Who Bears Climate-Related Physical Risk?*†

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Abstract

This paper combines data on current and future property-level physical risk from major climate-related perils (severe convective storm, inland floods, hurricane storm surge, hurricane wind, winter storms, and wildfires) that single-family residences (SFRs) face with data on local economic characteristics to study the geographic and demographic distribution of such risks in the contiguous United States. Current expected damage to SFRs from climate-related perils is approximately $39 billion per year and will rise to $48 billion by 2050 under a "middle-of-the-road" emissions scenario. Severe convective storms are the leading contributor to expected damage, however the riskiest areas are predominantly areas facing hurricane and/or inland flood risk on the Gulf and South Atlantic coasts. Higher current physical risk is associated with lower household incomes, lower labor market participation rates, lower education attainment, higher in-migration, higher increase in expected physical risk by 2050, lower belief in climate change, and greater Republican vote shares. Overall, the results suggest that climate risk mitigation policies are likely to be progressive now and into the future.

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† This paper subsumes Section 2 of the OFR Brief "The Uneven Distribution of Climate Risk and Discounts", which also documented cross-sectional heterogeneity in climate risk factors using CoreLogic data.

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For the majority of American homeowners, housing is, by far, the largest component of their net worth.[1] An open question in the climate risk literature is who bears the current and future climate-related physical risk to residential properties? Since floods are among the most damaging natural disasters related to climate change, the literature has mostly focused on flood risk.[2, 3, 4] However, flooding is just one of several disasters that are influenced by expected changes in climate patterns.[5] Therefore, studies that focus exclusively on floods cannot yield a comprehensive picture of the magnitude and distribution of climate-related physical risk.

We fill this gap by using novel data on current and future property-level physical risk from six major climate-related perils (severe convective storms, winter storms, inland floods, wildfires, hurricane wind, and hurricane storm surge) that single-family residences (SFRs) face in the contiguous U.S. The physical risk data are produced by CoreLogic, a major commercial catastrophic risk modeler and property data vendor used by private industry and government. CoreLogic's proprietary models incorporate natural hazard information with detailed structure and property characteristics to generate structure-level estimates of loss for several different perils.

Our analysis is based on property-level average annual loss (AAL), provided under 2021 conditions and 2050 conditions. AAL is the expected annual loss to structure and contents generated by simulating *many* possible iterations of a given year and then calculating the average loss across all iterations. Thus, AALs account for the magnitude of damage resulting from events of different severity *as well as* the likelihood of events of different severities occurring. CoreLogic reports AALs as share of total insurable value (TIV), which can be understood as the replacement cost of the structure.

Combining the property-level physical risk data with property-specific transactions data, local economic conditions data from the American Community Survey (ACS), and county-level data on climate change beliefs and voting behavior allows us to paint a more comprehensive picture of the magnitude and the (geographic and demographic) distribution of climate-related physical risk in the U.S. In addition, we can identify the specific climate-related perils that are likely to be the costliest now and in the future. The knowledge of the distribution of climate-related physical risk along different dimensions informs policymakers on the segments of the U.S. population that are likely to benefit from policies that aim to mitigate such risks and whether such policies are likely to be regressive or progressive with respect to key socioeconomic characteristics such as income and education attainment, which are proxies for earning potential.[6]

Results

Who geographically bears the current physical risk?

Many of the climate-related perils examined in our analysis are geographically concentrated. As shown in Table 1, the most concentrated peril is hurricane storm surge, which only affects five percent of SFRs, all of which are located near the Gulf and Atlantic coastal waters. Hurricane wind is also concentrated in coastal states, but the extent of potential damage extends further inland than it does for hurricane storm surge. About half of SFRs in the contiguous U.S. are exposed to some hurricane wind. That is also true to for inland flood risk, which is concentrated along rivers, lakes, and streams, as well as in regions that are susceptible to flash flooding. Inland flood risk is also present in coastal areas since ground flooding from hurricane precipitation and non-hurricane coastal flooding are classified as inland flooding. Wildfires are mostly limited to the western half of the country, with the notable exception of Florida.

[TABLE 1 HERE]

In contrast, severe convective storms and winter storms reach a substantially larger share of SFRs in the contiguous U.S. Severe convective storms, which include thunderstorms, hailstorms, and tornadoes, are the only true nationwide peril — nearly every SFR in the contiguous U.S. has some exposure. Winter storm risk is close to nationwide, with 86 percent of SFRs having non-zero expected losses from this climate-related peril. However, severe convective storms are the leading risk across much of the U.S.; with a few exceptions, winter storms are the leading risk only in parts of New England (see Appendix Figure 1).

The wide geographic reach of severe convective storms plays a key role in them having the highest expected loss averaged over all SFRs, which amounts to 0.06 percent of TIV, compared with 0.01 percent of TIV for both hurricane storm surge and wildfire. However, when we look at expected losses conditional on having some risk of damage, we see that flood- and hurricane-related perils are the most damaging in the areas that they can potentially impact. Hurricane storm surge has the largest average AAL (0.18 percent) among SFRs with some risk of damage, followed by inland floods (0.10 percent). The magnitude of the expected damage is driven by the long right tail of the distribution. As shown in Table 1, SFRs at the 99th percentile of non-zero AALs for hurricane storm surge and inland floods both face expected losses of over 2 percent of TIV. Hurricane wind and wildfire are the next closest at 0.60 percent and 0.45 percent, respectively.

We look at the regional breakdown of expected losses in Table 2. We find that severe convective storms are the greatest contributor to overall expected losses in the U.S. and the leading component in four of the nine census regions. Inland floods are the second-largest contributor to overall expected losses and the leading component in three of the nine regions. Only in the South Atlantic (hurricane wind) and New England (winter storm) do different perils play the largest role in expected losses.

[TABLE 2 HERE]

The greatest expected losses are in the West South Central (0.32 percent), East South Central (0.21 percent), West North Central (0.21 percent), and South Atlantic (0.19 percent). Collectively, these regions encompass the "tornado alley" in the central U.S., the hurricane-prone Gulf and southern Atlantic coasts, and flood-prone Appalachia. The least risky regions, on average, are the Pacific (0.07 percent) and Mountain (0.11 percent) regions, where wildfires and inland floods are the main contributors to expected losses and severe convective storm risk is relatively low. On average, the West South Central, the riskiest region in terms of AAL as a share of TIV, is more than four times riskier than the least risky region, the Pacific.

In Figure 1(a), we take a more granular look at the geographic distribution of risk by sorting Census Tracts into deciles of average AAL. Most of the safest tracts are in the Pacific and Mountain regions. In fact, 59 percent of Pacific tracts are in the lowest decile of risk, and the Pacific region accounts for 87 percent of first-decile tracts. Most of the remaining safest tracts are in the Mountain region. The highest-decile tracts are mostly spread among the West South Central (35 percent), South Atlantic (30 percent), and East South Central (9 percent) regions.

[FIGURE 1(a)(b) HERE]

The riskiest tracts are distinctive both in terms of their magnitude of expected damage and their peril composition. As shown in Figure 1(b), the distribution of tract-level average AALs is highly right-skewed;

tracts in the highest deciles of expected losses are over five times as risky as the median tract and more than twice as risky as tracts in the ninth decile, on average.

Tracts in the top decile face a substantially higher level of risk compared with other tracts, largely because of hurricane- and inland flood-related damage. Hurricane storm surge and hurricane wind make up nearly half of expected losses, on average, in the top decile tracts. These two perils comprise less than one-fifth of expected losses, on average, in all other deciles. Together with inland floods, the three perils comprise over 80 percent of expected losses in the top decile tracts. Despite severe convective storm accounting for the greatest share of expected damage across the country, expected damage in the riskiest areas of the U.S. is driven by hurricane and flood risk.

In fact, if we examine the very top of the risk distribution, the differences in magnitude and composition of risk become even starker. Tracts in the top one percent of the distribution have an average AAL of 1.65 percent of TIV, over 14 times as large as the median tract AAL. Moreover, hurricane storm surge makes up 42 percent of expected losses, on average, in these tracts (see Appendix Table 1). Together with hurricane wind and inland flood, they comprise 96 percent of expected losses in these very risky tracts. The locations of these top one percent tracts are concentrated along the Gulf and South Atlantic coasts. Among the top one percent tracts, 30% are in Louisiana, 26% are in Florida, 12% are in Texas, and 8% are in Mississippi. Nearly half of them are in either New Orleans-Metairie (28%), Miami-Fort Lauderdale (12%), or Gulfport-Biloxi (7%). Outside of the Gulf and South Atlantic coasts, areas of Appalachia (inland flood) and the northeast Atlantic coast (hurricane and inland flood) have the largest presence of very risky tracts.

We also provide estimates of AAL in 2021 dollars in Table 2. In aggregate, annual expected losses for SFRs due to all climate-related perils are $39 billion, based on 2021 conditions (see Methods section for full description of methodology). Roughly $12 billion (30 percent) is attributable to severe convective storms, $10 billion (25 percent) to inland floods, and $8 billion (20 percent) to hurricane wind. The West South Central had the largest average AAL of $648, over 60 percent greater than the U.S. average AAL ($410). The full regional and peril breakdown of AALs in terms of dollars is provided in Appendix Table 2.

In Appendix Figure 2, we plot the tract-level average AALs in terms of dollars, by the percentile of tract average AAL. We again see the right-skew nature of the distribution as well as the dominance of hurricane-related damage in the riskiest tracts. We estimate that the top 1% of tracts in terms of expected losses in dollars account for 10% of total expected dollar losses in the US; the top 10% of tracts account for 40% of total expected dollar losses.

Who demographically bears the current physical risk?

Table 3 shows select tract characteristics by AAL (as percent of TIV) decile based on the 2019 five-year ACS. Tracts in the highest-risk decile have, on average, lower education attainments, lower household incomes, lower prime age (16 to 54) labor force participation rates, and higher non-seasonal vacancy rates, a proxy of neighborhood quality.[7] The differences between the highest-risk decile and the fifth decile are significant: 18 percent lower higher education attainment rate, 16 percent lower household income, 5 percent lower prime age labor participation rate, and 74 percent greater non-seasonal vacancy rate. The differences are even greater between the highest-risk decile and the lowest-risk decile. Notably, we do not see a clear pattern in White population share across the deciles of physical risk.

[TABLE 3 HERE]

Urban status is a contributor to the pattern shown in Table 3. Urban tracts face less physical risk, on average, than rural tracts as illustrated by the fact that the share of tracts that are urban core tracts decreases across tract AAL deciles, while the share of rural tracts increases. The share of tracts that are suburban (not shown in Table 3) also tends to be larger in higher risk tracts. However, the differences in tract characteristics remain qualitatively and quantitatively similar when we limit the analysis to only urban core tracts (see Appendix Table 3), so the empirical pattern that we observe in Table 3 is not purely driven by the degree of urbanization. Overall, current climate-related physical risks appear to be disproportionately borne by homeowners who live and/or own SFRs in less economically viable areas.

To further investigate the drivers of regressive impact of physical risk, we look at tract average AALs broken down by peril for each decile of median household income. Appendix Figure 3(a) shows a near-linear decrease in expected losses from the lowest to highest tract income deciles. The highest-income decile faces only about two-thirds of the risk that the lowest income decile faces, on average. Notably, the share of AAL that comes from inland floods increases substantially as we move down the income deciles. In fact, in the bottom quintile income tracts, inland floods are the primary contributor to average expected losses. We see similar patterns when examining educational attainment, labor force participation rate, and vacancy rate (see Appendix Figure 3(b)(c)(d)).

Additionally, the pattern in local economic characteristics we observe appears to be driven more by cross-metro than intra-metro differences. The income difference between high- and low-risk tracts attenuates when we sort tracts within metropolitan statistical area (MSA) average AAL deciles (see Appendix Table 4). The prime age labor force participation rate, vacancy rate, and educational attainment patterns show similar attenuation. We do see larger White population share in riskier areas using the within-MSA sort.

Next, we investigate whether climate risk is related to changes in tract characteristics from 2010 to 2019 across 2021 average tract AAL deciles. Appendix Table 5 shows larger increases in the vacancy rate, larger decreases in prime age labor force participation, and smaller increases in education attainment in tracts in the upper AAL deciles. We again see similar patterns if we limit to only urban core tracts. The findings suggest that currently high-risk tracts are not only just currently less economically vibrant when compared with currently low-risk tracts but also that the gap in economic performance between the two groups has been increasing over time. The empirical patterns might suggest that climate-related physical risk itself and/or the realization of such risk may be important determinants of economic performance and outcomes, although it is not the focus of the current paper to evaluate these mechanisms.[8]

While we do see smaller average 2010–2019 total population change in riskier areas (see Appendix Table 5), we do not find evidence that, in aggregate, people are migrating away from higher-risk areas during that period. The results in Appendix Table 6 suggest net movement *into* higher risk areas based on the tract composite AAL (see Methods section for a complete description of methodology). When broken down by peril, we see greater average in-migration in the riskiest decile than the safest decile for all perils except winter storm. In aggregate, climate-related physical risk does not appear to be a significant deterrent of in-migration to high-risk places.[9]

Finally, we examine how voting behavior and beliefs about climate change are related to physical risk faced across the contiguous U.S. Due to data limitations, we perform this analysis using county-level observations. We find that counties with the greatest physical risk were least likely to believe global warming is happening (see Appendix Table 7). We also find that a more muted but directionally similar pattern using the share of respondents in the county who say they have been personally affected by global warming. Together, the results suggest that the personal experience of climate-related events as well as the real physical risk faced are not deterministic in forming beliefs about whether climate change is happening. In addition, local differences in beliefs may contribute to the net migration pattern that we document. One potential driver to these observed patterns is political beliefs. In Appendix Table 7, we find a strong relationship between physical risk and Republican vote share in 2020 – counties with the larger AALs, on average, have larger Republican vote share.[10]

What does future physical risk look like?

Physical risk is expected to increase in the future because of climate change. [11] Future climate scenarios are characterized by Representative Concentration Pathways (RCPs), which depict different trajectories of greenhouse gas emissions that then affect different climate-related outcomes. Under the middle-of-the-road scenario, RCP 4.5, we estimate that expected losses for SFRs in the contiguous U.S. will increase by 3.8 basis points of TIV by 2050 (See Table 4). This represents a 22 percent increase, on average. Under a more severe emissions scenario, RCP 8.5, we estimate an average increase in expected losses of 5.6 basis points of TIV, a 33 percent increase.

In dollar terms, we estimate expected damages will increase by 24 percent to $48 billion under RCP 4.5 and by 36 percent to $53 billion under RCP 8.5. These estimates are based on the 2021 inventory of SFRs and therefore do not consider future changes in development and home values. In other words, these are estimates of the change in expected dollar losses that are attributable exclusively to the change in risk from the six climate-related perils.

As shown in Table 4, the majority of the increase in physical risk will be due to severe convective storms. Severe convective storms will be the largest contributor to the increase in expected losses in all regions except the Pacific and Mountain regions, where wildfires are the chief contributor, as well as in the South Atlantic, where hurricane wind are the largest component. Overall, hurricane wind will make up 17 percent of the national increase. Despite its limited geographic scope, hurricane storm surge will make also up 19 percent of the national average increase in expected losses.

[TABLE 4 HERE]

The largest increases in AAL will occur in the regions where current AALs are the greatest. Figure 2 plots the tract-average change in AAL by the tract-average 2021 AAL. There is a clear positive relationship — higher-risk tracts today will, on average, experience greater increases in physical risk. There is also a right-skew to the distribution of changes in tract-average AALs — tracts in the highest 2021 AAL decile have an average increase in AAL that is about three times the average increase of those in the ninth decile. The changes in AAL in the highest decile are driven more by hurricane wind and hurricane storm surge than they are in the other deciles, where severe convective storm dominates.

[FIGURE 2 HERE]

Discussion

In this analysis, we provide a comprehensive accounting of the climate-related physical risk to SFRs in the contiguous U.S. However, our study has several notable limitations. Because of data limitations, we cannot make claims about the expected damage to other property types (e.g., multifamily residential properties, commercial properties, public infrastructure, etc.). Additionally, we are not capturing non-property or indirect losses, such as loss of business, hardship costs, mortality costs, or the cost of potential lost future growth.[12] Last, we do not differentiate between the proportion of the cost that will be borne by insurance companies and the proportion of the cost that will be borne by homeowners.[13]

The 2021 damage estimate of $39 billion is relatively small when compared with the size of the national economy — it represents about 0.2 percent of the U.S. gross domestic product (GDP) in 2021. However, expected losses should not be confused with realized losses. Realized losses from natural disasters tend to be temporally lumpy (see Appendix Figure A1), and they are not evenly distributed across the entire U.S. For example, in 2005, the U.S. experienced close to $150 billion in property losses, with most of that occurring in a few Gulf Coast states, like Louisiana.

Our distributional analysis provides insights into where and who bear the physical risk. Geographically, the safest areas tend to be in the Pacific and Mountain regions while the riskier areas tend to be in the southeastern and central parts of the country. Within those riskier areas, it is the hurricane- and flood- exposed areas on the Gulf and South Atlantic coasts that face the greatest risk, along with some inland flood exposed areas, like parts of Appalachia. Severe convective storms are estimated to be the largest contributor to expected losses across the U.S., but the areas with the largest expected losses are largely hurricane- and flood-exposed areas. Demographically, we find that low-income, less educated, low labor market participation, and high vacancy rate areas face the greatest physical risk. Inter-metro differences in local economic conditions across the distribution of physical risk appear larger than intra-metro differences.

Altogether the results suggest that areas that are already economically struggling face the greatest risk of disruption from climate-related perils. Thus, policies that aim to decrease the underlying physical risk (e.g., slowing global temperature increases) and/or mitigate the impacts of these climate-related perils will likely be progressive now and into the future. With insurance markets in place, realized damages are likely to manifest in the form of higher insurance premiums and disruption to general economic activities in the affected areas. However, as insurance companies pull out of risky markets, realized damages are likely to fall fully on homeowners, or, in the case of rental SFRs, on a combination of homeowners and renters.[14]

While a full investigation of the mechanisms driving the regressivity of climate-related physical risk is beyond the scope of this paper, we do offer a few possibilities for further exploration. First, the income pattern we observe is consistent with climate-related physical risk being viewed as a "bad amenity" by households.[15,16] Second, the strength of the inter-metro differences we observe is consistent with lower income households being priced out of more expensive metro areas that tend to face less physical risk. Barriers to new housing development (e.g., regulatory and physical constraints) may be of particular importance.[17,18] Lastly, the relationship between beliefs about climate change and physical risk suggests that people may have beliefs about climate change that differ from the objective measure of risk we employ. Therefore, the regressivity of climate-related physical risk may be partly driven by the correlation between income, education attainment, and access to accurate information.

Looking to the future, the riskiest areas today will, by and large, still be the riskiest areas in 2050. In fact, the changes over the next 30 years will be most dramatic for the areas already facing the highest risk. The largest contributors to the change in physical risk are severe convective storms, hurricane storm surge, and hurricane wind. Given that the gap in economic performance between high- and low-risk tracts has been increasing over time and that aggregate migration patterns do not appear to be sensitive to the geographic distribution of climate-related physical risk, it is plausible that policies that aim to mitigate such risk will continue to be progressive with respect to local economic conditions and will benefit a larger proportion of the U.S. population.[19]

In terms of targeting specific perils, we find that inland floods are the largest contributor to expected losses in the areas that appear worst off in terms of income, college attainment, vacancy, and labor force participation. This finding is relevant to both mitigation investment decisions and insurance take-up efforts. Flood insurance take-up through the government-operated National Flood Insurance Program (NFIP) is low, particularly in many inland areas that may still face risk of flooding despite being outside of the FEMA-designated floodplain.[20,21] Moreover, within the FEMA floodplain, NFIP-insured homeowners have about 60 percent higher incomes than uninsured homeowners, suggesting that the insurance gap is more pronounced among low-income households.[22] Consequently, efforts to increase flood insurance take-up in areas at risk of flooding will likely be disproportionately beneficial to low-income households.

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Methods

Estimates of Average Annual Loss (AAL)

The AALs used in this analysis are sourced from CoreLogic, which is a major commercial catastrophic risk modeler and property data vendor. CoreLogic's estimates are used in private industry as well as by various government agencies.[23] CoreLogic's inland flood and storm surge models were recently used in the Federal Emergency Management Agency's (FEMA's) "Risk Rating 2.0", which revamped the National Flood Insurance Program's (NFIP's) rate-setting procedures to better align charged insurance premiums with property-specific risk.[24]

CoreLogic provides AAL estimates for approximately 190 million structures in the contiguous United States. AALs are expected losses, meaning they represent the loss per year averaged over many possible iterations of that year. Mathematically, the AAL is the area under the exceedance probability curve, which, for every possible loss amount, provides a likelihood that the loss amount will be met or exceeded for a given structure. Importantly for our multiperil analysis, AALs are additive because they are expectations.

CoreLogic's AALs are *ground-up losses*, meaning they represent gross losses to the structure and contents prior to applying any insurance policy terms (e.g., deductible). The AALs are expressed as a share of total insurable value (TIV), and therefore range from 0 to 1 for any single peril. CoreLogic uses replacement cost as its measure of TIV.

This paper uses AALs based on current conditions (circa 2021) and on conditions in 2050 under two different greenhouse gas emissions pathways: Representative Concentration Pathways (RCPs) 4.5 and 8.5, as specified in the Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC AR5).[25] Our main 2050 risk estimates are based on RCP 4.5, which depicts a "middle-of-the-road" climate scenario. RCP 4.5 is associated with a global mean surface temperature increase of 0.9–2.0 degrees Celsius by the mid-21st century (relative to 1986–2005), while the more severe business-as-usual scenario, RCP 8.5, is associated with an increase of 1.4–2.6 degrees Celsius. In terms of global mean sea level rise, the increase by the mid-21st century under RCP 8.5 is expected to be about 15 percent larger than it would be under RCP 4.5.[26]

The AALs are generated by CoreLogic's proprietary climate, hazard, and vulnerability models. Inputs to CoreLogic's modeling consist of natural hazard information and "industry-leading property data."[27] These models account for future changes to environmental conditions, but they do not incorporate any changes to development. All 2050 AAL estimates are based on the current stock of structures.

It is important to note that the AAL estimates are model-generated and, hence, they inherently contain a degree of uncertainty around the point estimates that we use in our analyses. The sources of uncertainty include CoreLogic's modeling choices and the choice of historical data sets used to feed the models. We cannot assess the degree of uncertainty because CoreLogic does not provide the necessary data.

Validating AAL estimates is difficult because the ground truth is unknown. CoreLogic performs validation exercises on its model output to test reasonableness. While specific validation analyses vary by peril, they typically involve comparison with data on historical events and, if available, damages from those events. In our own validation exercise, we find our national expected loss total to be reasonable when compared with long-run historical losses recorded in the Spatial Hazard Events and Losses Database for the United States (SHELDUS). The SHELDUS comparison and full methodology is discussed in Appendix A.

Additionally, as a robustness check on our distributional analyses, we show that tract-level averages based on CoreLogic's AALs correlate moderately well with tract-level averages based on AAL estimates from a different risk modeler for a subset of perils (see Appendix B). Agreement between the two sets of tract-level estimates is strongest at the top end of the risk distribution.

Perils

We focus on AALs for six climate-related perils provided by CoreLogic: inland floods, hurricane wind, hurricane storm surge, severe convective storms, winter storms, and wildfires. We selected these perils because they are likely to be affected by future environmental changes brought on by climate change. By this logic, we ignore data on earthquake-related perils. The perils are defined to be mutually exclusive and consistent with insurance industry practices. For example, water damage resulting from hurricane wind tearing off part of a roof and allowing for rainfall to enter the home would be considered hurricane wind damage and would be covered under a standard homeowner's insurance policy. However, water damage resulting from a stream overflowing because of hurricane precipitation would be considered inland flooding damage and would not be covered under a standard homeowner's insurance policy.

The peril descriptions from CoreLogic are as follows:

1. *Inland Flooding* – Inundation caused by (1) water in an existing waterway (river, stream, or pond) rising overtop the normal banks and spreading onto adjacent land, (2) ponding of rainwater in low-lying areas, and/or (3) coastal flooding from unusually high tides, strong onshore winds, and storm surge associated with a landfalling strong storm (other than a hurricane). Water depth, flow velocity, building age, first floor height, construction type, occupancy type, number of stories, and presence of a basement are considered in determining damage.
2. *Hurricane Wind* – Damage caused by sheer force of hurricane wind (>74 mph one-minute sustained wind speed at landfall) and any resulting water damage from precipitation entering the structure. The peak gust, flood depth and velocity, structure type, occupancy type, and total value of the exposure are considered in determining damage.
3. *Hurricane Storm Surge* – Inundation caused by hurricane-force winds (>74 mph) pushing shallow coastal waters in such a way that the sea level rises. Powerful storms can cause up to 30 feet of storm surge. Storm surge flood depth and velocity can depend on factors like variations in astronomical tides, flood defense systems, and first floor elevation of building. Storm surge flood depth and velocity, structure type, occupancy type, and total value of the exposure are considered in determining damage.
4. *Severe Convective Storm* – Damage caused by one of three different types of storms: tornadoes, hailstorms, or straight-line winds (e.g., squall or derecho). The hazard intensity, structure type, occupancy, building material, cladding, and height of structure are considered in determining damage.
5. *Winter Storm* – Damage caused by winter storm precipitation and prolonged cold temperatures. Types of damage include roof damage due to snow accumulation, frozen and ruptured pipes, and ice dams on roofs and gutters causing flooding from melting snow. Snow depth, snow and ice thickness, wind speed, as well as structure and occupancy types are considered in determining damage.
6. *Wildfire* – Damage caused by fire and smoke from combustion of vegetative fuel. Fire behavior is modeled considering available fuel load, topography of area, prevailing weather conditions, and

fire suppression factors, including firefighting resources. Structure type, occupancy type, age of structure, number of stories, vegetation clearance, roofing fire class, and the presence of fire resistive windows or siding are considered in determining damage.

Some of the perils are not modeled for the entire contiguous U.S. Hurricane wind and hurricane storm surge are only modeled for states on the Gulf and Atlantic coasts. Wildfires are only modeled for the western U.S. and Florida. Nonmodeled areas are considered to have negligible risk, according to CoreLogic. Consequently, when aggregating the AALs over the different perils, we consider structures in nonmodeled areas to have an AAL of zero for the geographically limited perils.

Sample Construction

The analyses in this paper are based on property-level estimates of AAL. Thus, we do not aggregate over all structures in the CoreLogic data. Instead, we select one structure per property. If a primary structure is identifiable, we use that structure. If the primary structure is unknown, we take the structure with the largest AAL.

We then use CoreLogic's property tax assessment data to identify properties that are single-family residences (SFRs). To determine SFR status, we use the CoreLogic-standardized land use code. For tax year 2021, we identify about 96.7 million SFRs in the contiguous US.

To generate tract-level average AALs, we identify each property's census tract by performing a spatial join of the chosen properties (using structure-specific coordinates) and 2010-vintage census tracts. We find that 70,558 out of the total 72,247 land area tracts in the contiguous US have at least one SFR. Then, for each property, we sum the AALs over all perils and calculate the average all-peril AAL for properties in the tract. Among the 70,558 tracts, we exclude about 4 percent of the tracts that had fewer than 30 non-missing AAL values for SFRs. These are either tracts with a very small number of SFRs or tracts where data limitations prevented CoreLogic from providing an AAL estimate for most properties. Together, these excluded tracts contain about 0.2 million SFRs. We are left with 67,487 tracts in the final sample covering 96.5 million SFRs.

Census Tract Characteristics

Census tract characteristics are produced using 2019 five-year American Community Survey (ACS) estimates. The 2019 ACS was chosen because of the economic activities and migration patterns that were driven by the COVID-19 pandemic.[28] However, migration and economic shocks related to COVID-19 do not materially affect our conclusions. All the results shown in Table 3 are quantitatively and qualitatively similar when we use the 2021 five-year ACS estimates, as opposed to the 2019 five-year ACS estimates.[29]

The 2019 ACS fields used were:

1. Median Household Income (B19013_001)
2. Total Households (B17017_001)
3. Total Households – Income in the Past 12 Months Below Poverty Level (B17017_002)
4. Population 25 Years and Over (B15003_001)
5. Population 25 Years and Over – Bachelor's Degree (B15003_022)
6. Population 25 Years and Over – Master's Degree (B15003_023)
7. Population 25 Years and Over – Professional Degree (B15003_024)

8. Population 25 Years and Over – Doctorate Degree (B15003_025)
9. Population 16 Years and Over (B23025_001)
10. Population 16 Years and Over – In Labor Force (B23025_002)
11. Male: 25 to 29 Years: In Labor Force (B23001_025)
12. Male: 30 to 34 Years: In Labor Force (B23001_032)
13. Male: 35 to 44 Years: In Labor Force (B23001_039)
14. Male: 45 to 54 Years: In Labor Force (B23001_046)
15. Female: 25 to 29 Years: In Labor Force (B23001_111)
16. Female: 30 to 34 Years: In Labor Force (B23001_118)
17. Female: 35 to 44 Years: In Labor Force (B23001_125)
18. Female: 45 to 54 Years: In Labor Force (B23001_132)
19. Male: 25 to 29 years (B01001_011)
20. Male: 30 to 34 years (B01001_012)
21. Male: 35 to 39 years (B01001_013)
22. Male: 40 to 44 years (B01001_014)
23. Male: 45 to 49 years (B01001_015)
24. Male: 50 to 54 years (B01001_016)
25. Female: 25 to 29 years (B01001_035)
26. Female: 30 to 34 years (B01001_036)
27. Female: 35 to 39 years (B01001_037)
28. Female: 40 to 44 years (B01001_038)
29. Female: 45 to 49 years (B01001_039)
30. Female: 50 to 54 years (B01001_040)
31. Housing Units (B25002_001)
32. Housing Units — Vacant (B25002_003)
33. Vacant Housing Units – For Seasonal, Recreational, or Occasional Use (B25004_006)
34. Total Population (B03002_001)
35. Total Population – Not Hispanic or Latino: White Alone (B03002_003)
36. Total Population – Not Hispanic or Latino: Black or African American Alone (B03002_004)
37. Total Population – Hispanic or Latino (B03002_012)
38. Total Population – Hispanic or Latino: White Alone (B03002_013)

Urban/Rural Tract Classification

Tracts are designated as urban core, suburban, or rural based on 2010 Census Urban Areas and Core-Based Statistical Area (CBSA) definitions. A tract is classified as "urban core" if the tract centroid intersects with a Census "Urbanized Area" (not "Urban Cluster"). A tract is defined as "suburban" if it is located within a Census CBSA or Census Urban Cluster but not within a Census Urbanized Area. All tracts outside CBSAs are considered "rural".

Generating Tract Characteristics by Average AAL Decile

In Table 3, we examine tract characteristics by tract average AAL deciles. We do this as follows. First, we sort our sample of 67,487 tracts into deciles based on the tract average AAL. Second, we winsorize the distribution of the tract characteristics at 0.01 and 0.99 within each AAL decile to mitigate the influence of extreme values. Last, we take averages of the tract characteristics within each decile.

Generating AALs in Dollars

We use the following procedure to convert the property-level CoreLogic AALs, which are normalized by TIV, to dollar values.

We employ several different data sources to estimate AAL in dollars. We first use a combination of CoreLogic public records and the Zillow Home Value Index (ZHVI) to calculate home values for each SFR in the contiguous US.[30] For SFRs where we observe an arm's length transaction in the CoreLogic public records data, we use the latest observed transaction and impute the 2021 home value using the ZHVI, which we transform from ZIP code- to tract-level using the Housing and Urban Development (HUD) crosswalk.[31] We are able to impute the 2021 home value from transaction data for just over half of the SFRs in our data. We winsorize the imputed values at the 1st and 99th percentile and we top code the values at $10 million to address extreme outliers. For the vast majority of the remaining SFRs, we use the December 2021 tract-level ZHVI value as the home value. For the small set of remaining SFRs, we use the county-level average home value. The national average and median home value from our estimates are $385,000 and $276,000, respectively.

Next, we merge in land value share of home value estimates from Davis et al. (2021), which provides, to our knowledge, the most granular estimates of land value shares. [32] Davis et al. provides tract-level measures for over three-quarters of tracts in the U.S. When a tract measure is not available, we use the most granular option available among ZIP code-, county-, or state-level measure.

We then calculate the AAL in dollars for each SFR as *AAL*Home Value*(1 – Land Share of Home Value)*.

Net Migration by Tract AAL Decile

We examine net migration between 2010 and 2019 for areas of different climate risk levels using the anonymized FRBNY Consumer Credit Panel /Equifax data (CCP) (see Appendix Table 6). The CCP is a 5 percent random sample that is representative of all U.S. individuals who have a credit history. It is widely used in consumer finance research, but it has also been used in several studies of mobility and migration.[33] We use the CCP because its size (about 10 million borrowers per year) enables us to generate more granular migration estimates than some other sources of migration data allow. For example, ACS data only provide county-level flows based on five years of pooled data. We provide a county-level comparison of those sources below to help validate our CCP-derived migration estimates in Appendix C.

Using the CCP, we generate census tract-level net migration estimates and then group tracts by the same AAL deciles that are used in the main analyses. The migration estimation proceeds as follows.

1. Identify individuals in the CCP who have a different reported street address and zip code in year *t* compared with year *t*-1 for t = 2010 to t = 2019 and generate counts by 2000 census block. The CCP provides a scrambled address where the trailing characters are affected by small variations such as whether "Unit" or "Apt" is used. To deal with this issue, we only use the first five characters of the scrambled address in conjunction with the zip code to avoid falsely identifying movers that result from small variations in address syntax.
2. Merge counts with the National Historical Geographic Information System (NHGIS) 2000–2010 block crosswalk to convert to 2010 census geography definitions.[34] Using the weights provided in the crosswalk, we allocate each 2000 block migration count to a 2000 block to a 2010 block pair. Then we aggregate to the 2010 block level.

3. Aggregate counts to the 2010 tract level.
4. Multiply counts by 22 because the CCP is a 5 percent nationally representative sample among those with credit histories. We multiply by 22 instead of 20 to account for individuals without credit histories. We implicitly assume that the migration pattern of individuals who lack credit histories is similar to that of individuals who have credit histories.
5. Scale migration counts by 2010 tract population.
6. Group tracts by AAL decile and winsorize the distribution of net migration at 1st and 99th percentiles within each decile.
7. Calculate average net migration as share of 2010 population within AAL tract deciles.

We also consider migration within MSAs to investigate if people are moving to or away from riskier areas within their original MSA. In this case, we generate AAL deciles within the MSAs instead of across all tracts. We also calculate the average net migration among movers who moved within the same MSA, excluding the relatively small percentage of movers who move across different MSAs.

Climate Change Beliefs and Voting Data

Climate change beliefs survey data is sourced from the Yale Climate Opinion Map 2021, which is based on the methodology developed in Howe et al. (2015).[35] We draw on county-level results for two survey questions:

1. "Recently, you may have noticed that global warming has been getting some attention in the news. Global warming refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result. What do you think: Do you think that global warming is happening?" RESPONSES: *Yes, No, Don't Know.*
2. "How much do you agree or disagree with the following statement: "I have personally experienced the effects of global warming"?" RESPONSES: *Strongly agree, Somewhat agree, Somewhat disagree, Strongly disagree.*

In the first question we use the share of respondents who responded "Yes". In the second question, we use the share of respondents who responded, "Strongly agree" or "Somewhat agree".

The county-level 2020 voting data is sourced from the MIT Election and Science Lab.[36]

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Tables

Table 1. Average Annual Loss (AAL) for Single-Family Residences (SFRs) in 2021, by Peril

				AAL Among SFRs with >0 AAL					
Peril	**Average AAL Among All SFRs**	**Percent of SFRs with >0 AAL**	**Average AAL Among SFRs with >0 AAL**	*p10*	*p25*	*Median*	*p75*	*p90*	*p99*
Severe Convective Storm	0.06%	99.8%	0.06%	*	0.01%	0.04%	0.08%	0.12%	0.26%
Inland Flood	0.05%	47.6%	0.10%	*	*	0.01%	0.03%	0.13%	2.46%
Hurricane Wind	0.03%	48.0%	0.07%	*	*	0.02%	0.07%	0.19%	0.60%
Winter Storm	0.02%	86.4%	0.02%	*	0.01%	0.02%	0.03%	0.04%	0.09%
Hurricane Storm Surge	0.01%	5.2%	0.18%	*	*	0.01%	0.11%	0.50%	2.16%
Wildfire	0.01%	27.2%	0.03%	*	*	*	0.01%	0.05%	0.45%

Note: The table shows summary statistics of AAL by peril. AAL is presented as percentage of total insurable value. Asterisks indicate values greater than 0% but less than 0.005%.

Table 2. Average Annual Loss (AAL) for SFRs in 2021, by Census Region Division and Peril

	Percent of Census Region Division's Average AAL									
	East North Central	**East South Central**	**Middle Atlantic**	**Mountain**	**New England**	**Pacific**	**South Atlantic**	**West North Central**	**West South Central**	**U.S.**
Severe Convective Storm	53%	36%	19%	24%	13%	2%	23%	56%	40%	**33%**
Inland Flood	26%	40%	35%	39%	19%	52%	19%	33%	25%	**28%**
Hurricane Wind	0%	16%	10%	0%	17%	0%	39%	0%	24%	**19%**
Winter Storm	21%	5%	28%	7%	46%	6%	7%	11%	3%	**11%**
Hurricane Storm Surge	0%	3%	8%	0%	5%	0%	11%	0%	7%	**6%**
Wildfire	0%	0%	0%	30%	0%	40%	1%	0%	2%	**4%**
Avg AAL (% of TIV)	0.12%	0.21%	0.14%	0.11%	0.15%	0.07%	0.19%	0.21%	0.32%	**0.17%**
	Property Exposure									
Count SFRs (millions)	14.2	7.3	10.0	7.6	3.7	11.8	21.9	7.1	12.9	**96.5**
Avg Structure Value ($)	172,861	188,445	252,229	365,063	269,502	413,085	257,413	193,591	211,948	**256,423**
	Expected Loss in Dollars									
Avg AAL ($)	192	342	350	385	411	267	513	392	649	**401**
Total AAL ($ Billions)	2.7	2.5	3.5	2.9	1.5	3.2	11.2	2.8	8.4	**39**

Note: By-peril contribution to average AAL in 2021, measured as share of total insurable value (TIV). Results shown by Census Region Division. Structure value does not include land value. Dollar values are shown in 2021 dollars.

Table 3. 2019 Census Tract Characteristics by Tract AAL Decile

	Mean (Standard Error)									
	Decile of Tract Average AAL (measured as % of TIV)									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Percent White	45.2	56.7	65.4	64.0	66.1	68.6	68.3	66.5	63.4	62.3
	(0.3)	(0.4)	(0.4)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)	(0.4)	(0.4)
Percent with Bachelor's Degree or Higher	34.4	33.3	31.4	31.9	31.8	31.0	29.8	27.2	26.1	26.1
	(0.3)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Median Household Income	84,244	78,522	72,682	73,289	72,185	70,578	68,947	65,684	63,161	60,906
	(477)	(481)	(433)	(418)	(401)	(386)	(384)	(362)	(344)	(331)
Home Value	838,602	491,514	353,840	388,196	353,773	333,720	343,697	317,659	282,167	343,244
	(6,983)	(4,767)	(3,005)	(3,267)	(2,934)	(2,658)	(3,296)	(2,950)	(2,436)	(3,869)
Percent Prime Age Labor Force Participation	82.7	82.4	82.5	82.6	83.0	82.8	82.3	81.3	80.4	78.9
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Percent Vacant (Excluding Seasonal Units)	5.0	7.6	8.2	7.9	8.3	8.2	8.7	9.4	10.1	11.3
	(0.04)	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
Percent of Tracts Rural	0.5	2.3	3.9	4.3	4.8	7.0	9.1	11.7	12.7	12.5
Percent of Tracts Urban Core	90.1	76.5	69.5	68.6	64.5	59.5	54.2	49.3	50.1	50.9

Note: Census tract average characteristics by tract-level average AAL decile. Dollar values are in 2021 dollars.

Table 4. Change in Average Annual Loss (AAL) 2021–2050 Under RCP 4.5 and RCP 8.5, by Census Region Division

Panel A: Change in AAL 2021-2050 Under RCP 4.5

	Percent of Change in AAL by Census Region Division									
	East North Central	**East South Central**	**Middle Atlantic**	**Mountain**	**New England**	**Pacific**	**South Atlantic**	**West North Central**	**West South Central**	**U.S.**
Severe Convective Storm	83%	68%	40%	37%	36%	2%	33%	90%	56%	**51%**
Inland Flood	15%	8%	8%	3%	6%	32%	3%	8%	-2%	**6%**
Hurricane Wind	0%	15%	10%	0%	23%	0%	35%	0%	19%	**17%**
Winter Storm	3%	-1%	5%	-1%	14%	-2%	-1%	1%	-1%	**1%**
Hurricane Storm Surge	0%	10%	36%	0%	21%	0%	29%	0%	26%	**19%**
Wildfire	0%	0%	0%	60%	0%	68%	1%	0%	2%	**6%**
Avg Change in AAL (bps of TIV)	2.7	3.9	2.8	2.2	2.4	1.4	4.9	4.8	7.0	**3.8**

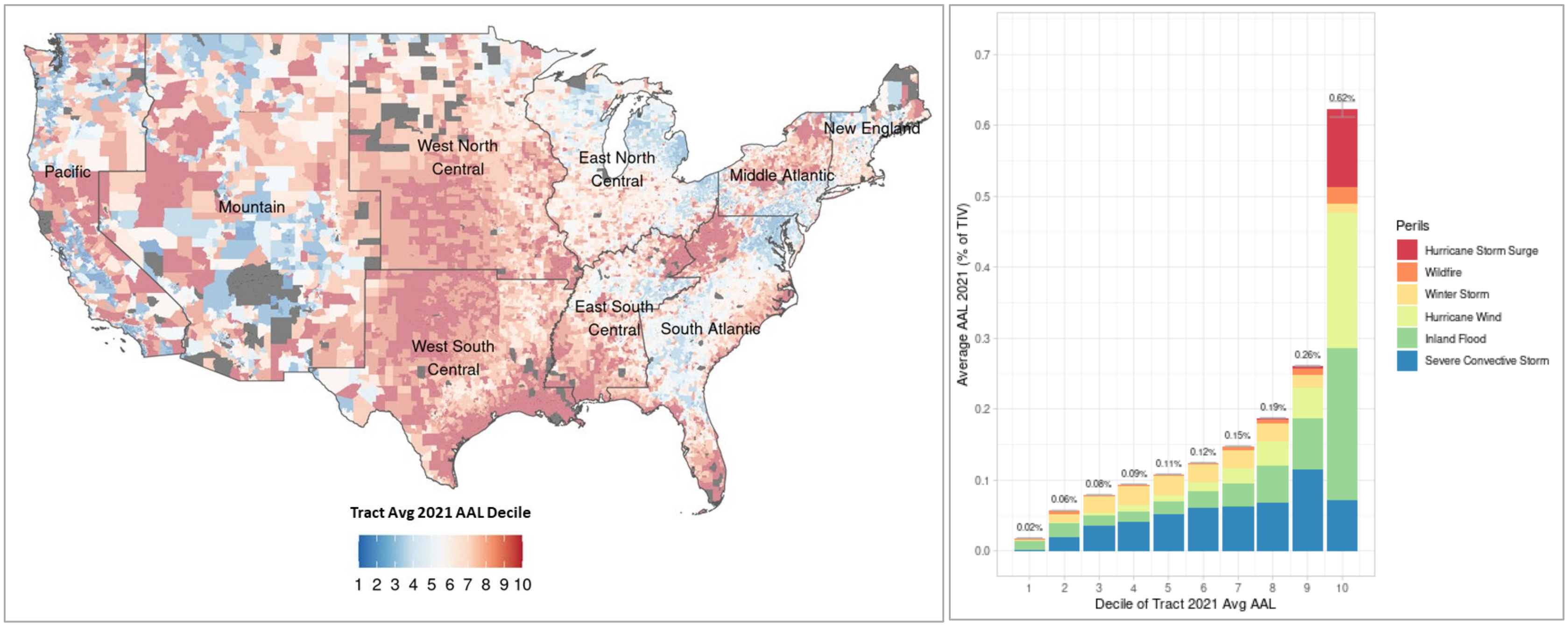
Panel B: Change in AAL 2021-2050 Under RCP 8.5

	Percent of Change in AAL by Census Region Division									
	East North Central	**East South Central**	**Middle Atlantic**	**Mountain**	**New England**	**Pacific**	**South Atlantic**	**West North Central**	**West South Central**	**U.S.**
Severe Convective Storm	77%	65%	33%	40%	28%	3%	26%	87%	50%	**45%**
Inland Flood	19%	2%	9%	0%	4%	17%	1%	11%	-2%	**4%**
Hurricane Wind	0%	22%	13%	0%	28%	0%	44%	0%	25%	**23%**
Winter Storm	4%	0%	8%	0%	21%	-1%	0%	2%	0%	**2%**
Hurricane Storm Surge	0%	11%	36%	0%	19%	0%	29%	0%	26%	**20%**
Wildfire	0%	0%	0%	60%	0%	82%	1%	0%	2%	**6%**
Avg Change in AAL (bps of TIV)	3.8	5.2	4.2	2.9	3.8	1.5	7.9	6.7	10.4	**5.6**
Count SFRs (millions)	14.2	7.3	10.0	7.6	3.7	11.8	21.9	7.1	12.9	96.5

Note: By-peril contribution to change in average AAL, measured as share of total insurable value (TIV), from 2021 and 2050 under RCP 4.5 and RCP 8.5. Results shown by Census Region Division. Negative value indicates a decrease in average AAL. RCP = Representative Concentration Pathway.

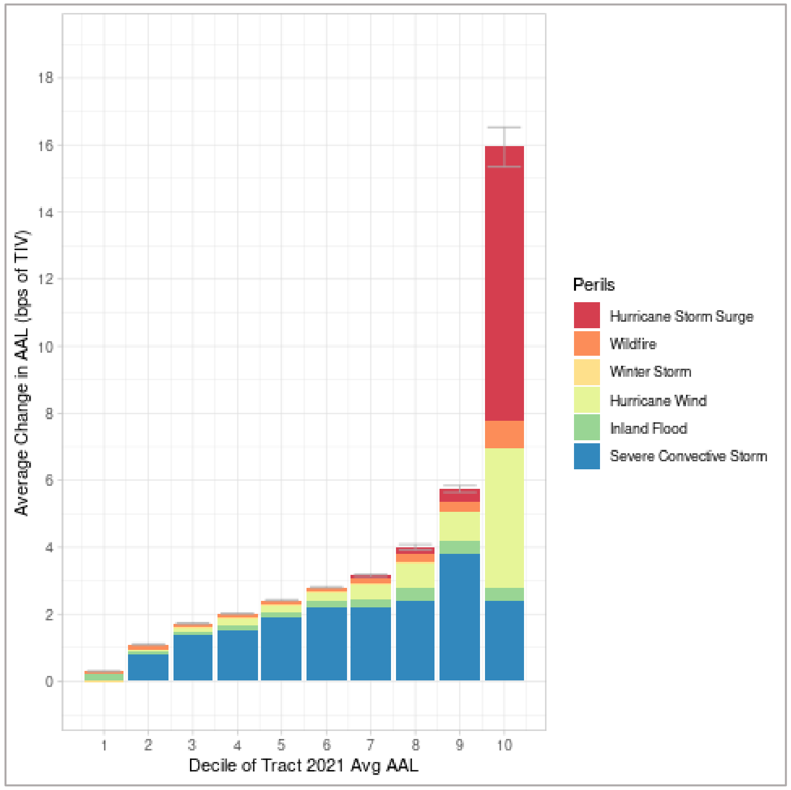
Figures

Figure 1(a)(b). Deciles of Tract Average AAL for SFRs in 2021 and By-Peril Contribution Within Each



(a) Tract-level average composite AAL. Tracts without sufficient data to calculate an average AAL are shown in dark gray. (b) By-peril contribution of average AAL in each decile of tract average AAL. Ninety-five percent confidence intervals for decile average AALs appear in gray. The confidence intervals characterize the cross-sectional variation in tract-level average AALs and do not account for model uncertainty because CoreLogic does not provide sufficient information for us to account for such uncertainty; TIV = total insurable value.

Figure 2. Average Change in AAL 2021–2050, by 2021 Tract AAL Decile



Average change in AAL between 2021 and 2050 sorted by 2021 average tract AAL decile. Ninety-five percent confidence intervals for decile average AALs appear in gray. The confidence intervals characterize the cross-sectional variation in tract-level average AALs and do not account for model uncertainty because CoreLogic does not provide sufficient information for us to account for such uncertainty.

Appendix Tables

Appendix Table 1. By-Peril, By-State, and By-MSA Summary of Tracts in Top 1% of Tract AAL

By-Peril		*By-State*		*By-MSA*	
Peril	**Percent of AAL**	**State**	**Percent of Tracts**	**MSA**	**Percent of Tracts**
Hurricane Storm Surge	42%	LA	30%	New Orleans-Metairie, LA	28%
Inland Flood	28%	FL	26%	Miami-Fort Lauderdale-Pompano Beach, FL	12%
Hurricane Wind	25%	TX	12%	Gulfport-Biloxi, MS	7%
Severe Convective Storm	3%	MS	8%	Houston-The Woodlands-Sugar Land, TX	6%
Wildfire	1%	WV	5%	Tampa-St. Petersburg-Clearwater, FL	5%
Winter Storm	0.4%	NY	5%	New York-Newark-Jersey City, NY-NJ-PA	4%
		KY	2%	Key West, FL	3%
		CA	2%	Beaumont-Port Arthur, TX	3%
		AL	1%	Charleston, WV	2%
		NJ	1%	Sebastian-Vero Beach, FL	2%

Note: By-peril contribution and top geographic locations of the top one percent of riskiest tracts in the U.S. based on AALs measured as share of total insurable value.

Appendix Table 2. AAL in Dollars for SFRs in 2021, by Peril

	Percent of Census Region's Expected Losses (in terms of dollars)									
	East North Central	**East South Central**	**Middle Atlantic**	**Mountain**	**New England**	**Pacific**	**South Atlantic**	**West North Central**	**West South Central**	**U.S.**
Severe Convective	55%	42%	18%	24%	13%	1%	21%	58%	43%	**30%**
Storm Inland Flood	23%	32%	28%	36%	17%	52%	14%	32%	23%	**25%**
Hurricane Wind	0%	15%	14%	0%	18%	0%	43%	0%	23%	**20%**
Winter Storm	22%	6%	28%	8%	46%	6%	6%	11%	3%	**10%**
Hurricane Storm Surge	0%	4%	13%	0%	5%	0%	15%	0%	7%	**8%**
Wildfire	0%	0%	0%	31%	0%	41%	1%	0%	1%	**6%**
Avg AAL ($)	192	342	350	385	411	267	513	392	649	**401**
Total AAL ($ Billions)	2.7	2.5	3.5	2.9	1.5	3.2	11.2	2.8	8.4	**39**

Note: By-peril contribution to average dollar-value AAL. Dollar values are shown in 2021 dollars.

Appendix Table 3. Urban Core 2019 Census Tract Characteristics by Tract AAL Decile

	Mean (Standard Error) *Decile of Tract Average AAL (% of TIV)*									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Percent White	43.7	51.1	57.4	55.7	57.4	59.8	58.2	55.4	51.4	49.7
	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.5)	(0.5)	(0.5)	(0.5)
Percent with Bachelor's Degree or Higher	35.1	34.5	33.4	34.8	35.6	35.9	35.4	32.3	30.6	31.0
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Median Household Income	85,026	78,720	73,430	75,757	75,287	74,487	73,645	70,334	66,651	63,905
	(505)	(573)	(556)	(543)	(547)	(552)	(591)	(593)	(571)	(523)
Home Value	866,904	506,944	371,729	431,469	399,194	386,362	419,675	384,883	330,175	424,745
	(7,457)	(5,661)	(3,813)	(4,193)	(3,985)	(3,669)	(4,948)	(4,612)	(3,750)	(6,042)
Percent Prime Age Labor Force Participation	83.0	82.7	82.9	83.3	83.8	83.9	83.6	82.9	82.0	81.5
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Percent Vacant (Excluding Seasonal Units)	4.9	7.8	8.4	7.7	8.1	7.7	8.0	8.2	9.0	10.0
	(0.05)	(0.11)	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)
Number of Urban Core Tracts	6,084	5,166	4,689	4,628	4,352	4,016	3,655	3,325	3,378	3,437

Note: Urban core census tract average characteristics by tract-level average AAL decile. Dollar values are in 2021 dollars.

Appendix Table 4. 2019 Census Tract Characteristics by Tract AAL Decile Sorted Within MSA

	Mean (Standard Error)									
	Decile of Tract Average AAL (% of TIV) within MSA									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Percent White	59.2	56.8	57.1	56.9	56.4	57.7	59.0	61.2	63.2	64.6
	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)
Percent with Bachelor's Degree or Higher	33.8	33.1	33.2	32.7	32.7	32.2	32.2	32.3	31.8	30.7
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Median Household Income	75,302	74,338	74,052	74,013	73,898	74,558	75,300	76,488	76,259	73,852
	(474)	(468)	(466)	(465)	(475)	(475)	(480)	(486)	(488)	(482)
Home Value	439,936	435,164	443,989	436,560	440,513	436,495	448,987	448,828	454,085	473,207
	(4,450)	(4,336)	(4,605)	(4,567)	(4,716)	(4,575)	(5,032)	(4,853)	(5,120)	(5,823)
Percent Prime Age Labor Force Participation	83.1	82.9	82.8	82.8	83	82.8	82.6	82.6	82.5	81.4
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Percent Vacant (Excluding Seasonal)	7.4	7.8	7.7	7.8	7.8	7.7	7.7	7.6	7.9	8.6
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)

Note: Census tract average characteristics by within-MSA tract-level average AAL decile. Dollar values are in 2021 dollars.

Appendix Table 5. Change in Census Tract Characteristics (2010–2019) by Tract AAL Decile

	Mean (Standard Error)									
	Decile of Tract Average AAL									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Change in Percent with Bachelor's Degree or Higher	4.2	3.7	3.8	3.9	3.9	3.8	3.5	3.3	2.8	3.3
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Percent Change Median Household Income	9.5	4.3	4.1	4.3	4.0	4.3	4.9	5.4	4.3	4.3
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)
Change in Percent Prime Age Labor Force Participation	0.7	0.1	0.2	0.1	0.0	-0.2	-0.4	-0.4	-0.7	-0.5
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Change in Percent Vacant (Excluding Seasonal Units)	-0.9	-0.6	-0.4	-0.1	-0.2	-0.2	-0.1	0.2	0.4	0.2
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Percent Change in Total Population	8.4	7.0	4.6	4.7	5.5	6.3	6.9	6.6	6.9	5.5
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.2)

Note: Average change in select census tract characteristics by 2021 tract average AAL decile.

Appendix Table 6. Net Migration (2010–2019) by Tract Average AAL Decile and Tract Average AAL Decile Sorted Within MSA

Panel A: Mean Tract Net Migration (2010-2019) as % of 2010 Population										
	Decile of Tract Average AAL									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
All Perils	**-1.7**	**-1.0**	**-1.3**	**-1.8**	**-0.9**	**0.1**	**0.3**	**0.8**	**1.0**	**0.6**
	(0.2)	**(0.2)**	**(0.2)**	**(0.2)**	**(0.2)**	**(0.2)**	**(0.2)**	**(0.2)**	**(0.2)**	**(0.2)**
Severe Convective Storm	-1.5	2.7	1.8	-2.2	-3.2	-1.7	0.5	0.7	-1.2	0.4
	(0.2)	(0.3)	(0.3)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)
Inland Flood	-2.7	-1.3	-0.2	-0.1	0.4	0.2	0.1	0.9	0.3	-1.4
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Hurricane Wind	-2.7	-0.7	0.3	0.4	0.1	-3.2	-2.5	0.2	6.3	2.9
	(0.2)	(0.3)	(0.4)	(0.4)	(0.3)	(0.3)	(0.3)	(0.4)	(0.5)	(0.4)
Winter Storm	-3.4	7.1	3.6	2.8	-0.4	0.0	-1.7	-3.3	-3.7	-4.1
	(0.2)	(0.3)	(0.3)	(0.3)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Hurricane Storm Surge	2.4	1.2	-4.4	-6.9	0.5	-2.0	1.8	1.9	1.1	5.9
	(0.4)	(0.3)	(0.2)	(0.2)	(0.3)	(0.2)	(0.5)	(0.4)	(0.4)	(0.4)
Wildfire	3.4	-0.8	1.8	4.8	0.2	-0.5	2.0	5.7	6.3	4.6
	(0.5)	(0.5)	(0.5)	(0.6)	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.4)

Panel B: Mean Tract Net Migration (2010-2019) as % of 2010 Population Within MSA										
	Decile of Tract Average AAL Within MSA									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
All Perils	-0.8	-1.3	-0.4	-0.4	-0.7	-0.7	-0.2	0.6	0.4	-0.3
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)

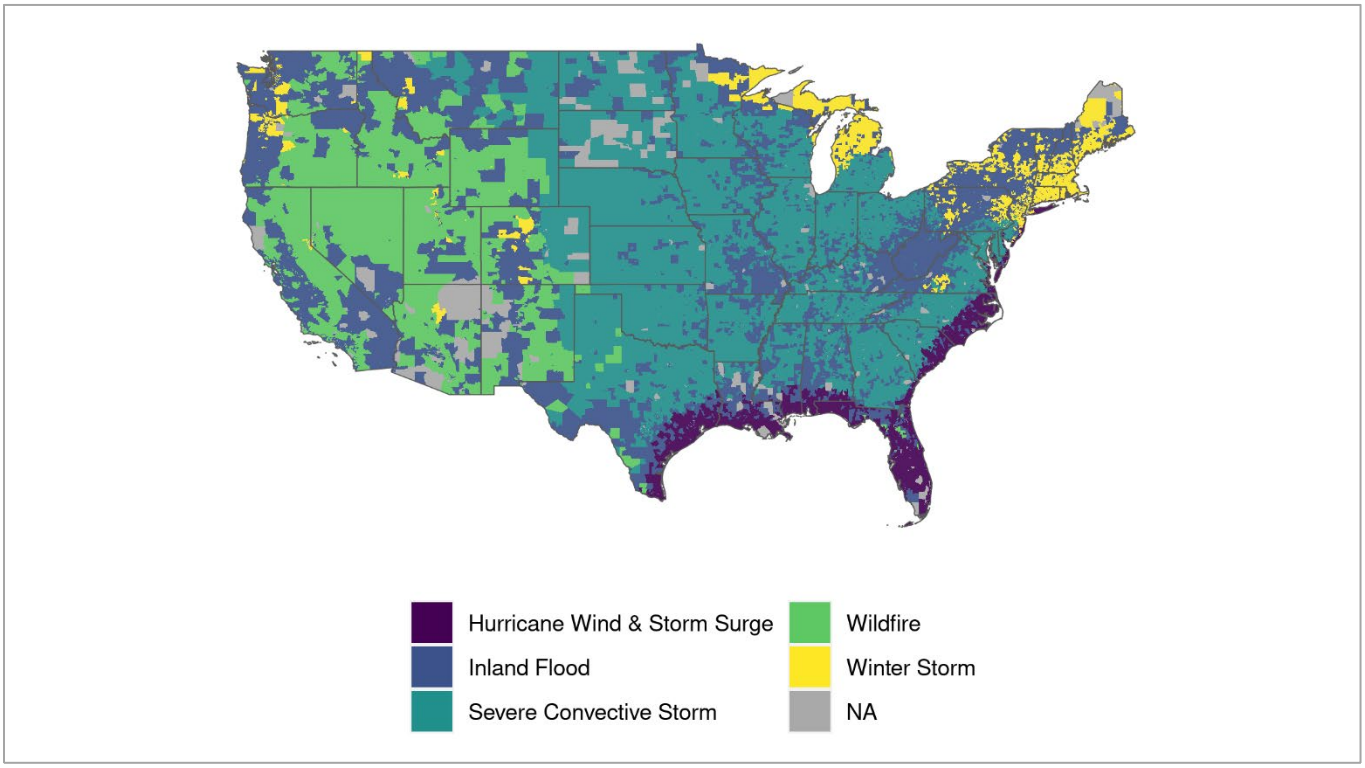
Standard errors in parentheses. Panel A: Average tract net in-migration during 2010–2019 by decile of tract composite peril average AAL and decile of tract sub-peril average AAL. Perils with non-modeled areas (Wildfire, Hurricane Storm Surge, and Hurricane Wind) exclude tracts outside the modeled area. For example, Hurricane Wind only includes tracts in states on the Gulf and Atlantic coasts. Panel B: Average tract net in-migration during 2010–2019 among the set of movers who moved within the same MSA by decile of tract composite peril average AAL sorted within MSA.

Appendix Table 7. Climate Change Beliefs and 2020 Voting Behavior by County AAL Decile

	Mean (Standard Error)									
	Decile of County Average AAL									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Percent Believe Global Warming is Happening	69.9	66.6	66.4	65.2	64.8	64.9	63.9	64.3	62.7	63.1
	(0.4)	(0.4)	(0.4)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Percent Said Personally Affected by Global Warming	44.4	42.0	41.5	40.5	40.7	41.0	40.4	40.8	39.8	40.5
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.2)	(0.3)	(0.3)	(0.3)
Percent Voted Republican in 2020	54.7	61.2	61.4	64.4	65.7	67.2	70.0	70.9	73.8	72.7
	(1.0)	(1.0)	(0.9)	(0.8)	(0.9)	(0.9)	(0.7)	(0.8)	(0.8)	(0.8)

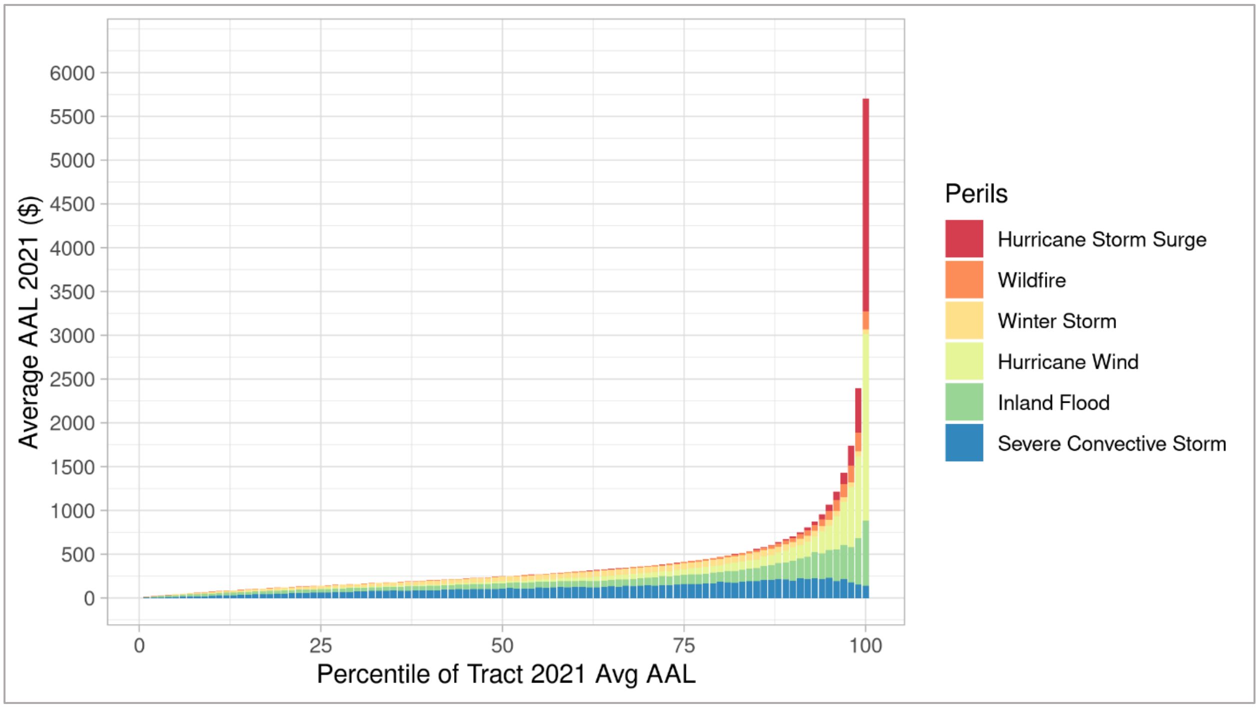
Note: Average county climate change beliefs survey response and 2020 voting behavior by 2021 tract average AAL decile. AALs measured as share of total insurable value.

Appendix Figure 1. Peril with Largest Proportion of All-Peril Tract AAL, 2021



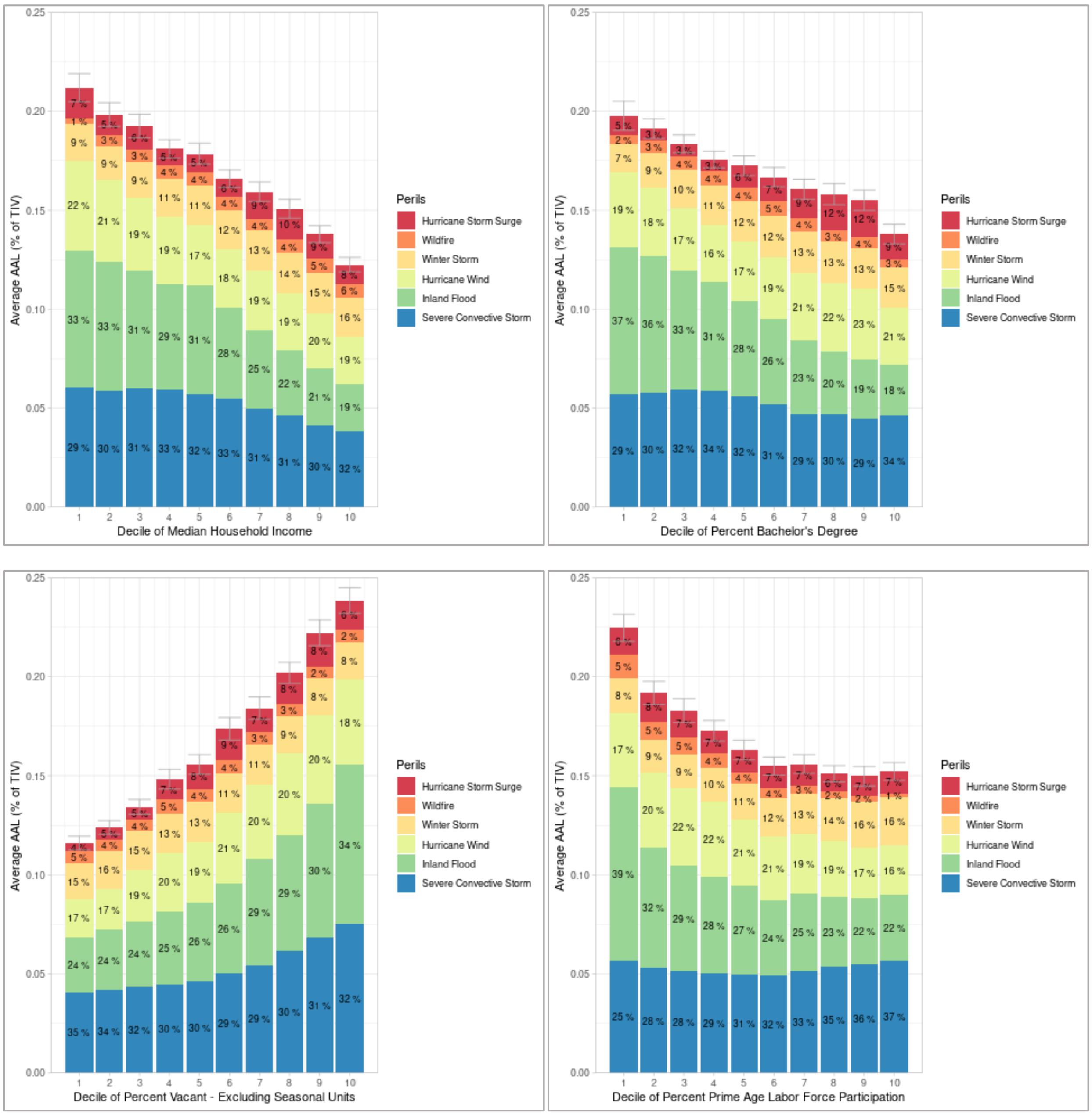
The peril or set of perils that make largest contribution to tract average all-peril AAL in 2021. AAL measured as share of total insurable value.

Appendix Figure 2. By-Peril Contribution to AAL in Dollars by Percentile of Tract AAL in Dollars



By-peril contribution of average AAL in dollars in each percentile of tract average AAL in dollars.

Appendix Figure 3(a)(b)(c)(d). By-Peril AAL by Deciles of Median Household Income, Bachelor's Degree or Higher Share, Vacancy Rate, and Prime Age Labor Force Participation Rate



Note: (a) By-peril average contribution to tract-level average AAL sorted by 2019 median household income. (b) By-peril average contribution to tract-level average AAL sorted by average 2019 share of adults with bachelor's degree or higher decile. (c) By-peril average contribution to tract-level average AAL sorted by average 2019 percent vacant home (excluding seasonal units) decile. (d) By-peril average contribution to tract-level average AAL sorted by average 2019 prime age labor force participation decile. Ninety-five percent confidence intervals for decile average AALs appear in gray. The intervals characterize the cross-sectional variation in tract-level average AALs and do not account for model uncertainty because CoreLogic does not provide sufficient information for us to account for such uncertainty.

Appendix A: ***Comparing Expected Dollar Losses with Realized Historical Losses in SHELDUS***

One way to assess the reasonableness of our estimates of expected losses is to compare them with historical losses. SHELDUS is a public database of historical direct losses caused by natural disasters in the U.S. The database contains county-level information on property and crop losses as well as injuries and fatalities from 1960 to the present for a wide selection of hazards. The data are primarily sourced from the National Centers for Environmental Information (NCEI) *Storm Data* publication, which catalogs information on "storm paths, deaths, injuries, and property damage."[37] SHELDUS is updated regularly with data additions and corrections. The subsequent analysis is based on SHELDUS 21.

We expect SHELDUS to systemically underreport losses because, when the original data source reports a loss estimate as a range, SHELDUS uses the lower bound of that estimate. In fact, prior to 1994, all NCEI *Storm Data* estimates were reported as logarithmic ranges ($<50, $50-500, $500-5,000, $5,000-50,000, $50,000-500,000, $500,000-$5 million, $5 million-50 million, $50 million to 500 million, $500 million to 5 billion).[38]

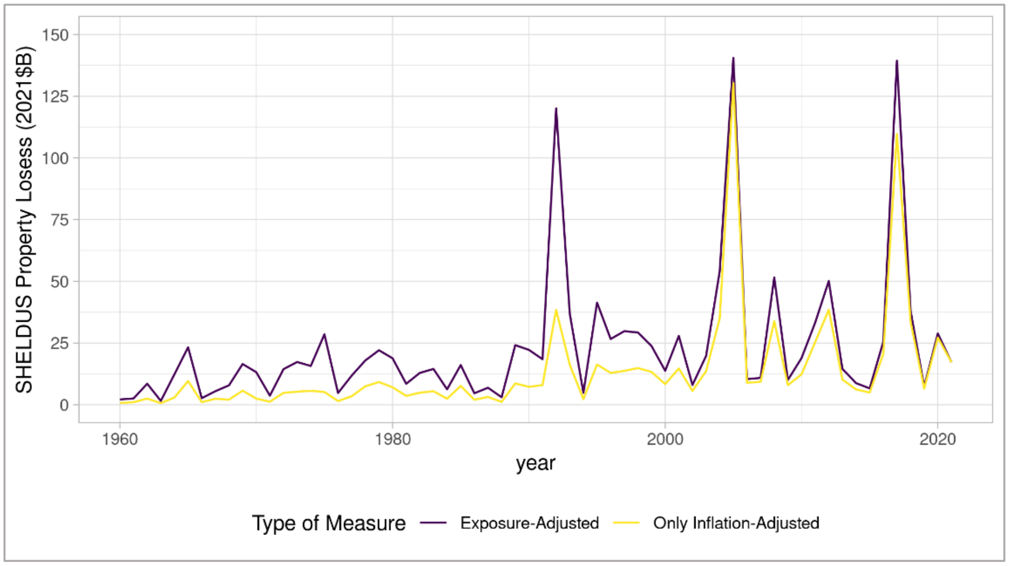
There are several additional considerations when trying to compare our expected losses for 2021 with historical losses in SHELDUS. The main ones are hazard types, property types, and time frame. Regarding hazard types, SHELDUS classifications allow us to construct a collection of hazards that are comparable in the aggregate with the set of hazards included in our expected loss estimates. We exclude losses from the following SHELDUS hazard types: heat, tsunamis/seiches, earthquakes, volcanoes, avalanches, fog, droughts, and landslides.

Regarding property types, our estimate of expected losses is for SFRs only. SHELDUS property losses include damages to all property types as well as damage to vehicles and infrastructure like roads and power lines.[39] We cannot isolate types of property losses in SHELDUS and so this feature will be a countervailing force against the underestimation stemming from SHELDUS using lower bound estimates.

The trickiest consideration is time frame. CoreLogic AALs are based on many simulations of a given year and therefore represent a large-sample average for a given point in time. The same quantitative exercise cannot be applied to the SHELDUS data. If conditions were held constant, we could "observe" annual expected loss by averaging across a very long period of historical losses. However, conditions are not held constant, which leaves a fundamental tradeoff between getting a historical average that is "longer-run" and one that better reflects current conditions. Thus, on one hand, we would like to go as far back in time as possible to avoid being misled by "lucky" or "unlucky" periods. On the other hand, environmental conditions and property exposure are not held constant over time, so the underlying risk may be less reflective of current conditions as one looks further into the past.

To address this issue, we examine multiple time frames and explicitly adjust for changes in exposure. The exposure adjustment accounts for the fact that the number of properties that is exposed to losses from hazards has increased over time. If we are trying to make a comparison between SHELDUS losses and expected losses in 2021, we want SHELDUS losses to be scaled to 2021 exposure. Consequently, we perform an exposure adjustment similar to the one performed in Wiese (2020).[40] In short, we construct county-year-level aggregate housing values using county-level data on total housing units for census years 1970, 1980, 1990, 2000, 2010, and 2020; county-level housing values for 2021 derived from our estimates described in methods section; the state-level Federal Housing Finance Agency (FHFA) All-Transactions House Price Index for the period from 1970 to 2022; and the GDP Price Deflator for the period from 1960 to 2021.[41, 42] We then use the ratio of the real housing exposure values with the 2021 housing exposure value to inflate the SHELDUS county-year damages, which are adjusted to 2021 dollars using the GDP price deflator.

Appendix Figure A1. SHELDUS Property Losses (1960–2021)



Note: SHELDUS property losses (1960–2021): exposure-adjusted and not exposure-adjusted.

The exposure-adjusted property damages for the entire history of SHELDUS (1960–2021) and for the post-2000 period are shown in Appendix Table A1. The average annual damage recorded in SHELDUS for 1960–2021 and for 2000–2021 are $23 billion and $33 billion, respectively, when adjusted for exposure. Given worsening environmental conditions and the underestimation built into SHELDUS estimates, it is not surprising our 2021 expected damage estimate of $39 billion for SFRs is larger than the SHLEDUS annual averages but is closer to the 2000-2021 annual average than the 1960-2021 annual average. Overall, we assess our current expected damage estimate of $39 billion to be in a reasonable range of exposure-adjusted average historical losses.

Appendix Table A1. Exposure-Adjusted SHELDUS Damages (1960–2021 and 2000–2021)

SHELDUS Hazard	Exposure-Adjusted Damage 1960-2021 (Billions of 2021 $)	% of Damage 1960-2021	Exposure-Adjusted Damage 2000-2021 (Billions of 2021 $)	% of Damage 2000-2021
Hurricane/Tropical Storm	495	34.5%	265	36.0%
Flooding	424	29.5%	266	36.2%
Tornado	111	7.7%	51	6.9%
Severe Storm/Thunder Storm	94	6.5%	7	1.0%
Wildfire	84	5.9%	48	6.5%
Hail	83	5.8%	48	6.6%
Wind	81	5.6%	32	4.3%
Winter Weather	55	3.8%	17	2.3%
Lightning	7	0.5%	1	0.2%
Coastal	4	0.3%	0.5	0.1%

Total	**1,437**	**100%**	**736**	**100%**
Annual Average	**23**	**N/A**	**33**	**N/A**

Note: By-hazard exposure-adjusted SHELDUS property losses for 1960-2021 and 2000-2021. "Hurricane/Tropical Storm" category includes some flooding from hurricanes and tropical storms.

In addition to assessing the aggregate damage estimate, we can also compare the breakdown of historical losses among hazards with the breakdown of our estimated expected losses by hazard. In this case, the best comparison is with the peril shares provided in Appendix Table 2 because those shares were determined using dollar-value AALs instead of AALs as a share of TIV. The crosswalk between SHELDUS hazards and CoreLogic perils is provided in Appendix Table A2. In the case of "hurricane/tropical storm", there is no clear 1:1 match to a CoreLogic peril. For example, some non-surge hurricane-related ground flooding is counted as "hurricane/tropical storm" in SHELDUS, while some is counted as "flooding".[27] Non-surge hurricane-related ground flooding (as well as non-hurricane coastal flooding) is classified as inland flooding in the CoreLogic data. Thus, the hurricane/tropical storm category is somewhat inflated relative to what it would be under CoreLogic classifications. For the same reason, flooding is smaller than what it would be under CoreLogic classifications.

Appendix Table A2. Crosswalk of SHELDUS Hazards and CoreLogic Perils

SHELDUS Hazard	**CoreLogic Peril**
Hurricane/tropical storm	Hurricane wind/inland flooding/hurricane storm surge
Flooding	Inland flooding
Tornado	Severe convective storm
Severe storm/Thunderstorm	Severe convective storm
Hail	Severe convective storm
Wind	Severe convective storm
Wildfire	Wildfire
Winter weather	Winter storm
Lightning	Severe convective storm
Coastal	Inland flooding

Note: Crosswalk between SHELDUS hazard names and CoreLogic perils.

One way to deal with this problem is to combine hurricane and flooding categories. For SHELDUS, this would include hurricane/tropical storm, flooding, and coastal (non-hurricane coastal flooding); for CoreLogic, it would include hurricane wind, hurricane storm surge, and inland flooding. Over the entire SHELDUS history, hurricane and flooding damages have been 65 percent of damages, while they are 53 percent of our estimate of 2021 expected losses (see Appendix Table A3). The difference suggests that we may be understating the influence of hurricanes and flooding. Conversely, the SHELDUS data suggest that we overstate the role of severe convective storms as well as winter storm. The damage share for wildfires lines up exactly. Overall, the by-peril share of expected damage from CoreLogic appears to be qualitatively similar to the realized damage share from SHELDUS.

Appendix Table A3. Hazard Shares of SHELDUS Damages and Our Estimate of Expected Losses

Hazard Category	**SHELDUS Damage Share (1960–2021)**	**Estimated 2021 Expected Loss Share Based on CoreLogic AALs**
Hurricane and flooding	65%	53%
Severe convective storm	25%	30%
Winter storm	4%	10%

Wildfire	6%	6%

Note: Comparison of peril share of property losses recorded in SHELDUS (1960–2021) and peril share of estimated 2021 expected losses based on CoreLogic AALs translated to dollar values.

We posit that there are several factors contributing to the observed differences. First, to the extent that environmental conditions have changed from 1960 to 2021, they may differentially impact the contribution of individual hazards. (Of course, if one thinks that hurricanes and flooding have been most acutely affected by environmental changes over the 1960–2021 period, then this explanation only exacerbates the difference). Similarly, it's possible that hazards have differential impacts on property types that may drive the differences because of the difference in property types included in our expected loss estimate compared with SHELDUS losses. For example, if hurricanes and flooding have a disproportionate impact on public infrastructure, then that would drive up the SHELDUS share compared with the share we estimate based on SFRs. Third, there is very likely overreporting of flood events in SHELDUS data relative to other hazards due to the collection procedure requirement that a monetary loss amount be provided for all flood events, even if it is a "guesstimate." For other events, the reporting entity is allowed to provide an unknown amount if they cannot provide a monetary loss estimate based on authoritative data.[43] Fourth, hurricane wind is only modeled by CoreLogic for states on the Gulf and Atlantic coasts. Elsewhere, we assume hurricane wind damage is zero. To the extent that hurricane winds have the potential to reach areas further inland, this assumption would cause us to underestimate the expected losses from hurricane wind.

Appendix B: Analyzing CoreLogic Risk Estimates Using Alternative Risk Estimates

Validating the average annual loss (AAL) values from CoreLogic, in the context of using these values for our research, is inherently difficult because the ground truth is unknown. One check of reasonableness is to compare to historical loss data, which we do in Appendix A. In that check we focus on the level of aggregate damage and the by-peril contribution to aggregate damage. However, our distributional analysis relies on the risk estimates from CoreLogic being ordinally accurate across geographies. One way to assess that is to examine how well CoreLogic's AAL estimates correlate with estimates from another catastrophic risk modeler. While we take no position on whether estimates from a different modeler are more or less accurate, we think rank-order agreement among the different sets of estimates provides more confidence in our distributional analyses.

We are able to perform this exercise for a subset of perils in our analysis using property-level AAL estimates from First Street Foundation (FSF). FSF is a non-profit organization that models flood, hurricane wind, wildfire, and extreme heat risk for the contiguous U.S. FSF's "flood" peril is equivalent to the combination of CoreLogic's Inland Flooding and Hurricane Storm Surge perils. Detailed methodology for all of First Street Foundation's models can be found on their website.[44]

We compare the rank-order of AAL estimates between CoreLogic and FSF for Inland Flooding and Hurricane Storm Surge (together referred to as "Flood"), Hurricane Wind, and Wildfire. We compare tract-level average AALs among SFRs. In order to conduct the comparison, we match the SFRs identified in the CoreLogic data to properties in the FSF data using a nearest-neighbor geospatial match. Like in the main analysis, we limit the comparison to tracts where at least 30 SFRs have a non-missing AAL value reported in the CoreLogic and First Street Foundation data. We normalize the nominal AALs provided by FSF by their estimate of rebuilding cost in order to be consistent with how CoreLogic expresses AAL values. Because nominal AAL values can infrequently exceed FSF's rebuilding cost measure, we top-code AAL values at 1. Note that because we have to normalize FSF's AALs, differences between each entity's AAL estimates could be driven by the underlying the hazard risk estimates, FSF's rebuilding cost estimate, or a combination of both.

There are a few notable differences between the two data sources beyond the inherent differences in their risk modeling approaches. First, the climate modeling data and emissions pathways underlying the risk modeling are of slightly different vintages. The CoreLogic estimates used in this analysis are based on the climate modeling data featured in the Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report (AR5) completed in 2014. Consequently, their baseline estimate is based on Representative Concentration Pathway (RCP) 4.5, which is the "middle-of-the-road" emission pathways featured in AR5. The FSF estimates used in this analysis rely on the latest climate modeling data from the IPCC's Sixth Assessment Report (AR6), which was completed in 2022. Therefore, their baseline estimates are based on Shared Socioeconomic Pathway (SSP) 2-4.5, which is the "middle-of-the-road" emission pathways featured in AR6.

Second, FSF and CoreLogic have different sources of property data that feed into their risk modeling. FSF licenses property data from the company LightBox. CoreLogic uses its own proprietary property data collection.

Third, the modeled areas for some perils differ between CoreLogic and FSF. As noted in the Methods section, CoreLogic only models Wildfire for the western half of the country plus Florida and only models

Hurricane Wind risk for states on the Gulf and Atlantic coasts. FSF estimates non-zero Hurricane Wind risk further inland, including properties in states like Tennessee, Arkansas, and Oklahoma. Similarly, FSF models wildfire risk for the entire contiguous U.S. and finds non-zero wildfire risk for properties outside of the CoreLogic modeled area. According to First Street Foundation's estimates, the areas with the greatest wildfire risk outside of CoreLogic's modeled area are Oklahoma, South Dakota, and parts of West Virginia, Kentucky, North Carolina, and Georgia.

Lastly, FSF does not provide an AAL estimate for wildfire. However, they provide a "destruction probability", which represents the annual likelihood of a structure being destroyed. Given that conditional on a structure combusting, it is very likely to be completely destroyed, the destruction probability can substitute well as an approximation of the AAL (as share of rebuilding cost).[45]

With those caveats in mind, Appendix Table B1 provides the correlation between the average tract AALs and average tract AAL deciles from CoreLogic and FSF. In constructing the composite AAL (Flood + Hurricane Wind + Wildfire), we assume the expected loss is zero if it is outside the CoreLogic modeled area for Hurricane Wind and Wildfire. The composite AAL deciles correlate moderately well at r = 0.58. The tract average AAL values correlate similarly at r = 0.49. The by-peril correlations suggest that there is greater rank-order agreement for Hurricane Wind damage than for Flood and Wildfire damage.

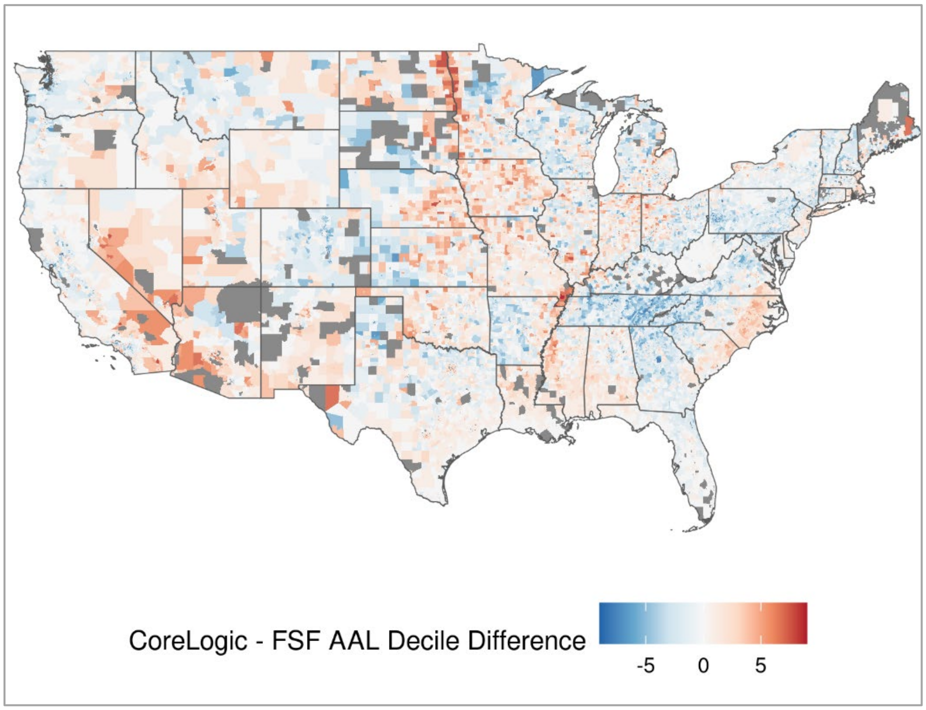
Appendix Table B1. Correlation Between CoreLogic and First Street Foundation Tract Average AALs

Peril	Correlation of Tract Average AAL Decile	Correlation of Tract Average AAL
Flood	0.41	0.37
Hurricane Wind	0.88	0.82
Wildfire	0.56	0.34
Composite (Flood + Hurricane Wind + Wildfire)	**0.58**	**0.49**

Note: In the case of Hurricane Wind and Wildfire, analysis limited to areas modeled by both CoreLogic and First Street Foundation. Tracts outside of peril's modeled area are considered to have no risk for that peril when generating composite AAL.

Notably, agreement between the two sets of composite AAL estimates is strongest among the riskiest tracts – 54 percent of tracts in the 10th decile of AAL according to CoreLogic were also in the 10th decile of AAL according to FSF. Another 21 percent of CoreLogic's 10th decile tracts were in FSF's 9th decile. This is evident in Appendix Figure B1, which maps the difference in tract AAL decile, and shows strong agreement along the Gulf and southern Atlantic coasts, where many of the riskiest tracts are located.

Appendix Figure B1. Difference between CoreLogic and First Street Foundation Tract Average AAL Decile for Flood, Hurricane Wind, and Wildfire



Note: Difference between tract average AAL decile using CoreLogic and First Street Foundation data. Positive number (red) indicates the CoreLogic decile is greater than the First Street Foundation decile. The maximum difference in decile placement is nine. Tracts in grey have fewer than 30 single-family residences with AAL estimates in CoreLogic and/or First Street Foundation data.

Appendix C: Validating the CCP Migration Measure Against ACS County-to-County Flows Data

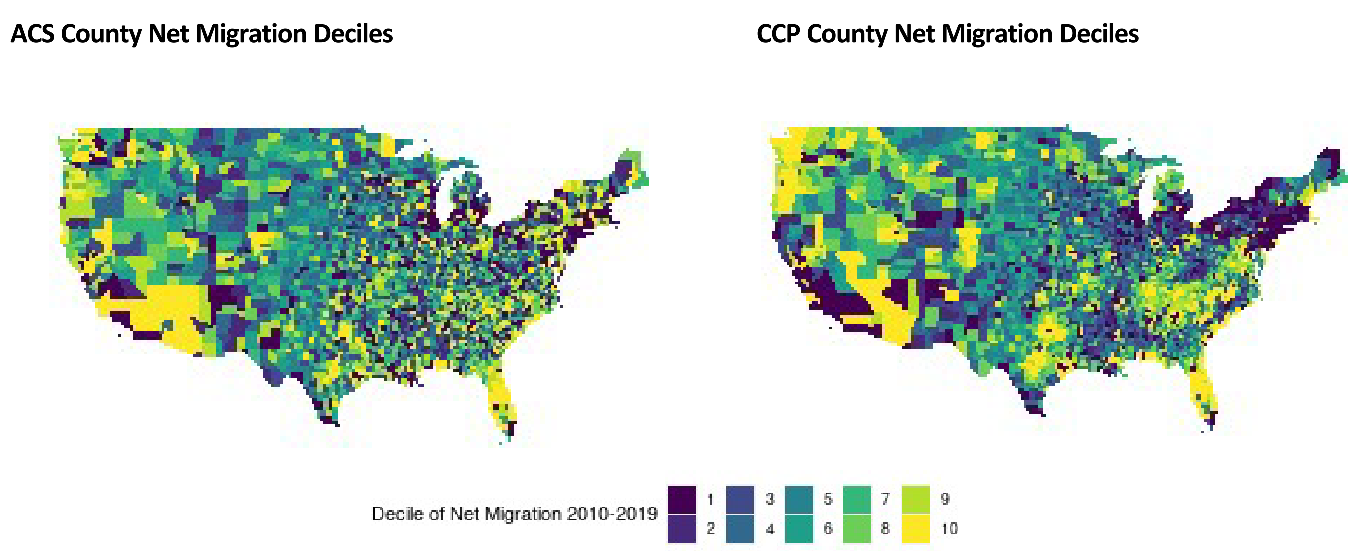
We examine net migration between 2010 and 2019 for areas of different climate risk using the FRB NY/Equifax CCP data (see Appendix Table 6). One concern with using the CCP data set is its selection criteria of individuals with credit histories, which skews the sample towards older and more financially sophisticated individuals. Thus, CCP-based migration estimates would be biased to the extent that migration patterns systematically differ between those with and without credit histories.

We test the reasonableness of the CCP-based migration measure by comparing its county-level migration estimates with the ACS county-to-county migration flows for 2010–2019. For this comparison, we perform steps (1)-(4) from above using the CCP, except that we aggregate to the county level, which precludes the need to convert to 2010 census tract definitions. For the ACS-based measure, we use the 2010–2014 and 2015–2019 county-to-county flows data and sum the values to generate a total 2010–2019 net migration estimate for each county.

The ACS and the CCP net migration counts correlate relatively strongly (r = 0.84), which lends support to use of the CCP-based net migration estimates at the tract level. This result is consistent with more comprehensive assessments of migration estimates from the CCP using different sources of data, including the ACS data.[46]

The deciles of ACS and CCP county net migration counts are shown in Appendix Figure C1. The highest decile represents the counties with the most net in-migration. The CCP-based deciles suggest more severe out-migration in the Northeast than the ACS-based deciles, but overall, the deciles are consistent with one another.

Appendix Figure C1. Comparison of ACS and CCP County-Level Net Migration Estimates, 2010–2019



Note: Deciles of county-level net in-migration during 2010–2019 using ACS (left) and CCP (right) data.

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