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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 (storms, floods, hurricanes, and wildfires) that owner-occupied single-family residences 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 from climate-related perils is approximately $19 billion per year. Severe convective storms and inland floods account for almost half of the expected damage. The central and southern parts of the U.S. are most exposed to climate-related physical risk, with hurricane-exposed areas on the Gulf and South Atlantic coasts being the riskiest areas. Relative to currently low-risk areas, currently high-risk areas have lower household incomes, lower labor market participation rates, and lower education attainment, suggesting that the distribution of climate-related physical risk is correlated with economic inequality. By 2050, under business-as-usual emissions, average expected damage is projected to increase monotonically with current average expected damage, which implies that long-term policies that aim to mitigate climate-related physical risk are likely to be progressive.

JEL Codes: G5, Q54, D63

Keywords: Climate Risk, Physical Risk, Inequality, Housing

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For the average American, 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, prior research works have mostly focused on the impact that flood risk has on real estate.[2, 3] However, climate change is likely to affect many forms of natural disasters.[4] Therefore, studies that leave out other climate-related perils 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 major climate-related perils (severe convective storms, winter storms, inland floods, wildfires, hurricane winds, and hurricane storm surges) that owner-occupied single-family residences (SFRs) face in the contiguous U.S. The physical risk data are produced by CoreLogic, which is a major commercial catastrophic risk modeler and property data vendor. Its proprietary models incorporate natural hazard information with detailed structure and property characteristics to generate structure-level estimates of loss for several different perils. The base measure of our analysis is 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. The AALs provided by CoreLogic are not dollar values; they are provided as shares of total insurable value (TIV), which can be understood as the replacement cost of the structure.

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. With this limitation in mind, we perform several validation exercises and find that the AAL estimates appear to be in a reasonable range with respect to relevant historical data (see Appendix A for more details). The result gives us confidence that group averages at the tract level and above are likely to be directionally and ordinally accurate.

Combining the property-level physical data with precise property location and local economic conditions data from the American Community Survey (ACS) 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.[5]

Results

Which perils are currently most damaging and which regions are most affected?

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 owner-occupied 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 within those coastal states than it does for hurricane storm surge. Thus, more than nine times as many SFRs are exposed to hurricane wind damage. Inland floods can potentially affect about the same proportion of SFRs as hurricane wind, but it is not geographically concentrated in the same way. Inland flood risk is concentrated along rivers, lakes, and streams, as well as in pockets of mountainous regions that are susceptible to flash flooding. Inland floods are also relevant in coastal areas, since ground flooding from hurricane precipitation and nonhurricane coastal flooding are classified as inland floods. Wildfires are mostly limited to the western half of the country, with the notable exception of Florida.

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 87 percent of SFRs having nonzero expected losses from this climate-related peril.

The wide geographic reach of severe convective storms plays a key role in them having the highest expected loss averaged over all SFRs. Averaged across all SFRs in the contiguous U.S., severe convective storms cause expected losses of 0.06 percent of TIV, compared with 0.01 percent for both hurricane storm surge and wildfires. 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 (0.16 percent) among SFRs with some risk of damage, followed by inland floods (0.09 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 nonzero AALs for hurricane storm surge and inland floods both face expected losses of over 2 percent of TIV. Hurricane winds and wildfires are the next closest at 0.59 percent and 0.43 percent, respectively.

We take a more detailed look at the regional breakdown of expected losses in Table 2. Figure 1(a) presents a visual representation of the AAL geographic distribution. 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 winds) and New England (winter storms) do different perils play the largest role in expected losses.

The greatest expected losses (as a share of TIV) are in the West South Central (0.31 percent), East South Central (0.22 percent), West North Central (0.20 percent), and South Atlantic (0.18 percent). Collectively, these regions encompass the tornado-prone heartland, the hurricane-prone Gulf and southern Atlantic coasts, and flood-prone Appalachia and the Mississippi River basin. The least risky regions, on average, are the Pacific (0.06 percent) and Mountain (0.10 percent) regions, where wildfires and inland floods are the main contributors to expected losses. On average, the riskiest region in terms of AAL as a share of insurable value, the West South Central, is more than five times riskier than the least risky region, the Pacific.

In Table 2, we also provide estimates of AAL in 2020 dollars. We translate AALs into dollar values by multiplying property-level AALs by an estimate of structure value generated using tract-level ACS median home value estimates and tract-level land share of home value estimates.[6] We use median home values in this calculation; as a result, we are likely underestimating average structure values because of the right-skewed distribution of home values.[7]

Average expected losses in dollars are greatest in the West South Central ($456) region. However, expected losses in the East South Central ($260) and West North Central ($280) are surpassed by the South Atlantic ($313) when using AALs in terms of dollars because of the higher structure values in the region. Similarly, on the lower end, the East North Central ($149) has the smallest expected losses because of the relatively low structure values compared with the Pacific ($167) and Mountain ($219) regions. In dollar terms, the average expected losses in the region with the greatest average expected loss (West South Central) are close to three times as large as the average expected losses in the region with the lowest average expected losses (East North Central).

In aggregate, our analysis indicates that annual expected losses for SFRs due to all climate-related perils are $18.9 billion, based on 2021 conditions. The West South Central and South Atlantic have the largest aggregate expected losses because of a combination of high average risk and large SFR exposure. The full region and peril breakdown of AALs in terms of dollars is provided in Appendix Table 1. Roughly $6.1 billion (32 percent) is attributable to severe convective storms, $4.6 billion (24 percent) to inland floods, and $3.6 billion (19 percent) to hurricane winds.

Who bears the current physical risk?

Having property-level estimates of expected losses enables us to analyze distributional impacts at a granular level. We use census tract-level measures of economic and demographic characteristics to study how they vary with the average physical risk in the tract. Specifically, we calculate the average all-peril AAL as a percentage of TIV for each tract and sort tracts into deciles. Figure 1(a) shows the AAL decile for each tract in the contiguous U.S.

The map highlights the varied risk across regions while also shedding light on the within-region variation. Most of the safest tracts are in the Pacific and Mountain regions. In fact, 60 percent of Pacific tracts are in the lowest decile of risk, and the Pacific region accounts for up to 85 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 (37 percent), South Atlantic (30 percent), and East South Central (10 percent) regions.

The distribution of tract-level average AALs is highly right-skewed. As shown in Figure 1(b), the difference between the average AAL of each decile increases rapidly as we approach the top decile. Tracts in the highest deciles of average expected losses are more than twice as risky as tracts in the ninth decile, on average. Tracts in the top decile seem to face a distinctively high level of risk compared with other tracts, largely because of hurricane-related damage. Hurricane storm surge and hurricane winds 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.

Table 3 shows select tract characteristics by AAL decile based on the 2015–2019 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 vacancy rates, a proxy of neighborhood quality.[8] The differences between the highest-risk decile and the fifth decile are significant: 19 percent higher education attainment rate, 16 percent lower household income, 8 percent lower labor participation rate, and 75 percent greater vacancy. The differences are even greater between the highest-risk decile and the lowest-risk decile.

Urban status is a contributor to the pattern shown in Table 3. Urban tracts face less physical risk, on average, than rural tracts. This statement is 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 2), 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 in less economically viable areas.

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.[9]

Additionally, the income pattern we observe appears to be driven by cross-metro, as opposed to intrametro, differences. The income difference between high- and low-risk tracts disappears when we sort tracts within metropolitan statistical area (MSA) average AAL deciles (see Appendix Table 3). This result is suggestive that a large component of the income effect may be caused by lower income households' inability to afford to live in more expensive MSAs, which tend to be safer. However, the prime age labor force participation rate, vacancy rate, and education attainment patterns remain, although with smaller differences across AAL deciles.

Similar patterns of economic inequality appear when we examine changes in tract characteristics from 2010 to 2019 across 2021 average tract AAL deciles. Appendix Table 4 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. Appendix Table 5 shows similar patterns for prime age labor force participation and education attainment among the subset of 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.[10]

Finally, we do not see much variation in 2010–2019 total population change across AAL deciles (see Appendix Table 5). Further, we examine net migration by AAL decile using the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP) (see the Methods and Data section for a complete description of methodology). We do not find evidence that, in aggregate, people are migrating away from higher-risk areas. The results in Appendix Table 6 seem to suggest the opposite. In aggregate, climate-related physical risk does not appear to be a significant deterrent of in-migration to high-risk places.[11]

To further investigate the potential regressive impact of physical risk, we look at tract average AALs by decile of median household income. Figure 2(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 expected losses, on average. Not surprisingly, average AAL is negatively correlated with educational attainment and the labor force participation rate, and it is positively correlated with the home vacancy rate (see Appendix Figure 1). In aggregate, it appears that climate-related physical risk is regressive with respect to current household income and related local economic characteristics. Hence, policies that mitigate such risk are likely to be progressive.

In contrast with the clear pattern that we see across household income deciles, the average AAL across deciles of the Black and non-White Hispanic population share show no such pattern, as displayed in Figure 2(b). The average AAL is similar in both the lowest and highest deciles of the Black and non-White Hispanic share. Hurricane-related damage plays a larger role for tracts with the greatest Black and non-White Hispanic share, while inland floods play an outsized role for tracts in the lowest decile of the Black and non-White Hispanic share. The geographic distribution of Black and non-White Hispanic populations contributes to these patterns. Tracts in the highest decile of the Black and non-White Hispanic share are concentrated in urban areas, including many along the Atlantic and Gulf coasts. Tracts in the lowest decile are less geographically concentrated and tend to be in more rural areas like Appalachia and the Mississippi River basin.

What does future physical risk look like?

Physical risk is expected to increase in the future because of climate change. 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. The middle-of-the-road 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.[12]

Under RCP 4.5, we estimate that expected losses for owner-occupied SFRs in the contiguous U.S. will increase by 3.6 basis points of TIV by 2050. This represents a 22 percent increase, on average. Under RCP 8.5, we estimate an average increase in expected losses of 5.3 basis points of TIV, a 33 percent increase (See Appendix Table 7). These estimates are based on the current inventory of SFRs and therefore do not consider future changes in development and structure quality.

As shown in Table 4, most 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 winds are the largest component. Overall, hurricane winds will make up 17 percent of the national increase. Despite its limited geographic scope, hurricane storm surge will make also up 17 percent of the national average increase in expected losses.

The largest increase in AAL will occur in the regions where current expected losses are the greatest. This finding suggests a positive relationship between current expected losses and the 2021–2050 change in expected losses. To examine this relationship more fully, we plot the tract-average change in AAL by the tract-average 2021 AAL in Figure 3(a). 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 more driven by hurricane winds and hurricane storm surge than they are in the other deciles. Figure 3(b) shows that, with respect to 2019 median household income deciles, the increase in AAL from

2021 to 2050 is regressive. Therefore, climate risk mitigating policies are likely to continue to be progressive in the future.

Discussion

In this analysis, we provide a comprehensive accounting of the climate-related physical risk to owner-occupied 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 nonproperty or indirect losses, such as loss of business, hardship costs, mortality costs, or the cost of potential lost future growth.[13] Our dollar-value estimate of expected losses for owner-occupied SFRs also serves as a lower bound because we use median home value estimates to generate expected losses in dollar terms. 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.[14]

Within the listed confines, we calculate a lower bound estimate of $18.9 billion in annual expected property losses to owner-occupied SFRs due to six climate-related perils. This number is relatively small when compared with the size of the national economy — it represents less than 0.1 percent of U.S. gross domestic product (GDP). Of course, 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 some insights into where and who bear the physical risk. Geographically, the southern and central parts of the country face the greatest physical risk because of a combination of hurricane- and flood-related damage and severe convective storms. Within those areas, it is the coastal, hurricane-exposed areas that face the most risk. The set of tracts with the greatest expected losses are dominated by tracts on the Gulf and South Atlantic coasts, where hurricane winds and hurricane storm surge are the predominant risks. 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-exposed areas.

Demographically, we find that low-income, less educated, low–labor market participation, and high–vacancy rate areas face the greatest physical risk. The finding is suggestive 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 in nature. 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 fully fall on homeowners.[15]

Moreover, 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 winds. 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.[16]

In terms of targeting specific perils, we find that inland floods are the largest contributor to expected losses in the lowest-income areas. 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 at-risk inland areas.[17] Moreover, insured households in at-risk areas have nearly double the household incomes of uninsured households in at-risk areas, suggesting the insurance gap is more pronounced among low-income households.[18] Consequently, efforts to increase flood insurance take-up in areas at risk of flooding will likely be disproportionately beneficial to low-income households.

References

[1] The 2019 Survey of Consumer Finance. December 9, 2022. Distributed by the Federal Reserve Board (Accessed August 2023). www.federalreserve.gov/econres/scfindex.htm.

[2] Wing, O. E. J. et al. "Inequitable patterns of US flood risk in the Anthropocene." *Nature Climate Change* 12(2), 156–62 (2022).

[3] Gourevitch, J. D. et al. "Unpriced climate risk and the potential consequences of overvaluation in US housing markets." *Nature Climate Change* 13(3), 250–57 (2023).

[4] IPCC. "Summary for Policymakers." In: *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC, Geneva, Switzerland, pp. 1–34 (2023).

[5] Taber, C. R. "The rising college premium in the eighties: Return to college or return to unobserved ability?" *The Review of Economic Studies* 68(3), 665–91 (2001).

[6] Davis, M. A., Larson, W. D., Oliner, S. D., & Shui, J. "The price of residential land for counties, ZIP codes, and census tracts in the United States." *Journal of Monetary Economics* 118, 413–31 (2021).

[7] Davis, M. A. & Palumbo, M. G. "The price of residential land in large US cities." *Journal of Urban Economics* 63(1), 352–84 (2008).

[8] Garvin, E., Branas, C., Keddem, S., Sellman, J., & Cannuscio, C. "More than just an eyesore: Local insights and solutions on vacant land and urban health." *Journal of Urban Health* 90, 412–26 (2013).

[9] Coven, J., Gupta, A. & Yao, I. "JUE Insight: Urban flight seeded the COVID-19 pandemic across the United States." *Journal of Urban Economics* 133, 103489 (2023).

[10] Boustan, L. P., Kahn, M.E., Rhode, P. W., & Yanguas, M. L. "The effect of natural disasters on economic activity in US counties: A century of data." *Journal of Urban Economics* 118, 103257 (2020).

[11] Indaco, A. & and Ortega, F. "Adapting to climate risk? Local population dynamics in the United States." IZA Institute of Labor Economics Discussion Paper Series (2023).

[12] Hayhoe, K. et al. "Our changing climate." In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II*. Washington, D.C.: U.S. Global Change Research Program, pp. 72–144 (2018).

[13] Hsiang, S. et al. "Estimating economic damage from climate change in the United States." *Science* 356(6345), 1362–9 (2017).

[14] Oh, S. S., Sen, I., & Tenekedjieva. A.-M. "Pricing of climate risk insurance: Regulation and cross-subsidies." Finance and Economics Discussion Series 2022-064. Washington, D.C.: Board of Governors of the Federal Reserve System. SSRN 3762235 (2022).

[15] Wagner, K. R. H. "Designing insurance for climate change." *Nature Climate Change* 12(12), 1070–2 (2022).

[16] Acemoglu, D., Johnson, S., & Robinson, J. A. "Institutions as a fundamental cause of long-run growth." *Handbook of Economic Growth* 1, 385–472 (2005).

[17] Kousky, C. "Financing flood losses: A discussion of the national flood insurance program." *Risk Management and Insurance Review* 21(1), 11–32 (2018).

[18] FEMA. *An Affordability Framework for the National Flood Insurance Program* (2018) (Accessed August 2023). www.fema.gov/sites/default/files/2020-05/Affordability_april_2018.pdf.

Methods and Data

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 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, 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.

The AALs are *ground-up losses*, meaning they represent gross losses to the structure and contents prior to applying any insurance policy terms, like the 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. Importantly for our multiperil analysis, AALs are additive because they are expectations.

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).[19] Our main results are based on RCP 4.5, which depicts a middle-of-the-road climate scenario.

The AALs are generated by CoreLogic's proprietary climate, hazard, and vulnerability models. Inputs to CoreLogic's modeling consist of "industry-leading property data with replacement costs, valuation elements, and natural hazard information."[20] 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. CoreLogic does not provide measures of uncertainty related to its AAL estimates.

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.

Perils

We focus on AALs for six climate-related perils provided by CoreLogic: inland floods, hurricane winds, 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 the same 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 winds 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 winds 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 owner-occupied single-family residences (SFRs). To determine SFR status, we use the CoreLogic-standardized land use code. To identify whether the SFR is owner-occupied, we use an owner occupancy code derived by CoreLogic, which mostly relies on the likeness of the owner's mailing address and the property's physical address. In instances in which the owner occupancy status is unknown, we treat the property as owner-occupied. Similarly, for instances in which properties are identified generically as "residential," we assume them to be SFRs. We do this because (1) most residential properties are SFRs and most SFRs are owner-occupied, and (2) we do not want to systematically exclude properties in counties where the underlying data collected from the county assessor offices prevent CoreLogic from determining absentee status or specific land use. These choices together mean our sample of properties likely includes some nonowner-occupied SFRs. Our sample of about 81 million properties overstates the number of owner-occupied SFRs by about 10 percent based on the ACS count of owner-occupied SFRs. We account for this when we later aggregate to higher geographic levels.

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 71,065 out of the total 72,247 land area tracts in the contiguous U.S. have at least one owner-occupied SFR, as identified by CoreLogic. 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 71,065 tracts, we exclude about 3 percent of the tracts that had fewer than 30 nonmissing AAL values for owner-occupied SFRs. These are either tracts with a very small number of owner-occupied SFRs or tracts where data limitations prevented CoreLogic from providing an AAL estimate for most properties. We are left with a final sample of 68,821 tracts.

Census Tract Characteristics

Census tract characteristics were 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.[21] The ACS fields used were:

1. Median Household Income (B19013_001)
2. Median Home Value (B25077_001)
3. Population 25 Years and Over (B15003_001)
4. Population 25 Years and Over – Bachelor's Degree (B15003_022)
5. Population 25 Years and Over – Master's Degree (B15003_023)
6. Population 25 Years and Over – Professional Degree (B15003_024)
7. Population 25 Years and Over – Doctorate Degree (B15003_025)
8. Population 16 Years and Over (B23025_001)
9. Population 16 Years and Over – In Labor Force (B23025_002)
10. Male: 25 to 29 Years: In Labor Force (B23001_025)
11. Male: 30 to 34 Years: In Labor Force (B23001_032)
12. Male: 35 to 44 Years: In Labor Force (B23001_039)
13. Male: 45 to 54 Years: In Labor Force (B23001_046)
14. Female: 25 to 29 Years: In Labor Force (B23001_111)
15. Female: 30 to 34 Years: In Labor Force (B23001_118)
16. Female: 35 to 44 Years: In Labor Force (B23001_125)
17. Female: 45 to 54 Years: In Labor Force (B23001_132)

18. Housing Units (B25002_001)
19. Housing Units — Vacant (B25002_003)
20. Vacant Housing Units – For Seasonal, Recreational, or Occasional Use (B25004_006)
21. Occupied Housing Units (B25032_001)
22. Occupied Housing Units – 1, Detached (B25032_003)
23. Occupied Housing Units – 1, Attached (B25032_004)
24. Occupied Housing Units – Mobile Home (B25032_011)
25. Total Population (B03002_001)
26. Total Population – Not Hispanic or Latino: White Alone (B03002_003)
27. Total Population – Not Hispanic or Latino: Black or African American Alone (B03002_004)
28. Total Population – Hispanic or Latino (B03002_012)
29. Total Population – Hispanic or Latino: White Alone (B03002_013)

Tracts were designated as urban core, suburban, or rural based on 2010 Census Urban Areas and Core-Based Statistical Area (CBSA) definitions. A tract was classified as urban core if the tract centroid intersected with a Census Urbanized Area. A tract was defined as suburban if it was located within a Census CBSA but not within a Census Urbanized Area. All tracts outside CBSAs were 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 68,821 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 decile to mitigate the influence of extreme values. Last, we take averages of the tract characteristics within each decile.

Generating AALs in Dollars

We convert the CoreLogic AALs, which are normalized by TIV, to dollar values so that we can estimate expected losses in dollars at the tract level and above (see Table 2 and Appendix Table 1). We generate an estimate of the median structure value for each census tract by adjusting the tract median home value by the land value share calculated in Davis et al. (2021).[22] We then multiply that measure of structure value by tract average AAL to generate an average AAL in dollars for each tract.

As far as we are aware, Davis et al. (2021) provide the most granular geographical estimates of land value that cover nearly the entire U.S. They generate average land share of SFR property value for over 53,000 census tracts based on 2012–2019 data. They also provide zip code-, county-, and state-level estimates, which allow us to fill in land value shares for the remaining tracts in order of decreasing geographical granularity. Ultimately, we were able to use a tract-level estimate for 77 percent of the tracts in our sample, a zip code-level estimate for 20 percent of the tracts, a county-level estimate for 1 percent of the tracts, and a state-level estimate for 2 percent of the tracts.

Unlike counties and states, zip codes are not coterminous with tract boundaries. Therefore, to apply zip code estimates to tracts, we needed a geographical crosswalk between tracts and zip codes. There is no well-established crosswalk for tracts to zip codes, so we generated a custom crosswalk using CoreLogic's property data. We map all properties with structures on them into 2010 tracts and 2010 Zip Code Tabulation Areas, which are polygon representations of zip codes, using Census shapefiles. From the property-level data, we can generate the count of properties in each zip code–tract pair. We merge that crosswalk with the Davis et al. zip code land value share estimates, and then we aggregate to the tract level using the zip code–tract property count as the weight in the weighted average.

Aggregating to Census Region Division and Contiguous U.S.

As mentioned in the prior section, for the entire contiguous U.S., our sample of properties in the CoreLogic data overstates the number of owner-occupied SFRs by about 10 percent compared with the ACS estimates. Consequently, when aggregating AALs to the Census Region Division– or national levels, like in Table 2, we use tract average AAL and then perform a weighted average using the ACS-provided count of owner-occupied SFRs in each tract as the weight instead of the count from CoreLogic.

Net Migration by Tract AAL Decile

We examine net migration between 2010 and 2019 for areas of different climate risk using the FRBNY Consumer Credit Panel/Equifax Data (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.[23] 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 B.

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

1. Identify individuals in the CCP who have a different reported (scrambled) 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 like 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.[24] 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. All results are qualitatively and quantitatively similar if we multiply by 20.
5. Scale migration counts by 2010 tract population.
6. Group by AAL decile and winsorize the distribution at 1 percent and 99 percent within each decile.
7. Calculate average net migration as share of 2010 population within AAL tract deciles.

We also consider migration within MSAs to see 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.

References (Methods and Data)

[19] IPCC. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* IPCC, Geneva, Switzerland (2014).
[20] CoreLogic, Climate Risk Analytics (Accessed July 2023). www.corelogic.com/data-solutions/property-data-solutions/climate-risk-analytics.
[21] Bloom, N., Davis, S. J., & Zhestkova, Y. "COVID-19 shifted patent applications toward technologies that support working from home." In *AEA Papers and Proceedings*, vol. 111, pp. 263–6 (2021).
[22] Davis, M. A., Larson, W. D., Oliner, S. D., & Shui, J. "The price of residential land for counties, ZIP codes, and census tracts in the United States." *Journal of Monetary Economics* 118, 413–31 (2021).
[23] DeWaard J., Johnson J., & Whitaker S. "Internal migration in the United States: A comprehensive comparative assessment of the Consumer Credit Panel." *Demographic Research*, 41, 953–1006 (2019).
[24] National Historical Geographic Information System. Geographic Crosswalks (Accessed August 2023). www.nhgis.org/geographic-crosswalks.

Tables

Table 1. Average Annual Loss (AAL) for Owner-Occupied 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	0.04%	47.3%	0.09%	*	*	0.01%	0.03%	0.12%	2.20%
Hurricane Wind	0.03%	47.2%	0.06%	*	*	0.02%	0.07%	0.18%	0.59%
Winter Storm	0.02%	86.6%	0.02%	*	0.01%	0.02%	0.03%	0.04%	0.09%
Hurricane Storm Surge	0.01%	4.8%	0.16%	*	*	0.01%	0.09%	0.44%	2.03%
Wildfire	0.01%	26.5%	0.02%	*	*	*	0.01%	0.05%	0.43%

*Note: The table shows summary statistics of AAL by peril. AAL is presented as percentage of total insurable value. * indicates a value greater than 0% but less than 0.005%. Data Sources: CoreLogic.*

Table 2. AAL for Owner-Occupied SFRs in 2021, by Census Region Division and Peril

	Percent of Census Region's Average AAL as % of TIV									
	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	55%	39%	21%	25%	15%	2%	23%	61%	40%	**34%**
Inland Flood	23%	37%	31%	38%	18%	53%	19%	28%	24%	**27%**
Hurricane Wind	0%	15%	11%	0%	17%	0%	41%	0%	25%	**19%**
Winter Storm	21%	6%	30%	7%	48%	6%	7%	11%	3%	**12%**
Hurricane Storm Surge	0%	2%	7%	0%	2%	0%	10%	0%	7%	**5%**
Wildfire	0%	0%	0%	29%	0%	40%	1%	0%	2%	**4%**
Avg AAL (% of Total Insurable Value)	0.11%	0.22%	0.13%	0.10%	0.14%	0.06%	0.18%	0.20%	0.31%	**0.16%**
	Property Exposure									
Count Owner-Occupied SFRs (millions)	11.8	4.8	8.3	5.5	3.3	9.4	14.9	5.6	8.7	**72.3**
Avg Structure Value ($)	136,992	130,280	195,247	209,208	192,821	269,922	171,869	144,944	146,171	**177,402**
	Expected Loss in Dollars									
Avg AAL ($)	149	260	246	219	278	167	313	280	456	**262**
Total AAL ($ Billions)	1.8	1.3	2.0	1.2	0.9	1.6	4.7	1.6	4.0	**18.9**

Note: By-peril contribution to average regional expected damage. Structure value does not include land value. Dollar values are shown in 2020 dollars. Data Sources: CoreLogic and the American Community Survey.

Table 3. 2019 Census Tract Characteristics by Tract Average AAL Decile

	Mean (Standard Error)									
	Decile of Tract Average AAL									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Percent White	45.6	57.4	63.8	63.4	65.7	68.1	68.0	66.9	63.6	61.8
	(0.3)	(0.4)	(0.4)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.4)
Percent with Bachelor's Degree or Higher	34.4	33.6	31.1	31.9	32.0	31.1	29.8	27.7	26.3	26.0
	(0.3)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Median Household Income	80,521	75,261	68,874	70,001	69,384	67,565	65,781	63,682	60,576	58,142
	(448)	(458)	(401)	(401)	(382)	(364)	(361)	(350)	(324)	(317)
Median Home Value	527,997	316,086	243,713	263,834	242,962	224,907	223,545	211,817	183,619	211,078
	(4,431)	(2,989)	(2,023)	(2,301)	(2,131)	(1,878)	(1,987)	(1,944)	(1,593)	(2,022)
Percent Prime Age Labor Force Participation	82.7	82.5	82.5	82.7	83.1	82.9	82.4	81.5	80.5	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)	5.0	7.7	8.3	8.0	8.3	8.2	8.7	9.2	10.0	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	0.6	2.3	3.8	4.5	4.5	6.6	8.9	11.4	12.6	12.4
Percent of Tracts Urban Core	89.6	76.0	70.2	68.7	65.6	60.0	55.1	50.4	50.4	51.6

Note: Census tract average characteristics by tract-level average AAL decile. Dollar values are in 2020 dollars. Data Sources: CoreLogic and the American Community Survey.

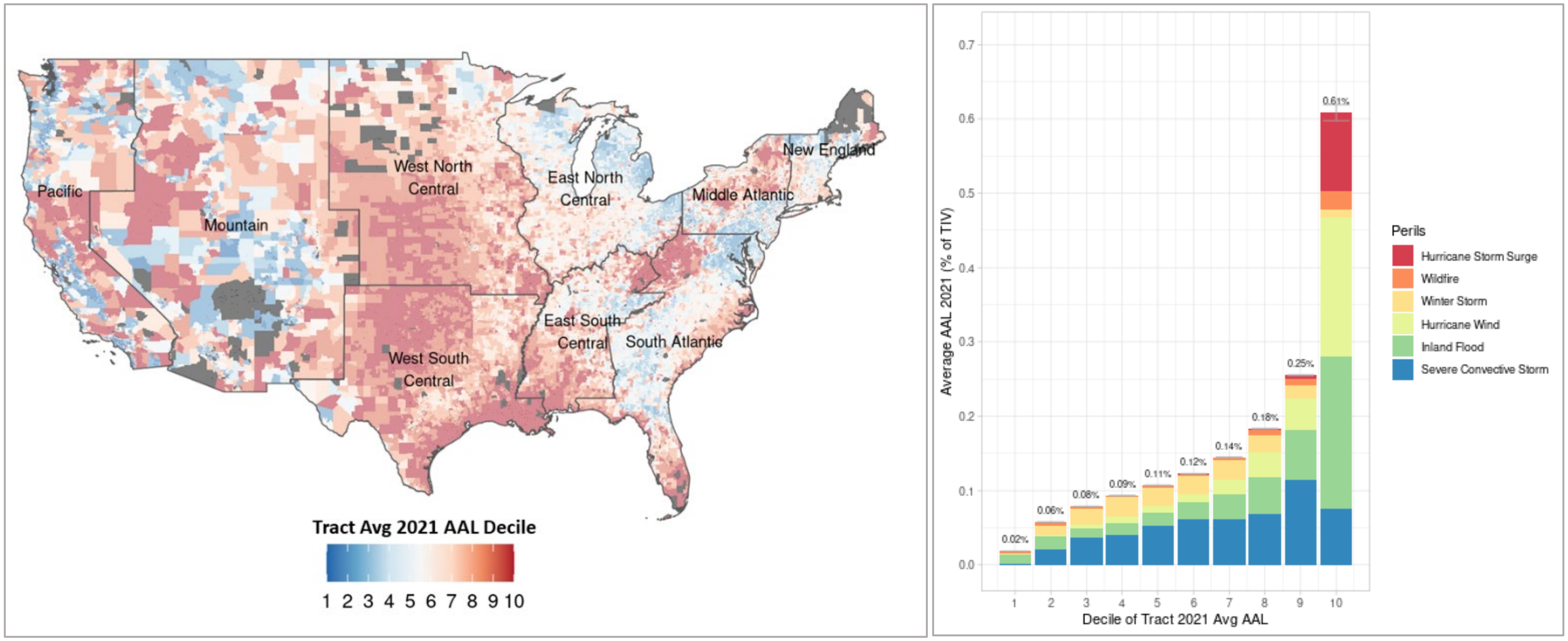
Table 4. Change in AAL 2021–2050 Under RCP 4.5, by Census Region Division

	Percent of Change in AAL (% of TIV) 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	84%	71%	45%	39%	42%	2%	33%	92%	55%	**53%**
Inland Flood	14%	7%	8%	4%	7%	32%	3%	7%	-2%	**6%**
Hurricane Wind	0%	15%	12%	0%	24%	0%	37%	0%	20%	**17%**
Winter Storm	2%	-1%	6%	-1%	16%	-2%	-1%	1%	-1%	**1%**
Hurricane Storm Surge	0%	8%	29%	0%	12%	0%	27%	0%	26%	**17%**
Wildfire	0%	0%	0%	58%	0%	67%	1%	0%	2%	**6%**
Avg Change in AAL (bps of Total Insurable Value)	2.7	4.2	2.5	2.1	2.2	1.2	4.8	4.8	7.1	**3.6**

Note: By-peril contribution to change in average AAL, measured as share of total insurable value (TIV), from 2021 and 2050 shown by Census Region Division. Negative value indicates a decrease in average AAL. Data Sources: CoreLogic.

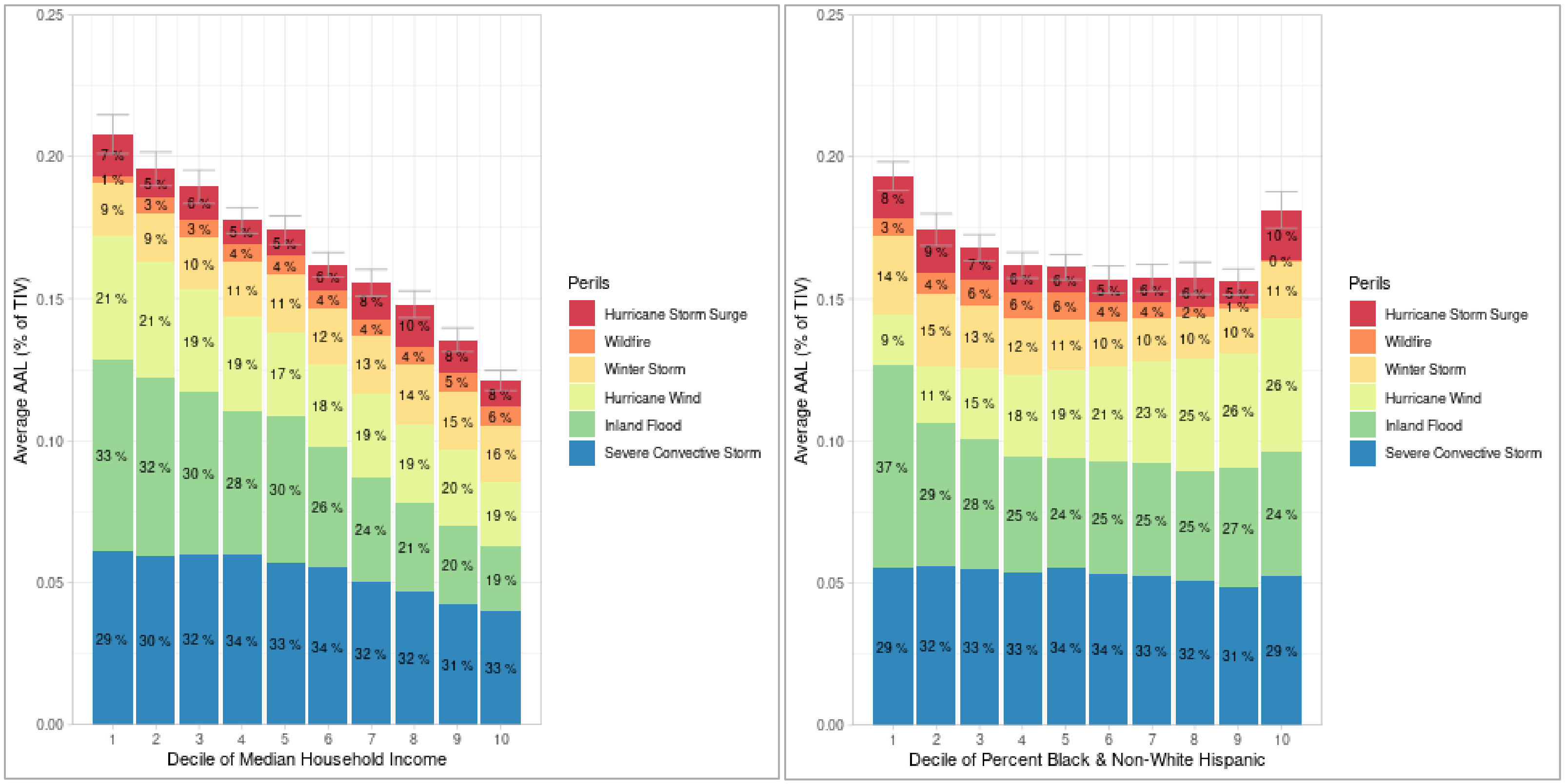
Figures

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



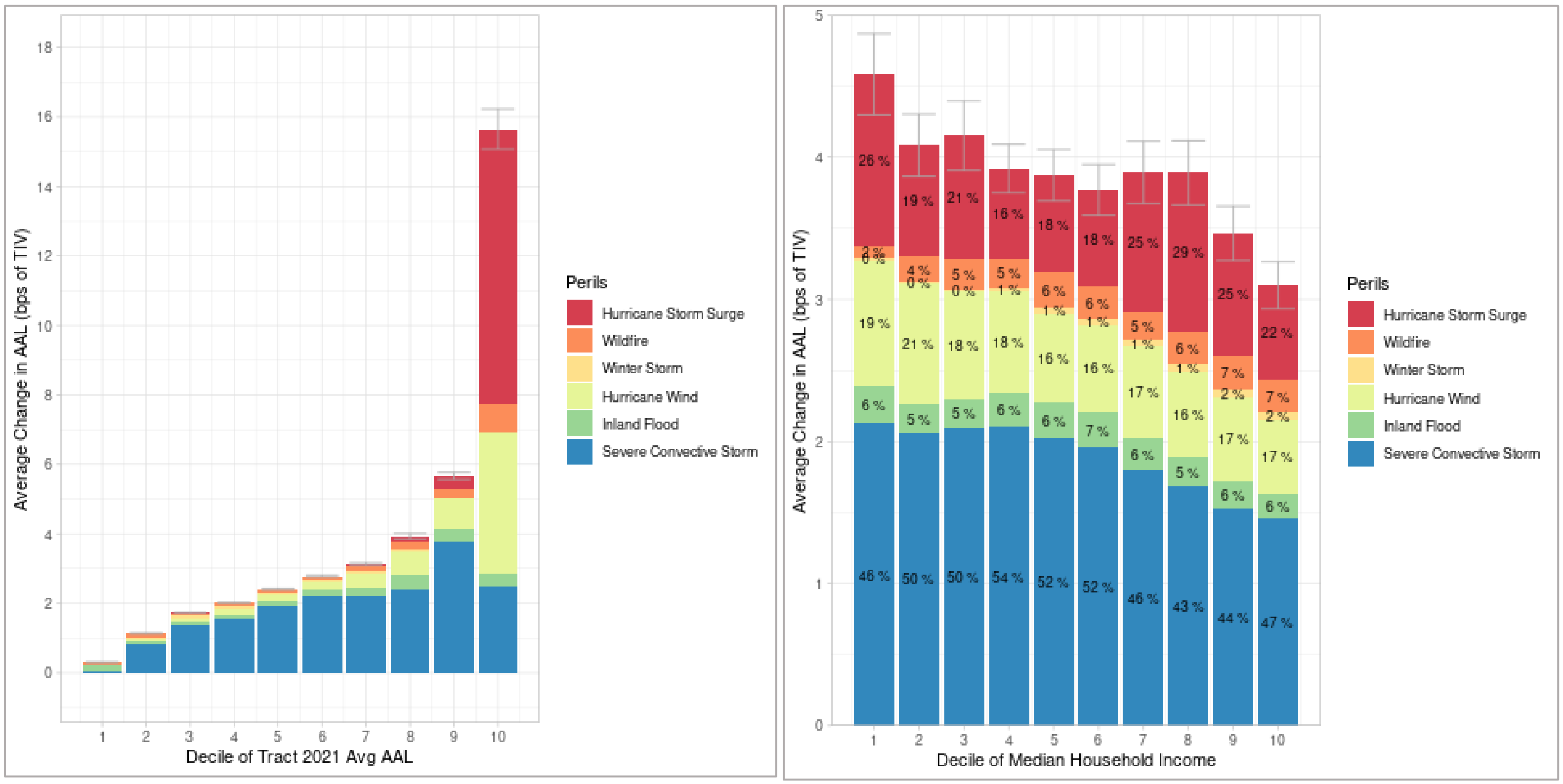
(a) Tract-level average composite AAL. Tracts without sufficient data to calculate an average AAL are shown in dark gray. (b) By-peril contribution of average AAL in each decile of tract average AAL. Ninety-five percent confidence intervals for decile average AALs appear in gray. The intervals characterize 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. Data Sources: CoreLogic and the American Community Survey.

Figure 2(a)(b). Tract Average AAL by Decile of Median Household Income and Percent Black and Non-White Hispanic, 2019



(a) By-Peril average contribution to tract-level average AAL sorted by average 2019 median household income decile. (b) By-peril average contribution to tract-level average AAL sorted by average 2019 Black and non-White Hispanic share 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. Data Sources: CoreLogic and the American Community Survey.

Figure 3(a)(b). Average Change in AAL 2021–2050, by 2021 Tract Average AAL Decile and 2019 Household Income Decile



(a) Average change in AAL between 2021 and 2050 sorted by 2021 average tract AAL decile. (b) Average change in AAL between 2021 and 2050 sorted by average 2019 median household income 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. Data Sources: CoreLogic and the American Community Survey.

Appendix Tables

Appendix Table 1. AAL in Dollars for Owner-Occupied SFRs in 2021, by Peril

	Percent of Census Region's Expected Losses (in 2020 USD)									
	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	57%	44%	20%	29%	15%	1%	23%	62%	42%	**32%**
Inland Flood	22%	31%	26%	34%	17%	51%	14%	27%	22%	**24%**
Hurricane Wind	0%	15%	15%	0%	17%	0%	43%	0%	25%	**19%**
Winter Storm	22%	6%	30%	8%	49%	5%	7%	11%	3%	**12%**
Wildfire	0%	0%	0%	30%	0%	43%	1%	0%	1%	**6%**
Hurricane Storm Surge	0%	3%	9%	0%	2%	0%	12%	0%	7%	**6%**
Avg AAL ($)	149	260	246	219	278	167	313	280	456	**262**
Total AAL ($ Billions)	1.8	1.3	2.0	1.2	0.9	1.6	4.7	1.6	4.0	**18.9**

Note: By-peril contribution to average dollar-value AAL. Dollar values are shown in 2020 dollars. Data Sources: CoreLogic and the American Community Survey.

Appendix Table 2. Urban Core 2019 Census Tract Characteristics by Tract Average AAL Decile

	Mean (Standard Error)									
	Decile of Tract Average AAL									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Density (per sq. mi.)	8,517	6,082	6,976	8,846	6,571	4,532	4,841	4,571	4,053	4,668
	(84)	(74)	(118)	(174)	(137)	(72)	(81)	(73)	(47)	(64)
Percent White	43.9	51.7	55.2	54.8	57.0	59.1	58.0	56.6	52.0	49.8
	(0.3)	(0.4)	(0.5)	(0.4)	(0.4)	(0.4)	(0.5)	(0.5)	(0.5)	(0.5)
Percent with Bachelor's Degree or Higher	35.0	35.0	32.9	34.7	35.7	35.8	35.4	32.9	31.0	30.9
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Median Household Income	81,272	75,641	69,295	72,365	72,432	71,012	70,385	68,472	64,012	61,253
	(477)	(549)	(510)	(523)	(517)	(515)	(550)	(565)	(531)	(498)
Median Home Value	546,013	328,317	255,139	293,491	272,078	255,991	266,858	250,349	209,192	249,753
	(4,739)	(3,638)	(2,575)	(3,021)	(2,917)	(2,655)	(2,995)	(3,050)	(2,500)	(3,046)
Percent Prime Age Labor Force Participation	83.0	82.9	83.0	83.3	83.9	83.8	83.8	83.1	82.1	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	7.9	8.6	7.9	8.1	7.7	7.9	8.0	8.9	9.9
	(0.04)	(0.11)	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)
Number of Urban Core Tracts	6,167	5,230	4,832	4,729	4,515	4,132	3,793	3,470	3,468	3,549

Note: Urban core census tract average characteristics by tract-level average AAL decile. Dollar values are in 2020 dollars. Data Sources: CoreLogic and the American Community Survey.

Appendix Table 3. 2019 Census Tract Characteristics by Tract Average AAL Decile Sorted Within MSA

	Mean (Standard Error)									
	Decile of Tract Average AAL Within MSA									
Description	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Percent White	59.0	56.2	56.3	56.4	56.6	58.2	59.1	61.1	62.9	64.4
	(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	32.8	33.0	32.9	32.6	32.8	32.4	32.5	31.8	30.9
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Median Household Income	71,661	70,472	70,450	70,810	70,668	72,324	72,424	73,298	72,698	70,766
	(439)	(434)	(447)	(446)	(442)	(460)	(457)	(453)	(460)	(457)
Median Home Value	291,121	287,204	290,281	286,951	284,223	288,055	291,496	293,234	290,272	294,662
	(2,946)	(2,859)	(2,995)	(2,957)	(2,920)	(2,979)	(3,106)	(3,055)	(3,078)	(3,259)
Percent Prime Age Labor Force Participation	83.3	82.9	82.8	82.9	83.0	82.9	82.8	82.7	82.5	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)	7.5	7.8	7.9	7.9	7.8	7.6	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 2020 dollars. Data Sources: CoreLogic and the American Community Survey.

Appendix Table 4. Change in Census Tract Characteristics (2010–2019) by Tract Average 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	3.8	3.8	3.9	3.9	3.7	3.5	3.3	2.9	3.2
	(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	8.6	3.9	3.2	3.5	3.1	3.5	4.2	4.4	3.7	3.3
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Change in Percent Prime Age Labor Force Participation	0.7	0.1	0.3	0.1	0.1	-0.2	-0.3	-0.4	-0.7	-0.6
	(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	-0.1	-0.2	0.0	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	6.8	4.2	4.3	5.1	6.4	6.8	6.5	6.7	5.8
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)

Note: Average change in select census tract characteristics by 2021 tract average AAL decile. Data Sources: CoreLogic and the American Community Survey.

Appendix Table 5. Change in Urban Core Census Tract Characteristics (2010–2019) by Tract Average 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	4.4	3.9	3.9	4.1	4.1	4.1	3.8	3.5	3.1	3.7
	(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	9.1	3.9	3.0	3.6	3.2	3.8	4.3	4.2	3.6	3.5
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.4)
Change in Percent Prime Age Labor Force Participation	0.9	0.2	0.7	0.5	0.5	0.2	0.2	0.1	-0.1	0.0
	(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)	-1.0	-0.8	-0.8	-0.4	-0.5	-0.6	-0.6	-0.6	-0.5	-1.1
	(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	7.8	6.0	4.0	4.2	5.2	7.3	8.2	8.2	9.1	8.7
	(0.2)	(0.3)	(0.2)	(0.2)	(0.2)	(0.3)	(0.3)	(0.3)	(0.3)	(0.4)
Number of Urban Core Tracts	6,167	5,230	4,832	4,729	4,515	4,132	3,793	3,470	3,468	3,549

Note: Average change in select census tract characteristics by 2021 tract average AAL decile. Urban core tracts only. Data Sources: CoreLogic and the American Community Survey.

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

	Mean Net Migration as % of 2010 Population (Standard Error)									
	Decile of Tract Average AAL									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
All Migration	-1.6	-1.0	-1.5	-2.0	-1.2	0.0	0.2	0.9	0.8	0.7
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
	Decile of Tract Average AAL Within MSA									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Migration Within MSA	-0.7	-1.3	-0.6	-0.5	-0.5	-0.3	-0.2	0.4	0.3	-0.2
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)

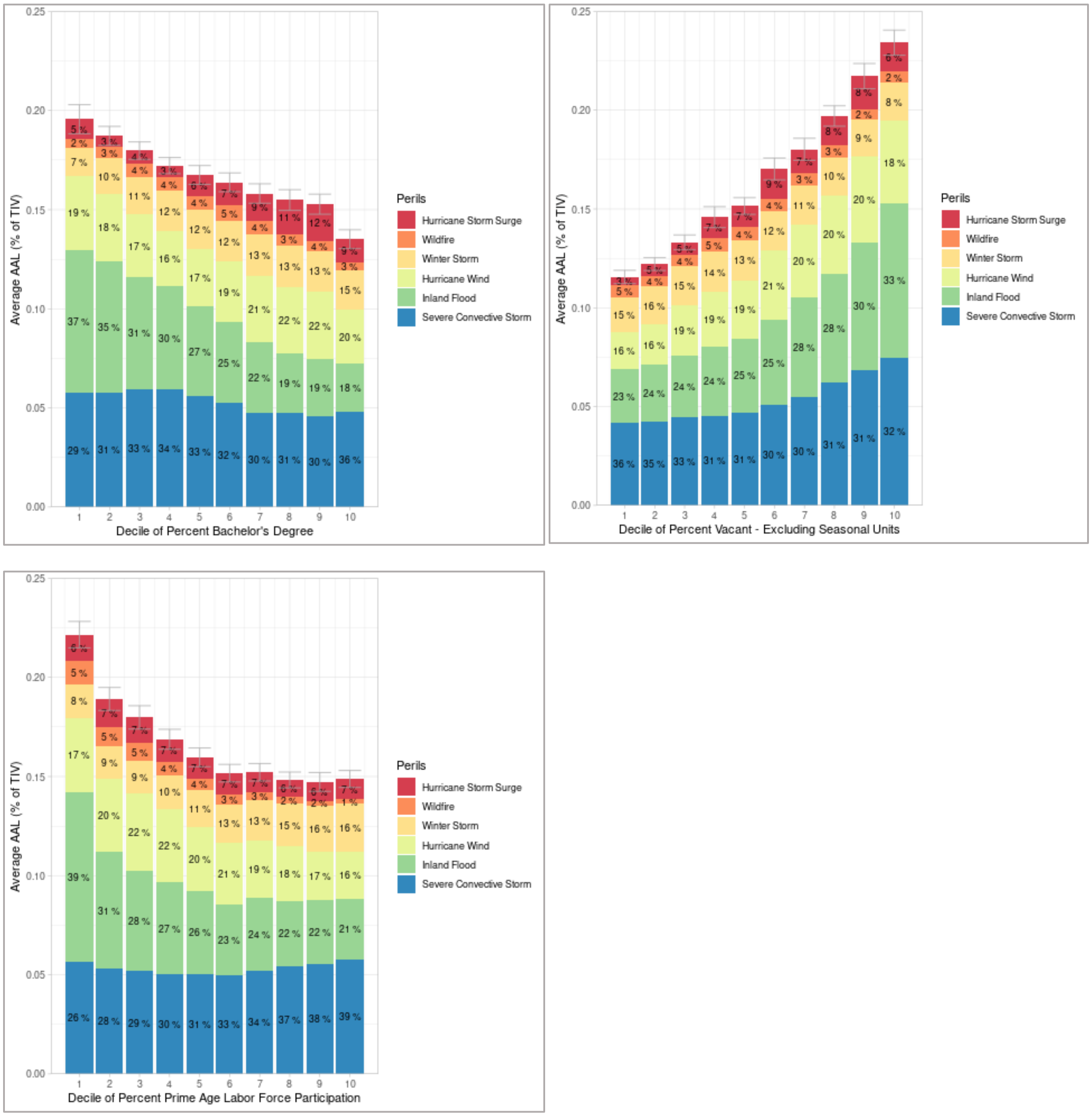
Note: Average tract net in-migration during 2010–2019 by tract average AAL and average tract net in-migration during 2010–2019 among the set of movers who moved within the same MSA by decile of tract average AAL sorted within MSA. Data Sources: CoreLogic and the CCP.

Appendix Table 7. Change in AAL for Owner-Occupied SFRs (2021–2050) Under RCP 8.5, by Peril

	Percent of Change in AAL (% of TIV) by Census Region Division									
	East North Central	**East South Central**	**Middle Atlantic**	**Mountain**	**New England**	**Pacific**	**South Atlantic**	**West North Central**	**West South Central**	**All US**
Severe Convective Storm	79%	69%	37%	42%	32%	3%	26%	89%	49%	**47%**
Inland Flood	17%	1%	9%	0%	5%	18%	1%	9%	-2%	**4%**
Hurricane Wind	0%	21%	15%	0%	29%	0%	46%	0%	26%	**23%**
Winter Storm	4%	0%	9%	0%	23%	-1%	0%	2%	0%	**2%**
Hurricane Storm Surge	0%	9%	29%	0%	12%	0%	26%	0%	26%	**17%**
Wildfire	0%	0%	0%	58%	0%	81%	1%	0%	2%	**6%**
Avg Change in AAL (bps of Total Insurable Value)	3.8	5.7	3.7	2.9	3.4	1.3	7.7	6.6	10.5	**5.3**

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

Appendix Figure 1(a)(b)(c). By-Peril Average AAL by Deciles of College Degree Population Share, Vacancy Rate, and Prime Age Labor Force Participation Rate



(a) By-peril average contribution to tract-level average AAL sorted by average 2019 share of adults with college degree or higher decile. (b) By-peril average contribution to tract-level average AAL sorted by average 2019 percent vacant home decile. (c) 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. Data Sources: CoreLogic and the American Community Survey.

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

One way to assess the reasonableness of our estimate of expected losses is to compare 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."[25] SHELDUS is updated regularly with data additions and corrections. The subsequent analysis is based on SHELDUS 21.

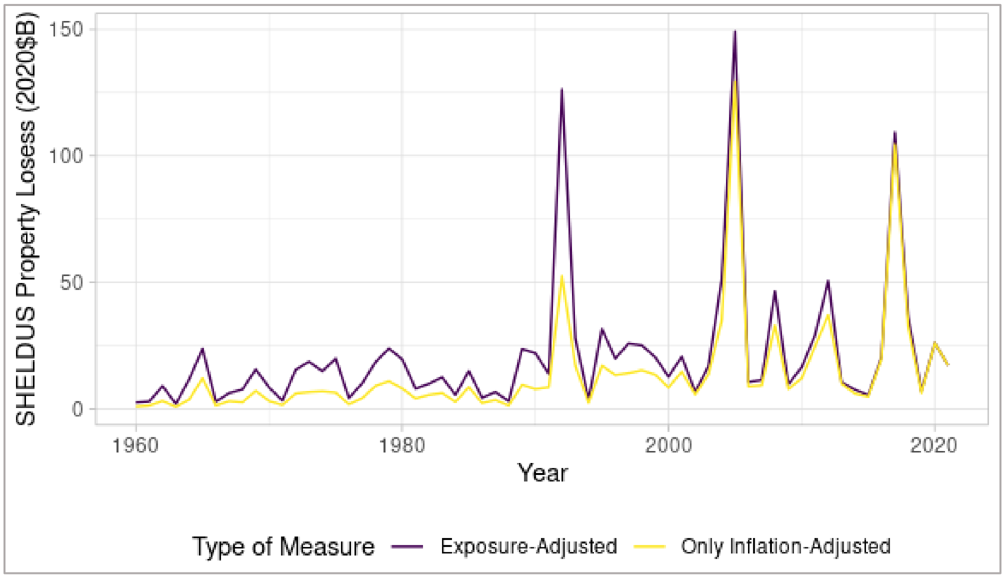
There are several considerations when trying to compare our expected losses for 2021 with historical losses in SHELDUS. The main ones are hazard types, property types, and time frame. Regarding hazard types, SHELDUS classifications allow us to construct a collection of hazards that are comparable in 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 owner-occupied SFRs. SHELDUS property losses include damages to all property types as well as damage to vehicles and infrastructure like roads and power lines.[26] Unfortunately, we cannot isolate types of property losses in SHELDUS, so, all else equal, we expect SHELDUS annual average loss to exceed our estimate of expected losses.

The trickiest consideration is time frame. CoreLogic AALs, which are the basis for our estimated loss estimate, 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 a "lucky" or "unlucky" period. 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.

The best we can do to address this issue is to examine multiple time frames and explicitly adjust for changes in exposure. The exposure adjustment is to account for the fact that the amount of property 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).[27] In short, we construct county-year-level real aggregate housing values using county-level data on total housing units for census years 1970, 1980, 1990, 2000, 2010, and 2020; county-level real housing values derived from county-level ACS median home values for 2020; 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 2022.[28, 29] We then use the ratio of those housing exposure values with the 2020 value to inflate the SHELDUS county-year damages.

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



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

The exposure-adjusted damages for the entire history of SHELDUS (1960–2021) and for the post-2000 period are shown in Appendix Table A1. As we expect, we find that AALs in SHELDUS are larger than our estimate of expected losses for owner-occupied SFRs in 2021. The AALs in SHELDUS for 1960–2021 and for 2000–2021 are $21.4 billion and $31.0 billion, respectively, when adjusted for exposure. The closeness of the 1960–2021 value to our expected loss estimate for 2021 in spite of the difference in property type coverage likely reflects, in part, the worsening environmental conditions over the period. In other words, the true expected losses in 2021 are likely higher than the true expected losses at the beginning of the 1960–2021 period. Overall, our aggregate expected damage number of $18.9 billion appears to be roughly consistent with the adjusted expected damage numbers from SHELDUS.

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

SHELDUS Hazard	Exposure-Adjusted Damage 1960–2021 (Billions of 2020$)	% of Damage 1960–2021	Exposure-Adjusted Damage 2000–2021 (Billions of 2020$)	% of Damage 2000–2021
Hurricane/Tropical Storm	472.8	35.6%	245.6	36.0%
Flooding	388.1	29.2%	249.9	36.7%
Tornado	103.4	7.8%	43.9	6.4%
Severe Storm/Thunderstorm	81.3	6.1%	7.1	1.0%
Hail	75.8	5.7%	44.5	6.5%
Wind	75.2	5.7%	30.8	4.5%
Wildfire	70.1	5.3%	42.8	6.3%
Winter Weather	50.7	3.8%	15.3	2.2%
Lightning	6.4	0.5%	1.3	0.2%
Coastal	3.9	0.3%	0.5	0.1%
Total	**1,328**	**100%**	**682**	**100%**
Annual Average	**21.4**	**N/A**	**31.0**	**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. Data Sources: SHELDUS.

In addition to the aggregate damage, 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 hazard shares provided in Appendix Table 1 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 and coastal, there are not clear 1:1 matches to CoreLogic perils. For example, some nonsurge hurricane-related ground flooding is counted as hurricane/tropical storm, while some is counted as flooding.[27] Nonsurge hurricane-related ground 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	Hurricane storm surge/Inland flooding

Note: Crosswalk between SHELDUS hazard name and CoreLogic perils. Data Sources: CoreLogic and SHELDUS.

One way to deal with this problem is to combine hurricane and flooding categories. For SHELDUS, this would be hurricane/tropical storm, flooding, and coastal, and for CoreLogic, it would be 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 50 percent of our estimate of 2021 expected losses (see Appendix Table A3). This 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 well. 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%	50%
Severe convective storm	25%	32%
Winter storm	4%	12%
Wildfire	5%	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. Data Sources: CoreLogic and SHELDUS.

We posit that there are several factors contributing to the 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 owner-occupied 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.[30] Fourth, as discussed in this paper, we likely understate expected losses because we use median home values. The impact of this choice may vary with geography and, thereby, hazard. For example, high-value beachfront properties in coastal areas where hurricanes are the primary source of damage may not be reflected in median home values for the area, which could lead to hurricane-related damage being understated in our estimate of expected costs. Fifth, hurricane wind is only modeled by CoreLogic for states on the Gulf and Atlantic coasts. Elsewhere, we assume hurricane damage is zero. In reality, hurricane winds have the potential to reach further inland. To the extent that this is true, the assumption would cause us to underestimate the expected losses from hurricane wind.

Appendix B: 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 FRBNY Consumer Credit Panel/Equifax Data (see Appendix Table 6). One concern with using the CCP data set is its selection criteria of individuals with credit histories makes it skewed toward 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.

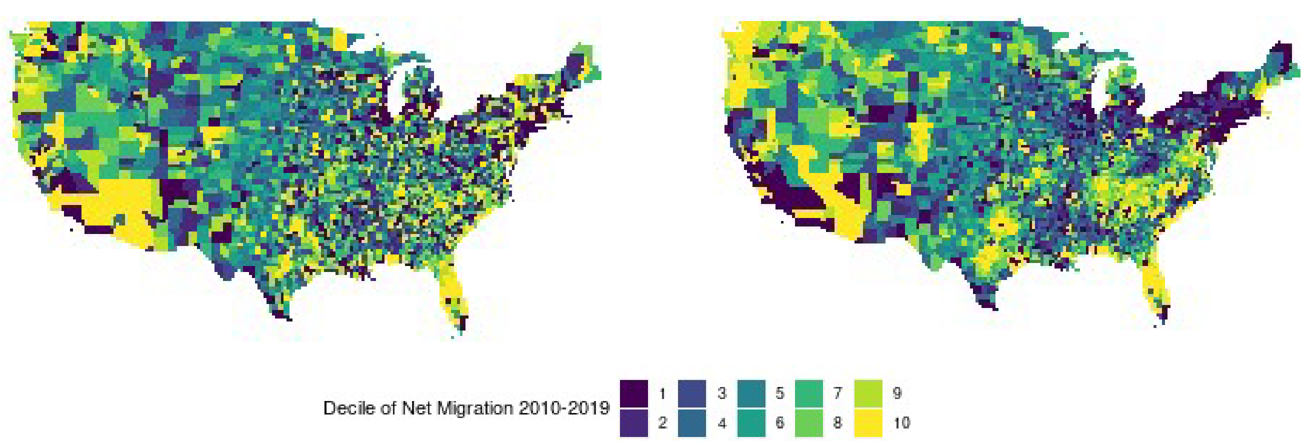
We test the reasonableness of the CCP-based migration measure by comparing its county-level migration estimates with the ACS county-to-county migration flows for 2010–2019. For this comparison, we perform steps (1)-(4) from above using the CCP, except that we aggregate to the county level, which precludes 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 using different sources of data, including ACS data, versus CCP-based migration estimates.[31]

The deciles of ACS and CCP county net migration counts are shown in Appendix Figure B1. 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 B1. Comparison of ACS and CCP County-Level Net Migration Estimates, 2010–2019

ACS County Net Migration Deciles **CCP County Net Migration Deciles**



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

References (Appendices)

[25] National Centers for Environmental Information. *Storm Data* (Accessed August 2023). www.ncdc.noaa.gov/IPS/sd/sd.html.
[26] Arizona State University, Center for Emergency Management and Homeland Security. SHELDUS Metadata (Accessed August 2023). cemhs.asu.edu/sheldus/metadata.
[27] Wiese, P. *Trends in Normalized Weather-Related Property Losses in the United States: 1960–2018.* Society of Actuaries (2020).
[28] FHFA. House Price Index Datasets, States All-Transactions Index (Accessed August 2023). www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx.
[29] FRED. Gross Domestic Product: Implicit Price Deflator (Accessed August 2023). fred.stlouisfed.org/series/GDPDEF.
[30] Gall, M., Borden, K. A., & Cutter, S. L. "When do losses count?" *Bulletin of the American Meteorological Society*, 90 (6), 799–810 (2009).
[31] DeWaard J., Johnson J., & Whitaker S. "Internal migration in the United States: A comprehensive comparative assessment of the Consumer Credit Panel." *Demographic Research*, 41, 953-1006 (2019).