fig. 3.

$$\text{NPV}_i = \sum_{t=0}^{30} \text{AAL}_{it}(1 + \rho)^{-t} \tag{2}$$

Historical flood insurance rate maps

We employed data from all FIRMs released across the United States between 2005 and 2019 to determine each property's FEMA-designated flood zone at the time of sale. We obtained these data through Freedom of Information Act requests and one-on-one meetings with former GIS analysts who performed contractual work for FEMA. Specifically, we used a digital version of the paper-based flood maps that were effective before 2005 (called the Q3 data product), combined with yearly snapshots of the National Flood Hazard Layer between 2012 and 2020. For each FIRM, we observed the date when the map became active (Supplementary Fig. 4), as well as the spatial extent of the 100 yr and 500 yr floodplains. Comparing the evolution of the spatial polygons through time allowed us to identify changes in floodplain boundaries at the property level. Currently, more than 115 million or 90% of residential properties are covered by the digital FIRMs. Details on the data collection and cleaning steps are provided in ref. [27].

Estimating flood risk capitalization

The extent to which exposure to flood risk is capitalized in property values is driven by many dynamic factors, including recent local experience with flooding, insurance mandates, the cost of insurance (not just in the NFIP, but also private sector options), awareness of non-insurable costs, perceptions of risk and available information, not just from mandated disclosures, but also from others involved in the market, such as realtors or neighbours. In this analysis, we necessarily averaged away some of this heterogeneity and examined capitalization of flood risk among properties located within the SFHA. Specifically, we used capitalization of updated information about flood risk as an imperfect proxy for capitalization of exposure to flood risk (relative to not being exposed to any risk).

We estimated the empirical flood zone discount (that is, observed capitalization) using a panel model for repeat property sales. This method has been applied by several other recent studies to estimate the effects of flood events and flood zone remapping on property

prices[59–63], and is considered best practice in this context[25]. Similar to the approach used in ref. [9], we identified the effect of flood zone status on property prices by comparing single properties to themselves over time, as they are rezoned from outside to within the SFHA due to FIRM updates. A key advantage of this identification approach, particularly compared with cross-sectional models, is that it is less vulnerable to the confounding effects of time-invariant property-specific attributes, such as waterfront amenities, which are often spatially correlated with flood risk[9,10].

As shown in equation (3), we estimated the effect of location within the SFHA (δ) on the sale price (p), where SFHA_{it} is a binary variable equal to 1 if property i is located in the SFHA at time t. Property-level fixed effects, γ_i, control for all time-invariant characteristics of a property. We also included county-by-year fixed effects, η_{ct}, to control for local market dynamics over time. These fixed effects absorb shocks to the housing market caused by natural hazards, including past flood events. α is a constant and ε_{it} is an error term. For a property to be included in the estimation sample, it must: (1) be outside of the SFHA in the old FIRM, (2) have a known floodplain status in the new FIRM and (3) be sold more than once while its flood zone status is known. Sales that occurred while the flood zone status was unknown were omitted from the dataset.

$$\log (p_{it}) = \alpha + \delta_g \text{SFHA}_{it} + \gamma_i + \eta_{ct} + \varepsilon_{it} \qquad (3)$$

We accounted for variation in the empirical flood zone discount, indicated by the subscript g, driven by differences among state-level flood risk disclosure laws and individual perceptions of climate risk by creating four groups of counties. Across the United States, states vary widely in what they require sellers to disclose to buyers. Based on data compiled by the Natural Resource Defense Council, we grouped states by their disclosure laws or lack thereof. Using the Yale Climate Survey, we also grouped counties based on average responses to the question "Do you think global warming will harm you personally?" (Supplementary Fig. 5). Group A comprises counties with no disclosure laws and below median climate concern; Group B comprises counties with at least one form of disclosure law and below median climate concern; Group C comprises counties with no disclosure laws and above median climate concern; Group D comprises counties with at least one form of disclosure law and above median climate concern. Due to the relatively small sample size of properties remapped into the 100 yr flood zone, we were unable to group counties with more granularity.

This approach makes two key assumptions about the dynamics of flood risk capitalization among rezoned properties and properties located outside the SFHA. First, we assume that properties rezoned into the SFHA are representative of all properties located in the SFHA. While rezoned properties may be on the margins of the SFHA and have lower flood risk than average SFHA properties, rezoned properties may also be less adapted to flood risk than average SFHA properties, since the latter have been subject to floodplain building codes for years. Respectively, these two potential differences may simultaneously lead to under- and overestimation of flood risk capitalization.

Second, we assume that only properties currently located within the SFHA capitalize flood risk, whereas properties located outside the SFHA do not experience any discount despite their exposure to flood risk. We make this assumption based on the results of refs. [9,10,24], all of which find that location in the FEMA-designated 500 yr floodplain (that is, 0.2–1% annual probability of flooding) has no effect on property sale prices. We describe two alternative analyses that test the sensitivity of this assumption at the end of the Methods section.

Estimating property overvaluation
We calculated overvaluation of properties exposed to flood risk (that is, both SFHA and non-SFHA properties with flood losses greater than zero) as the difference between their estimated current fair market value and their efficient price (equation 4). For properties where the fair market value is less than the efficient price, we calculated overvaluation as zero.

$$\text{Overvaluation}_i = \text{FairMarketValue}_i - \text{EfficientPrice}_i \qquad (4)$$

We estimated the current fair market value of properties using their most recent transaction price adjusted to the present using the Federal Housing Finance Agency's House Price Index (FHFA HPI). For properties with no transaction data, we instead used their assessed value, similarly adjusted to the present using the FHFA HPI, depending on the year of assessment. We accounted for differences in assessment methods across counties by fitting simple linear regression models between adjusted transaction prices and adjusted assessed values for all transacted properties in a county. We then applied the estimated coefficient as a scalar to the assessed values.

We estimated the efficient prices of properties exposed to flood risk as the difference between their fair market value in the absence of any flood risk (RiskFreeMV) and the NPV of AALs between 2020 and 2050 (equation 5). For properties where the NPV of AALs is greater than the RiskFreeMV, the efficient price is zero.

$$\text{EfficientPrice}_i = \text{RiskFreeMV}_i - \text{NPV}_i \qquad (5)$$

The use of AALs to determine efficient prices assumes that homebuyers have complete information about properties' exposure to flooding and price that risk according to the discounted value of future flood losses. Despite uncertainty in projections of future flood losses, this approach captures the potential cost of exposure to flood risk over the lifetime of a property more accurately than the current cost of NFIP premiums. In contrast to our estimates of AALs, NFIP premiums do not reflect future climate change, have been historically subsidized in many locations and have been based on FEMA flood maps, which are inaccurate and lack coverage in many parts of the United States. While some of these deficiencies in NFIP pricing have been addressed by Risk Rating 2.0, those data are not yet available at the property level. Further, given that housing markets have the potential to capitalize the total costs of flood risk under climate change, our estimates capture market overvaluation better than the costs of current NFIP premiums.

To calculate properties' RiskFreeMV, we removed the empirical flood zone discounts (δ) estimated with the hedonic model (equation 6). For example, if the fair market value for property i is US$500,000 and the flood zone discount for group g is −5%, then the RiskFreeMV for property i is US$526,315. As discussed in the previous section, we assume that properties outside the SFHA do not capitalize flood risk and that their RiskFreeMV is the same as their current fair market value.

$$\text{RiskFreeMV}_i = \begin{cases} \text{FairMarketValue}_i/(1 + \delta_g), & \text{SFHA} = 1 \\ \text{FairMarketValue}_i, & \text{SFHA} = 0 \end{cases} \qquad (6)$$

Importantly, the use of AALs to estimate efficient property prices inevitably results in the underestimation of overvaluation. Beyond structural damages, flooding is also associated with damages to contents and loss of sentimental items, debris clean up, evacuation expenses, and negative mental health impacts, none of which are included in the NPV of AAL estimates. While difficult to quantify, including these other forms of damage in the NPV calculation would invariably increase estimates of overvaluation.

Sensitivity and uncertainty analyses
In our main methods and results, we assume that properties located outside of the SFHA do not capitalize flood risk. However, particularly following recent flood events, exposure to flood risk may be temporarily capitalized by properties outside of the SFHA in localized areas[64]. To test the sensitivity of our results to this initial assumption, we reran

the analysis with two alternative assumptions regarding flood risk capitalization and subsequent overvaluation.

In our first sensitivity analysis, we assume that all properties exposed to flood risk are discounted at the same rate as was estimated for SFHA properties by the panel model described above. This provides an upper-bound estimate of non-SFHA capitalization and a lower-bound estimate of total overvaluation. Results under this alternative assumption are shown in Supplementary Figs. 11 and 14.

In our second sensitivity analysis, we implemented a cross-sectional regression model to identify flood risk capitalization among properties exposed to flood risk and that are located in the FEMA 100 yr flood zone, 500 yr flood zone or outside of any designated flood zone. While this approach allowed us to estimate flood risk capitalization among properties located outside of the SFHA, we prefer it less than the panel model because of how challenging it is to control for all the characteristics of a property that may be correlated with flood risk and prices. The results from this analysis are shown in Supplementary Figs. 8, 12 and 15.

For this alternative analysis, we estimated the effect of FEMA flood zone status (δ) on sale price (p) using a 6-level factor variable ($FZ_{it} * Risk_i$) that combines flood zone categories (that is, 100 yr, 500 yr or outside) and binary exposure to flood risk (equation 7). Properties located outside of any flood zone and that are not exposed to flood risk serve as the reference group. H_{it} is a vector of property-specific variables that includes number of bedrooms, building area and the age of the property at the time of sale; λ is a vector of estimated coefficients for these variables. Following ref. [40], we applied high-dimensional fixed effects, β, to control for a suite of location-specific characteristics (X_i). This term captures the interaction between a property's block group, distance to coast bins (0 to 10 m, 10 to 400 m, >400 m), presence of lake and river frontage on the property and elevation bins (0 to 5 m, 5 to 10 m, >100 m). We also applied fixed effects to control for seasonal market trends across states, τ_{sq}, and county-level market trends across years, η_{ct}. We performed this estimation for sales within each subset of Groups A–D defined above. To calculate overvaluation, we changed any estimate of δ that is greater than zero (that is, a price premium) or not significantly different ($P \geq 0.05$) to zero.

$$\log(p_{it}) = \alpha + \delta_g FZ_{it} * Risk_i + \lambda H_{it} + X_i + \tau_{sq} + \eta_{ct} + \varepsilon_{it} \quad (7)$$

Separate from these two sensitivity analyses, we also used a Monte Carlo simulation to evaluate the uncertainty bounds in our estimates of overvaluation. For each iteration of the simulation ($N = 1,000$), we randomly sampled normal probability distribution functions fitted to the empirical flood zone discounts estimated by the panel model (see equation 3). We also assessed the sensitivity of overvaluation to the applied discount rate, comparing discount rates of 1, 3, 5 and 7%, and inundation hazard scenarios. The low, mid and high hazard scenarios represent the 25th, 50th and 75th percentile estimates of the flood model simulations, respectively. Variation across flood model simulations is driven by uncertainty in global climate model outputs. In 2050, the 25th and 75th percentile estimates from the RCP 4.5 model roughly align with the mean estimates from the RCP 2.6 and 8.5 models. For more information on the uncertainty in flood model outputs, please see ref. [29]. Results from the uncertainty analysis are shown in Supplementary Fig. 16.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability
The input datasets used for this analysis are either already publicly available or cannot be made available due to restrictive data sharing agreements.

Code availability
The code used for this analysis is available in a Zenodo repository at https://doi.org/10.5281/zenodo.7420416.

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Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41558-023-01594-8.

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Peer review information *Nature Climate Change* thanks Katharine Mach, Amine Ouazad and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

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Last updated by author(s):   12/08/2022

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No data were collected for this analysis.
Data analysis	All analyses were conducted using Python v3.9.

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Behavioural & social sciences study design

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Study description	We calculate overvaluation of properties exposed to flood risk based on the difference between our estimates of their empirical and economically efficient price discounts. We estimate the empirical flood zone price discount using a repeat sales panel model, which controls for time-invariant characteristics of individual properties. This approach identifies the effect of rezoning properties into the Special Flood Hazard Area (SFHA; i.e., the 100-year flood zone) as the result of FIRM updates over time. We define the efficient price of properties exposed to flooding as the difference between property values in the absence of flood risk and the net present value (NPV) of average annual losses from flooding between 2020 and 2050, accounting for future impacts of climate change under RCP 4.5.
Research sample	To build the panel model, we employ an extensively processed version of the Zillow ZTRAX database, a comprehensive dataset of property transactions in the US over the last 30 years, joined with newly consolidated historical FIRM layers.
Sampling strategy	The ZTRAX database contains property transaction and tax assessment data for approximately 150 million parcels in over 3,100 counties nationwide.
Data collection	All data used in this analysis were collected by previous publications.
Timing	The ZTRAX database includes property transactions between 1996 and 2021.
Data exclusions	For a property to be included in the estimation sample, it must be outside of the SFHA in the old FIRM, it must have a known floodplain status in the new FIRM, and it must be sold more than once while its flood zone status is known. Sales that occur while the flood zone status is unknown are omitted from the dataset.
Non-participation	Not applicable.
Randomization	Not applicable.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	Antibodies
☒	Eukaryotic cell lines
☒	Palaeontology and archaeology
☒	Animals and other organisms
☒	Clinical data
☒	Dual use research of concern

Methods

n/a	Involved in the study
☒	ChIP-seq
☒	Flow cytometry
☒	MRI-based neuroimaging