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WP 26-35

PUBLISHED
July 2026

FRB CFI PHILADELPHIA

ISSN: 1962-5361

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DOI: https://doi.org/10.21799/frbp.wp.2026.35

Model Risk in Physical Risk Models*

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July 2026

Abstract

Model risk is the uncertainty in model-derived point estimates of unobserved risks. This paper studies model risk in the setting of residential physical risk assessment by analyzing the outputs of two prominent risk modelers. We document five facts about model risk in physical risk models, defined as the absolute difference in the two modelers' estimates of average annual loss (AAL) for the same property and set of perils (flood, hurricane wind, and wildfire). (i) For the average single-family residence, model risk is expected to cost $322 per year, which is approximately equal to the mean of each modeler's AAL estimates. (ii) Aggregating the risk estimates up to the tract or county level does not substantially reduce the disagreement. (iii) Model risk is disproportionately borne by economically vulnerable households. (iv) There is little association between model risk and insurance premiums. (v) Net migration rates are higher in places with higher levels of model risk. Taken together, these facts imply that uncertainty about estimates of physical risk is not appropriately priced by economic agents.

Keywords: Model risk, physical risk, natural disaster

JEL Codes: G5, G22, R00, Q5

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1 Introduction

Many financial variables that influence important economic decisions are model-produced point estimates with inherent uncertainty that results from modeling choices. However, in many contexts, these variables are used as exact data points that have no error. For example, home appraisal values that feed into loan-to-value (LTV) ratios are treated as precise point estimates in lending and loan pricing decisions (Bartlett et al., 2022; Amornsiripanitch et al., 2023; Amornsiripanitch and Ricks, 2025), even though research has shown that standard home valuation methods can produce large errors (Agarwal et al., 2020; Amornsiripanitch, 2020; Calem et al., 2021). Similar points can be made about credit scores. As such, model risk may be an underappreciated feature of financial markets and may have large economic consequences.

In this paper, we use natural disaster physical risk models for single-family residences (SFRs) in the contiguous US as a laboratory to document stylized facts about the model risk in physical risk estimates and study the consequences that this source of risk may have on important economic decisions such as homeowner's insurance pricing and migration decisions. Disagreements among modelers on physical risk estimates stem from the modeler's choice of raw data input (e.g., the set of historical natural disaster events, the property characteristic database, and reconstruction cost data) and modeling choice on the damage function, which is the function that maps disaster realizations (e.g., flood level) to property damage. Uncertainty in physical risk estimates matters for homeowner's insurance prices, coverage amounts, and insurers' ability to manage risk. Systematic errors in physical risk estimates imply the existence of systematic credit risk to banks and the financial system through the possibility that insurers, the first line of defense, become insolvent from unexpected losses from natural disasters and through insufficient insurance coverage via homeowners' inability to buy the correct amount of insurance. As such, model risk of this kind is important to study.

For each property, physical risk models produce average annual loss (AAL) from specific types of natural disasters, which represents the amount of damage that the property is expected to experience in a given year. Using current property-level AAL data from two prominent risk modelers, CoreLogic (CL) and First Street Foundation (FSF), we define model risk as the absolute difference in AAL between the two modelers for the same property and disaster type. We are able to compute this model risk measure for flood, hurricane wind, and wildfire risk for the near universe of single-family residences that existed in the contiguous United States as of 2023.

With the measure of model risk in hand, we begin our empirical analysis by documenting the magnitude and distribution of this source of risk. Model risks for the average SFR are approximately 9.0 basis points (bps), 3.2 bps, and 1.1 bps of replacement cost for flood, hurricane wind, and wildfires, respectively. In 2021 dollars, the amounts are $222, $88, and $39, respectively. These numbers are economically small. However, more importantly, these average amounts are comparable to each modeler's mean AALs. Mean CL AAL for flood, hurricane wind, and wildfire are 5.5 bps, 3.8 bps, and 0.7 bps, respectively. Mean FSF AAL for flood, hurricane wind, and wildfire are 5.8 bps, 4.4 bps, and 0.9 bps, respectively. Therefore, the summary statistics imply that, although the two modelers seem to agree on the level of risk that the average SFR faces, their disagreements are large enough that we cannot be sure about which properties face the average level of risk and which do not. An important implication of this finding is that such large amounts of model risk are likely to hinder homeowners' ability to make optimal insurance decisions.

Furthermore, the average levels mask the large variation in model risk. The standard deviations of the absolute differences in AAL are 57 bps, 11 bps, and 6.5 bps for flood, hurricane wind, and wildfire, respectively. In 2021 dollars, the values are $1,989, $501, and $274, respectively. The large standard deviation values imply that the model risk distributions have long right tails. Therefore, economically, the average homeowner faces little uncertainty in physical risk from flood, hurricane wind, and wildfire, but a small subset faces large amounts of this risk.

We may be asking too much of these models when we expect them to determine and agree on property-level risk, but they may be highly informative in telling us which areas are risky and which areas are safe. This information, if accurate, is extremely useful for policymakers when dealing with problems such as risk management for financial intermediaries or optimal resident settlement patterns in light of constrained government disaster aid funding. As such, the next part of the paper explores how model risk behaves when we aggregate physical risk estimates up to the tract and county levels.

For each disaster, we estimate the correlation in property-level physical risk between the two modelers and use this number as the benchmark. We then compute tract-level (neighborhood) and county-level (city) average risk for each disaster, compute the correlation between the two modelers, and compare it to the benchmark. For hurricane wind, property-level risk correlation is high (0.71). However, geographical aggregation does little to improve the correlation. The correlations are 0.85 and 0.81 for tract-level and county-level averages, respectively. Wildfire and flood seem to cause more disagreement between the two modelers. For wildfire, property-level risk correlation is 0.31, and the tract- and county-level correlations are 0.52 and 0.54, respectively. For flood, property-level risk correlation is 0.20, and the tract- and county-level correlations are 0.34 and 0.53, respectively. The low property-level risk correlations suggest that these perils are difficult to model at the property level. Unlike with hurricane wind, there are some gains from geographical aggregation for flood and wildfire; however, the tract- and county-level correlations still suggest that these perils are also difficult to model at the area level, i.e., individuals who wish to surely avoid risky areas cannot comfortably rely on outputs from these physical risk models.

Since model risk can be large for some households, it is important to study the distribution of these risks with respect to households' demographic and economic characteristics. To do so, we sort census tracts into five equal groups according to their combined wildfire, flood, and hurricane wind model risk levels and compare the average demographic and economic characteristics of the census tracts across groups. We find that, relative to other groups, census tracts that bear the highest level of model risk tend to have higher average physical risk, lower house prices, lower median household incomes, lower educational attainment, lower population density, higher White population shares, and higher senior population shares. Given that economically disadvantaged households tend to live in high-physical-risk areas (Wing et al., 2022; Wylie et al., 2025), this finding is not surprising because, in our sample, high-risk areas tend to have high model risk. However, this finding is still important because it shows that economically disadvantaged households disproportionately bear high levels of physical risk and high levels of uncertainty in physical risk, both of which rational economic agents should dislike. The results imply that improvements in physical risk models would be economically progressive.

Based on the intuition that model risk should be priced in standard economic models, a first-order question is whether insurance companies account for this type of risk when they price homeowner's insurance contracts. For this exercise, we focus on wildfire and hurricane wind risk because these perils are covered by homeowner's insurance policies, while flood risk is not. Using a sample of 9.5 million anonymized homeowner's insurance policies that were active as of June 2024, we regress insurance premium onto our measure of model risk while controlling for the average physical risk level (AAL) and standard determinants of homeowner's insurance premium (e.g., deductible, coverage, collateral value, and credit score). If model risk were priced by insurance companies and our measure of model risk is sufficiently correlated with the model risk that insurance companies observe, then the regression should show a positive association between premium and model risk. Surprisingly, we find a small but negative correlation.

To better understand the negative correlation, we estimate a horse race regression specification where we regress insurance premiums onto CL's AAL and FSF's AAL, separately. We find that insurance premiums are much more sensitive to the variation in CL's AAL than to the variation in FSF's AAL. Furthermore, we find that, conditional on the average level of risk (e.g., the average AAL between CL's and FSF's estimates), premiums tend to be higher when CL's AAL is larger than FSF's AAL and lower in the opposite case. Taken together, the results suggest that insurance companies use CL's AAL to price insurance contracts while mostly ignoring FSF's AAL and, hence, model risk.

In the last part of the paper, we turn our attention to how individuals internalize model risk. Following Wylie et al. (2025), we explore how tract-level net migration patterns in the FRBNY Consumer Credit Panel/Equifax Data are associated with model risk. We find that, from 2015 to 2024, net migration rates are positively correlated with model risk in hurricane wind and wildfire risk estimates. This pattern is robust to controlling for the average level of physical risk and the inclusion of county fixed effects. Overall, the results suggest that, in aggregate, migration patterns for both long- and short-distance moves are exposing more people to this type of model risk.

2 Literature Review and Contribution

This paper contributes to several strands of literature. First, there exists a large literature on Knightian uncertainty (Knight, 1921) and ambiguity aversion (Ellsberg, 1961), which studies how economic agents should behave when they are unsure about the probability of possible states of the world (Hansen and Sargent, 2001; Klibanoff et al., 2005). Direct applications of this theoretical framework are asset pricing (Chen and Epstein, 2002; Epstein and Schneider, 2007) and insurance contracts (Zhao and Zhu, 2011; Gollier, 2014; Dietz and Walker, 2019; Dietz and Niehörster, 2021), and the respective sub-literature generally concludes that assets and insurance contracts that carry larger degrees of Knightian uncertainty should command higher risk premiums when agents have ambiguity aversion. We contribute to this line of work by using nationwide physical risk data from prominent modelers to document descriptive facts about the size and distribution of model risk in physical risk estimates and how these quantities correlate with homeowner's insurance premiums and potential homeowners' migration decisions. Unlike Kunreuther et al. (1995), who use survey data, we use policy-level transaction data to estimate the correlation between insurance premiums and model risk.

Heitfield (2025) presents a stylized model of insurance price setting when model risk exists and shows that, in Florida, using ZIP code-level data, there is a positive relationship between homeowner's insurance premiums and model risk in hurricane damage models. Our work differs from Heitfield (2025) in several important ways. First, we use data that cover the contiguous United States to document stylized facts about model risk in physical risk modeling of hurricane wind, wildfire, and flood. Second, the facts that we document go beyond the relationship between homeowner's insurance premiums and model risk. Specifically, the facts speak to the size and distribution, both geographically and across demographic groups, of the particular type of model risk that we study. Third, we use *policy-level* data to investigate the empirical relationship between homeowner's insurance premiums and model risk. The granularity of the data allows us to include granular fixed effects (e.g., ZIP code, year-month, and insurer) and control for other important determinants of insurance premiums (e.g., deductible, coverage amount, credit score, and collateral value). Lastly, we document a new fact, which is that net migration patterns imply that, in aggregate, agents may not be properly accounting for model risk when making migration decisions.

3 A Simplified Framework of Physical Risk Modeling

As a simplification, the physical risk models that produce AALs have two main tasks: (1) characterize the hazard level at a specific location (e.g., depth of flood water) and (2) translate that hazard level into a damage amount to a physical structure.[1] These two components are commonly referred to as hazard modeling and vulnerability modeling, respectively.

Hazard modeling starts with generating a stochastic event set that serves as the inventory of possible events to be drawn from in the loss simulations. Each event must be characterized by a likelihood of occurrence and a geographic track (American Academy of Actuaries, 2018). The event sets are informed by historical event data, but because the event set needs to represent the full range of possible events, the modelers cannot rely solely on historical data.

By combining statistical techniques with natural science expertise and massive computing power, hazard models determine the level of hazard risk for a given event. For flood, this could be the flood depth at a certain location. For hurricane wind, this could be the wind speed at a certain location. Hazard models estimate the level of risk over space, which enables modelers to generate an event footprint, i.e., a map of hazard level (American Academy of Actuaries, 2018). Simulated over many events, the full distribution of hazard level at any location can be produced.

The vulnerability modeling applies a damage function that maps the hazard level to a damage amount, from which the expected loss can be calculated.[2] Damage functions are developed from engineering principles and modeling, as well as historical damage data. Damage functions are typically specific to structure type, so data on structural characteristics are critical. As is the case for hazard modeling, the vulnerability models differ by peril.

Both of these modeling components are complex, involving a large amount of input data. Hazard modeling can involve historical event catalogs, meteorological data, geological data,

[1] See FSF's website (`https://firststreet.org/methodology`) for details on its modeling methodology. See the supplemental material in Wylie et al. (2025) for the technical documentation on CL's modeling methodology.

[2] Damage functions may output damage as a share of replacement value (CL) or as a dollar value (FSF).

hydrological data, and digital elevation model data. Vulnerability modeling requires detailed data on property and structure characteristics, which can include precise coordinates, building footprints, construction types, roof materials, age, square footage, occupancy type, first-floor height, and replacement costs.

The scope of data required to produce physical risk estimates presents several avenues for differences between modelers. Modelers may incorporate more relevant data or have access to more accurate/higher quality data. However, even if the data inputs were identical, it is very likely that the loss estimates produced by different modelers would differ. Modelers have to manipulate the input data, which can lead to different approaches. For example, the way in which modelers "downscale" coarser data to finer geographic resolution can impact the model's output. Most consequentially, there are countless modeling decisions that need to be made, given the complexity of the processes involved. In short, model risk in physical risk modeling can stem from the modeler's choice of data input and how hazard levels (e.g., event footprints) and damages (e.g., damage functions) are modeled.

4 Data and Measurement

4.1 Data sources

The first data set that we use is the CoreLogic (CL) natural disaster physical risk data, which provides property-level AAL estimates for seven perils: inland flood, hurricane wind, hurricane storm surge, severe convective storms, winter storm, wildfire, and earthquakes. For the results presented below, we use the current risk estimates and discard the future risk estimates. CL's risk estimates are widely used by banks, insurance companies (Wylie et al., 2025), and academic researchers (Boomhower et al., 2024; Ge et al., 2025a; Jung and Jung, 2025; Blonz et al., 2026).[3]

The second data set that we use is First Street Foundation's (FSF) natural disaster physical risk data, which provides property-level AAL estimates for three perils: flood, hurricane wind, and wildfire.[4] FSF's risk estimates are widely used by real estate companies

[3]CL only models hurricane wind and wildfire for select geographies. CL indicates negligible risk for these perils outside the modeled areas, so we assume zero associated risk with the peril for properties outside the modeled areas.

[4]Both sets of estimates reflect risk as of ~2024.

(e.g., Redfin and Zillow), government agencies (e.g., FEMA), and academic researchers (Wing et al., 2022; Gourevitch et al., 2023; Amornsiripanitch et al., 2025a; Ge et al., 2025b).[5]

The third data set that we use is the anonymized ICE, McDash property insurance data. This data set provides policy-level information on insurance contracts that are associated with a subset of mortgages covered by the ICE, McDash mortgage performance data. The data set is a mortgage-by-month panel data set that allows us to observe basic information on homeowner's insurance policies and flood insurance policies that the homeowners carry. The information includes premium, coverage amount, deductible amount, policy start date, and policy end date. The data set is merged with the anonymized ICE, McDash mortgage performance data to obtain standard mortgage characteristics (credit score, LTV, debt-to-income (DTI) ratio, etc.).

Finally, we supplement this carefully constructed suite of data with variables from the CoreLogic Property Tax data set and; the CoreLogic Owner Transfer and Mortgage Basic data sets, aggregate migration rates derived from the FRBNY Consumer Credit Panel/Equifax Data (CCP) and census tract characteristics data from the 2019-2023 5-year American Community Survey (ACS).

4.2 Sample construction

The first sample is a cross-section of SFRs that existed in the contiguous United States as of 2023, and from which we can use to compute our measure of model risk. To construct this sample, we use the CL property tax data set to identify the relevant properties for analysis and merge in the AAL estimates from CL. Using a nearest-neighbor matching approach, we merge in the FSF physical risk data. Since CL separately estimates inland flood risk and hurricane storm surge risk, we combine the AAL estimates from these perils so that we can analyze them in relation to the flood peril in FSF.[6] The final sample consists of approximately 83 million SFRs for which we can observe AAL estimates for flood, hurricane wind, and wildfire from both modelers.

The second sample is a cross-section of homeowner's insurance policies that were active as of June 2024. To construct this sample, we first identify the relevant homeowner's insurance

[5]Both sets of estimates incorporate data from the IPCC Sixth Assessment Report (AR6).

[6]AALs are additive, so this transformation should not introduce any unwanted bias (Wylie et al., 2025).

policies and the associated mortgages in the ICE, McDash data set. We then use observable mortgage information to perform a fuzzy merge between the ICE, McDash data set and the housing stock sample described above to arrive at a subsample of homeowner's insurance policies where we can observe the insurance contract's characteristics and the associated home's risk estimates.[7] Mortgage characteristic information for the housing stock sample comes from the CoreLogic Mortgage Basic data set. The final sample consists of approximately 9.5 million mortgages and, hence, active homeowner's insurance policies. Appendix Table A1 presents summary statistics of the key variables that we use in our analysis.

4.3 Measuring model risk

The AAL can be interpreted as the modeler's best guess of the expected level of risk that the property faces in a given year. As such, for a given peril, we define property-level model risk as the absolute difference between CL's AAL estimate and FSF's AAL estimate. Formally, we use the following equation:

$$Model\,Risk_{ij} = |AAL_{ij}^{CL} - AAL_{ij}^{FSF}|. \tag{1}$$

Properties are indexed by i and perils are indexed by j. AAL^k is modeler k's AAL estimate.[8] The implicit assumption in the equation above is that AAL estimates from both modelers are equally informative; that is, a rational agent should pay equal attention to both.

In the CL data, AAL values are presented as a share of the total insurable value (TIV). In the FSF data, AAL values are presented as rebuilding costs in dollars. In order to make the AAL estimates comparable, we normalize FSF's AAL value by the replacement cost value provided by FSF for each structure. For the purpose of this paper, we assume that TIV equals replacement cost. Since AALs are additive, we can also aggregate AAL values across perils to come up with a measure of composite or multi-peril risk and, hence, a measure of model risk for multiple perils. In the results presented below, we also use the Pearson

[7] We merge on four variables: property ZIP code, year-month of origination, origination amount, and mortgage type (purchase vs. refinance). We keep only 1:1 matches.

[8] For flood and hurricane wind, FSF provides a range of AAL estimates to reflect uncertainty in its damage modeling, i.e., how the hazard level translates to the amount of damage to a structure. For this exercise, we use the 50$^{\text{th}}$ percentile value. CL provides one AAL number for each property-peril pair.

correlation as a measure of model risk. A low correlation between the two modelers' AAL estimates for a set of properties is consistent with a high degree of model uncertainty.

We also construct AAL in dollar terms by multiplying the AALs described above by property-specific estimates of structure value. Following the procedure in Wylie et al. (2025), we use property-level transaction data and tract-level land value shares of home values from Davis et al. (2021) to generate the structure value estimates.

5 Results

Fact 1: Property-level model risk is large

Table 1 presents summary statistics on CL's AAL estimates, FSF's AAL estimates, and our measure of model risk, which is the absolute difference between the two modelers' AAL estimates. We present the summary statistics for both by-peril AAL and composite AAL. We show two versions of the composite AAL because flood damages are not included in the standard homeowner's insurance policy, while damages from hurricane wind and wildfire are included. For ease of interpretation, we present the AAL estimates in both basis points (bps) of replacement cost and in 2021 USD.

It is helpful to begin the discussion by noting that CL's and FSF's by-peril mean AALs, and hence mean composite AALs, including or excluding flood, are comparable. For example, the mean CL flood AAL is 5.5 bps and the FSF flood AAL is 5.8 bps. Economically, this fact implies that CL's and FSF's estimates of the average level of physical risk that SFRs in the US face are similar.

This baseline observation is meaningful when we next consider the summary statistics of our measure of model risk. The mean composite (flood, hurricane wind, and wildfire together) model risk is 12.5 bps or approximately $322 per year. This 12.5 bps difference between the two modelers is larger than either modeler's mean AAL. The economic implication of this finding is profound because the result suggests that, although CL and FSF agree on the average level of risk for this sample of SFRs, their average disagreement is large enough to change the classification of a home from being a home that faces the average level of risk to a home that faces no risk or double the average risk. In other words, the two modelers significantly disagree on which homes are risky and which homes are safe; hence, the model risk, as defined and presented, is, on average, large.

This qualitative assessment holds true for individual peril AALs and composite AAL that excludes flood risk. Figure 1 presents the distribution of by-peril and composite AALs produced by each modeler. The four panels underline the same point, which is that a large part of the disagreement comes from the modelers' disagreement on which properties are safe and which are risky, as seen by the large differences in the tails of the distributions.

Figure 2 presents the geographical distribution of model risk. Panel A presents the model risk map for hurricane wind and wildfire risk estimates. Not surprisingly, the largest amounts of disagreement occur in areas with the highest levels of hurricane wind (e.g., the southern coast) and wildfire risk (e.g., the western parts). Panel B presents the model risk map that adds flood risk to the mix. Once again, we see that areas with darker shades, i.e., higher levels of model risk, are areas with high flood risk (e.g., the southern coasts and Appalachia).

Lastly, it is worth noting that the distribution of our measure of model risk has a long right tail, which means that, although the dollar amount of the average model risk is small ($322), some households face a large amount of this type of risk. For example, when we consider the right tail of the composite model risk distribution, we find that SFRs at the 95^{th} percentile face approximately $1,200 in model risk, and those at the 99^{th} percentile face approximately $5,600 in model risk. Economically, these numbers imply that, for a subset of households, model risk may make existing insurance coverage insufficient or may have caused the household to buy too much insurance by a large dollar amount.

In standard insurance demand models (Mossin, 1968), agents choose the optimal level of insurance coverage based on their knowledge of the cost of insurance, the risk that their home faces, and their wealth level. The key implication of this first fact is that, with high uncertainty in risk estimates and likely large information frictions that prevent households from learning about the degree of uncertainty (Collier et al., 2023; Amornsiripanitch et al., 2025b), households cannot make optimal homeowner's insurance coverage decisions because they cannot accurately learn about a key model parameter. The consequence is that, in expectation, many households will be underinsured (Amornsiripanitch et al., 2025a; Sastry et al., 2025) because they did not buy enough insurance or they will have spent money on insurance that they do not need.

Fact 2: Area-level model risk is large

The previous section demonstrates that it is difficult for the modelers to agree on which properties are safe and which are risky. In this section, we explore whether the two modelers agree more; i.e., whether model risk attenuates when we aggregate the estimates up to the tract or county level. In other words, we ask whether the two modelers are more likely to agree when they try to identify risky and safe *areas*, which is presumably a much easier task to perform than identifying risky and safe *properties*. This is a meaningful question to answer because, from the perspective of the location choice problem (Rosen, 1979; Roback, 1982), it is still extremely helpful for agents to know which neighborhoods are safe and which are not.

We begin by computing the correlation between the two modelers' aggregated AAL estimates at different levels of geographical granularity. Table 2a presents the results. The first column presents the correlation between the two modelers' property-level AAL estimates. For hurricane wind, we find that the correlation is quite high at 0.71, which means that across the entire country, the two modelers tend to reasonably agree on the ordering of riskiness across properties. This is not the case for wildfire and flood. The property-level AAL correlations for wildfire and flood are relatively low (0.31 and 0.20, respectively).

The second and third columns show how aggregation affects the correlations for each peril. Using the tract- and county-level average AALs, we see an improvement in the correlation for all perils compared to the property-level AAL correlation. In the case of wildfire and flood, each step of aggregation improves the degree of agreement, with the county-level correlation being the greatest (0.54 for wildfire and 0.53 for flood). However, for wildfire, the jump from property-level to tract-level generates the largest improvement, while for flood, the greatest improvement is from tract-level to county-level. In the case of hurricane wind, the tract-level correlation is the strongest (0.85), not the county-level (0.81).

Aggregation can strengthen a relationship by removing intra-area variance, in which case the improvement does not necessarily reveal a meaningful area-level relationship. In order to investigate this, we run the following ordinary least squares (OLS) regression to isolate the within-area effect (the relationship between individual property AALs within an area) from the between-area effect (the relationship between area-level average AALs):

$$AAL_{ik}^{FSF} = \alpha + \beta_{within} \times (AAL_{ik}^{CL} - \overline{AAL_k^{CL}}) + \beta_{between} \times \overline{AAL_k^{CL}} + \epsilon_i. \quad (2)$$

Properties are indexed by i and areas (e.g., tract or county) are indexed by k. The results of these regressions are shown in Table 2b for the tract- and county-level. For each peril and level, we find that the $\beta_{between}$ coefficients are significantly greater than the β_{within} coefficients, which suggests that the aggregation is revealing a stronger between-area relationship than the property-level relationship within the area. In other words, to the extent that there is agreement at the aggregate level, it is mostly driven by agreement on the classification of risky areas versus safe areas, instead of the classification of risky properties versus safe properties.

Comparing across perils, the between effect is strongest for hurricane wind. Particularly at the tract level, the within agreement is very small compared to the between agreement. The within agreement is strongest for wildfire and flood, which is consistent with the notion that there are more meaningful property-level factors impacting wildfire and flood risk compared to hurricane wind.

While aggregation does improve the relationship between the modelers' AAL estimates, it is important to emphasize, particularly in the context of model risk, that the area-level correlations for wildfire and flood are still relatively low (< 0.55). With the exception of hurricane wind, the two modelers largely do not agree on the relative risk level across places, which implies that physical risk from natural disasters is difficult to model even for large areas of land. From an economic perspective, this finding is important because it implies that economic agents cannot reasonably rely on these models to make migration decisions if they wish to avoid physical risk from natural disasters.

Fact 3: Vulnerable households bear more model risk

Now that we have established that model risk is large at both the property level and the area level, it is important to ask – who bears this set of model risk? Following Wylie et al. (2025), we sort census tracts into quintiles of tract-level composite wildfire, hurricane wind, and flood model risk, i.e., the average absolute difference in wildfire plus hurricane wind plus flood AAL. Then, for each quintile, we compute the average tract characteristics and their standard errors.

Table 3 presents the results. The first section of the table (rows one through three) shows the average combined model risk from hurricane wind, flood, and wildfire, and the average AAL levels estimated by CL and FSF. The first notable pattern is that places with high model risk (first row) are also places with high average risk (rows two and three). This pattern is not mechanical because one can easily imagine an alternative distribution where places with high model risk are also places with low average risk; i.e., the modelers tightly agree on the risk level estimates for very risky places but are relatively uncertain about the risk level in comparatively safer places. The economic implication of this pattern is that a rational agent who is risk averse should dislike high-risk places not only because they are risky places to live in but also because these are places with high levels of uncertainty in the distribution of outcomes (Ellsberg, 1961). In other words, people living in these risky areas are taking on two distinct types of risk.

The second section of Table 3 presents summary statistics on tract-level socioeconomic status and demographic characteristics. There are several interesting patterns. First, higher model risk is associated with lower home values, lower household incomes, lower educational attainment, and a higher share of the elderly population (65 years and older).[9] This set of correlations suggests that relatively more economically vulnerable households bear higher levels of physical risk and associated model risk. In terms of race and ethnicity, places with higher levels of model risk tend to have larger White population shares. Lastly, rural areas, as measured by population density, tend to have higher levels of model risk. Overall, this sorting exercise shows that uncertainty in physical risk levels tends to be disproportionately borne by economically vulnerable White households that live in rural areas. These patterns are likely driven by the well-established fact that less well-off households tend to live in areas with higher levels of physical risk (Wing et al., 2022; Wylie et al., 2025). More importantly,

[9]Old age is a proxy for financial vulnerability because the elderly tend to have lower income, less financial sophistication (Amornsiripanitch et al., 2026), and lower access to credit (Amornsiripanitch, 2023) compared to their younger counterparts.

the result suggests that improvements in physical risk modeling are likely to be economically progressive.

Fact 4: Insurance premiums are uncorrelated with model risk

A rational insurer, whether they are risk averse or risk neutral, should consider model risk when pricing insurance contracts; that is, all else being equal, contracts that face higher model risk should charge higher premiums because the expected payoff amounts have higher degrees of uncertainty due to ambiguity (Ellsberg, 1961). In other words, "risk refers to events for which the probabilities of the future outcomes are known. Ambiguity refers to events for which the probabilities of the future outcomes are unknown" (Dimmock et al., 2016).[10] We test this economic intuition by estimating variants of the following Poisson regression on our sample of homeowner's insurance policies:

$$Premium_i = e^{\alpha+\beta\times Model\,Risk_i + Control\,Variables + FE}. \tag{3}$$

Premium is the policy's premium measured in USD.[11] i is the index for homeowner's insurance policies. The control variables include various measures of the level of physical risk that the property faces, the deductible amount, the coverage amount, the credit score (Blonz et al., 2026), and the home value. We include both model risk and risk-level measures, both measured in AAL, because we want to study the correlation between the premium amount and model risk, conditional on the level of physical risk that the property faces. For fixed effects, we use ZIP code, policy start year-month, and insurer fixed effects. We exclude flood AAL from this regression analysis because homeowner's insurance does not cover flood damage.[12]

Table 4 presents the results. The first column presents the result where premium is regressed onto our measure of model risk. As a control for the property's physical risk level,

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[10]See Heitfield (2025) for a stylized model and a discussion of this point.

[11]Following the recent literature on econometric issues related to using OLS to estimate regressions with count-like outcome variables, we use the Poisson regression model instead of OLS, with the natural log of premiums as the outcome variable (Cohn et al., 2022; Chen and Roth, 2024).

[12]All results are qualitatively and quantitatively similar when we include flood AAL in the model risk and risk level terms. The coefficients on flood risk terms are never statistically different from zero, which is consistent with the institutional details that flood insurance is not included in the standard homeowner's insurance contracts.

we use the average between CL's and FSF's AAL, measured in bps of replacement value, along with their respective squared terms to account for non-linear relationships. In a world where insurers price model risk, the coefficient on the model risk term should be positive and statistically different from zero. The regression result presented in column 1 shows a small and negative coefficient on the model risk term.

The negative coefficient is counterintuitive. A potential explanation is that insurers may place much more weight on one modeler's AAL estimates than on those from the other modeler. Places with high levels of model risk are either places where CL's AAL is much larger than FSF's, or vice versa. Therefore, if, for example, insurers place much more weight on CL's AAL estimates, then the negative coefficient on the model risk term is likely driven by the relative over-representation of places where CL's AALs are much smaller than FSF's AALs in the regression sample. The remaining columns of Table 4 present regression results that aim to verify this hypothesis.

Column 2 presents the result from a specification where we regress premiums onto CL's and FSF's AALs, separately. We find that, on average, the variation in premiums is almost ten times more sensitive to the variation in CL's AAL than to that of FSF's AAL. In column 3, we include the respective squared terms and find the same qualitative conclusion, which is that insurers appear to place more weight on CL's AAL estimates when computing insurance premiums.

Column 4 presents results from another regression specification that tests whether insurers mainly use one modeler's estimates to price insurance contracts and, to a large extent, ignore model risk. The Poisson regression is specified as follows:

$$\begin{aligned} Premium_i = exp(&\alpha + \beta_1 \times Average\, AAL_i \\ &+ \beta_2 \times \mathbb{1}(AAL^{FSF} > AAL^{CL} + 1\, bp)_i \\ &+ \beta_3 \times \mathbb{1}(AAL^{CL} > AAL^{FSF} + 1\, bp)_i \\ &+ Control\, Variables + FE). \end{aligned} \tag{4}$$

The $Average\, AAL$ term controls for the level of physical risk from hurricane wind and wildfire that the property faces. The two indicator variables of interest are $\mathbb{1}(AAL^{FSF} > AAL^{CL} + 1\, bp)$ and $\mathbb{1}(AAL^{CL} > AAL^{FSF} + 1\, bp)$. The first indicator variable equals one when, for property i, FSF's hurricane wind plus wildfire AAL is greater than CL's hurricane wind plus wildfire AAL by at least 1 basis point and zero otherwise. The second indicator variable equals one for the opposite case. The 1 basis point wedge is chosen such that the margin of difference is sufficiently large for us not to be considering cases where the two AALs are too close together.[13] If insurers price model risk, then both β_2 and β_3 will be positive because, intuitively, they capture the two modelers' disagreement in different directions, and the relationship between premium and uncertainty in model estimates should be positive, i.e., direction-independent. However, if insurers mainly rely on CL's AALs and largely ignore the AALs' disagreement with FSF's AALs, then β_2 should be negative and β_3 should be positive. β_2 should be negative because these are properties that FSF considers are high-risk, but CL considers are low-risk, and, therefore, an insurer that only uses CL's AAL will charge a low premium. β_3 should be positive because of the opposite case. The results presented in column 4 are consistent with the idea that insurers mainly rely on CL's AALs and largely ignore model risk, as measured by differences in AAL estimates between CL and FSF. This result also suggests that the negative coefficient on the model risk term in column 1 is driven by the fact that properties with high model risks are properties that have high FSF AALs, but low CL AALs.

The important economic implication of this result is that insurers may be exposed to large losses from model uncertainty. For example, an insurer who relies solely on CL's AAL estimates may face large losses in areas that CL's model considers safe, but FSF's model considers risky. Although the opposite may be true, it is not obvious that the losses and gains from these two parts of the risk distribution would necessarily cancel each other out because the distribution is likely asymmetric. The only way for insurers to mitigate this risk is to systematically account for model uncertainty in their pricing schemes.

It is important to note that the results presented in this section are descriptive in nature and do not identify the economic parameter of interest (Kahn and Whited, 2018), which is the elasticity between homeowner's insurance premiums and uncertainty in physical risk model estimates, i.e., model risk. However, the regression results are still informative because unidentified correlations are highly suggestive of the underlying economics, as in the strong

[13]The results are qualitatively similar if we do not impose the 1 bps minimum margin of difference.

positive correlation between homeowner's insurance premiums and physical risk levels that we find in the same regressions. Therefore, we view the absence of the expected positive correlation between homeowner's insurance premiums and model risk as the first step in making progress on an important research question.

Fact 5: Migration increases exposure to model risk

Migration choices should reflect households' assessment of neighborhoods' economic opportunities, amenities (Tiebout, 1956), and risks (Boustan et al., 2020). Therefore, in the context of physical risk from natural disasters, households should account for both the level of risk and, in a world where physical risk models are imperfect, the uncertainty in risk estimates. All else being equal, rational agents should move *away* from places with higher levels of model risk.

We test whether the aggregate net migration patterns correlate with our measure of model risk in the way that the economic intuition outlined above suggests. Following Wylie et al. (2025), we use the CCP data to compute net migration rates from 2015 to 2024 at the tract level and analyze how net migration rates vary with tract-level average model risk, measured in basis points of replacement value. We do so by estimating variants of the following OLS regression equation:

$$M_k = \alpha + \beta \times Model\,Risk_k + Control\,Variables + FE + \epsilon_k. \tag{5}$$

M is the tract-level net migration rate, presented in pp, which is defined as the net number of migrants normalized by the tract's 2015 population, presented in percentage points. Census tracts are indexed by k. Table 5 presents the results. Column 1 presents results from a specification in which we regress net migration rate onto our measure of model risk for hurricane wind and wildfire risk and, separately, our measure of model risk for flood risk.[14] Here, we find that net migration rate is positively correlated with model risk in hurricane wind and wildfire AAL but not with model risk in flood AAL, which implies that, from 2015 to 2024, more people have been moving into areas with higher levels of model risk.

[14] The separation is motivated by the fact that flood insurance is not included in the standard homeowner's insurance contract. All results are quantitatively and qualitatively similar when we include flood AAL into the model risk term.

Columns 2 and 3 include risk level control variables, which enter the regressions as linear and squared terms. These risk level terms have negative coefficients that are, for the most part, statistically different from zero, which is consistent with the idea that people tend to avoid areas with high levels of physical risk. The coefficient on the model risk term remains positive and statistically different from zero. The robustness of the result indicates that, holding fixed the level of physical risk, people tend to move into areas with higher levels of model risk. Interestingly, the coefficient more than doubles in size, which suggests that the physical risk level is an important correlate.[15]

Long-distance migration rates have dropped dramatically in America (Adams et al., 2025; Wilson, 2026). With this stylized fact, it's worth exploring whether our migration results are robust with respect to migration distance. The results presented in column 4 show that the coefficient of interest remains largely unchanged when we include county fixed effects, which means that, for both cross-county (column 3) and within-county (column 4) moves, people tend to migrate into areas with higher levels of model risk. Taken at face value and in conjunction with the premiums regression results (Table 4), the results presented in this section are consistent with the idea that, in aggregate, economic agents appear to internalize physical risk levels in a rational way but ignore model risk. This behavior may be potentially driven by the finding that homeowner's insurance premiums price physical risk levels but ignore the uncertainty of such risks and, as a result, the distribution of homeowner's insurance premiums does not serve as sufficiently informative signals about the distribution of physical risk from natural disasters (Nyce et al., 2015).

Similarly to the results presented in the previous section, the results presented here do not identify the causal relationship between model risk and migration decisions. In other words, we are not showing that, at the margin, an increase in model risk causes people to make

[15] Wylie et al. (2025) find that tract-level net migration rate for 2010 to 2019 is positively correlated with CL's tract average all-peril physical risk, excluding earthquake risk. This is an unconditional statement. The results presented in Table 5 are not comparable to the migration result from Wylie et al. (2025) because our regressions include the model risk term, FSF's AAL measures, and separate peril-set-specific AAL terms. The regressions present a conditional correlation result, i.e., the correlation between net migration rates and physical risk levels, conditional on model risk levels. Furthermore, the measurement of physical risk levels differs between the two papers. A simple regression where net migration rate is regressed onto CL's tract average all-peril physical risk, excluding earthquake risk, gives a positive coefficient that is statistically different from zero at the 5% level.

certain migration decisions. Instead, we present correlations between aggregate migration and different measures of model risk, which are informative about changes in aggregate risk exposure but not marginal effects.

6 Conclusion

As the expected level of physical risk from natural disasters is difficult to measure, model risk is a material concern when physical risk estimates are used in empirical analysis.[16] This paper is among the first to quantify the model risk in physical risk estimates of flood, hurricane wind, and wildfire and to provide stylized facts on this source of risk.

In light of the results presented above, improving physical risk models so that this class of risk can be estimated more precisely will likely bring welfare gains. Large amounts of model risk at both the property and area levels (Facts 1 and 2) imply that lowering this type of risk will increase the likelihood that individuals make optimal insurance coverage and migration decisions (Fact 5). The marginal welfare gains are likely large, since vulnerable households disproportionately bear more model risk (Fact 3), and research has documented that insurance payouts are important for economic recovery (von Peter et al., 2024; You and Kousky, 2024). Improving physical risk models would also allow insurance companies to better manage risk (Fact 4), be more likely to provide insurance (Boomhower et al., 2024), and, hence, improve financial stability because insurance companies are less likely to fail (Amornsiripanitch, 2022).

A practical lesson from our work is that analysts who use physical risk estimates to perform empirical analysis should account for model risk. One way to do this is to properly account for model uncertainty by presenting the standard errors that reflect this source of uncertainty. Wing et al. (2022) is a great example. The researchers were able to do so because they had access to the modeler's full distribution of model estimates. Another way to address model risk is to ensure that the key results from the analysis are robust when using physical risk estimates from different modelers.

[16]See https://www.bloomberg.com/graphics/2024-flood-fire-climate-risk-analytics/.

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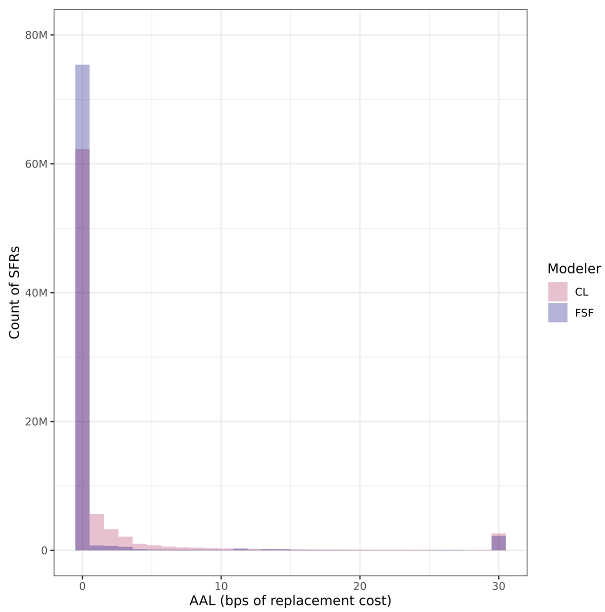
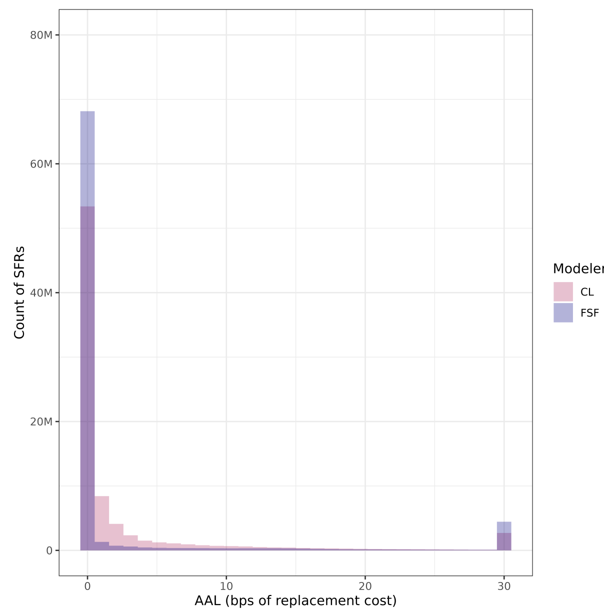
Figure 1: Distribution of AAL Estimates by Peril

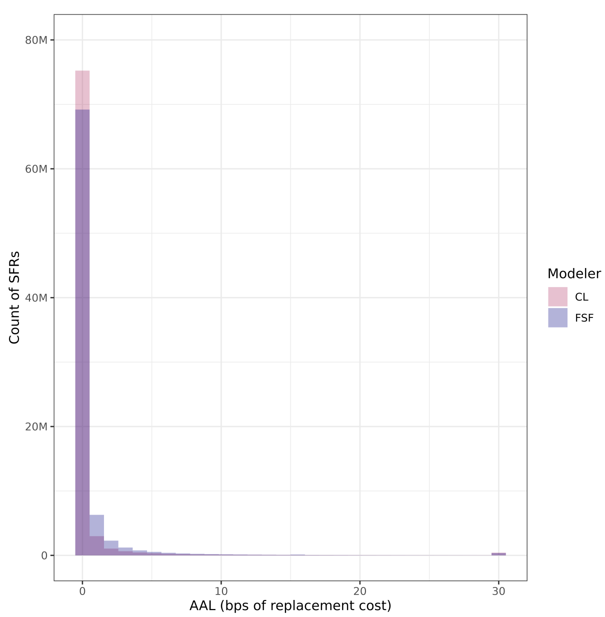
This figure presents the distribution of average annual loss (AAL) estimates from CoreLogic (CL) and First Street Foundation (FSF) for flood, hurricane wind, and wildfire. AALs are expressed as basis points of replacement cost. For presentation purposes, AALs are top-coded at 30 basis points of replacement cost with the exception of the composite figure, which is top-coded at 50 basis points of replacement cost. Data source: CoreLogic and First Street Foundation.



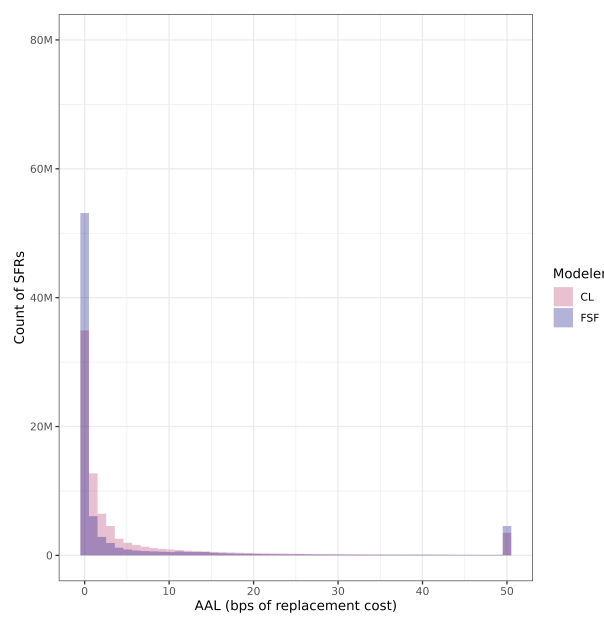
(a) Flood



(b) Hurricane Wind



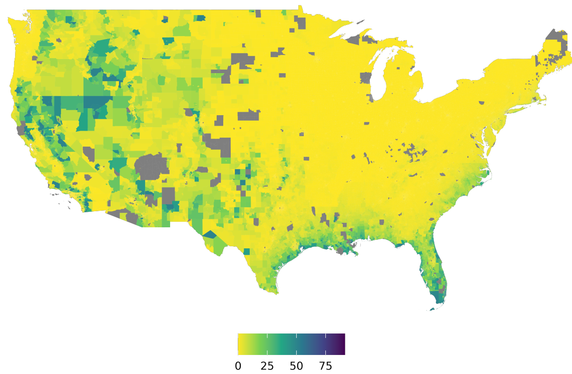
(c) Wildfire



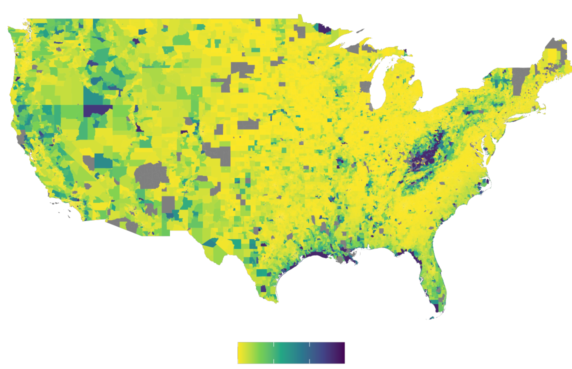
(d) Composite

Figure 2: Maps of Absolute Difference in Modelers' Estimates of Tract Average AAL

This figure presents tract-level maps of average absolute difference in property-level average annual loss (AAL) estimates between CoreLogic (CL) and First Street Foundation (FSF). Two different AAL composites are shown: hurricane wind and wildfire as well as hurricane wind, wildfire, and flood. AALs are expressed as basis points of replacement cost and aggregated from property-level AALs. AALs shown in maps are winsorized at 1st and 99th percentiles when aggregated to the tract level and top-coded at the 99th percentile of the distribution of tract-level average AALs. Tracts in gray do not have sufficient data to calculate a tract-level AAL from both modelers. Data source: CoreLogic and First Street Foundation.



(a) Absolute Difference in AAL (bps) - Hurricane Wind and Wildfire



(b) Absolute Difference in AAL (bps) - Hurricane Wind, Wildfire, and Flood

Table 1: Summary Statistics of CoreLogic and First Street Foundation AALs

This table presents summary statistics on CoreLogic's (CL) and First Street Foundation's (FSF) average annual loss (AAL) estimates for flood, hurricane wind, and wildfire. Panel (a) presents AALs expressed as basis points of replacement cost; Panel (b) presents AAL estimates in dollars based on property-specific home value estimates. Data source: CoreLogic, First Street Foundation, and Davis et al. (2021).

(a) Summary Statistics (bps)

	Count SFRs	*AAL*						*Absolute Difference in AAL*							
Peril	**(millions)**	**CL Mean**	**FSF Mean**	**CL Median**	**FSF Median**	**CL SD**	**FSF SD**	**Mean**	**SD**	**p10**	**p25**	**Median**	**p75**	**p95**	**p99**
Flood	81.6	5.5	5.8	0.0	0.0	40.0	50.2	9.0	56.9	0.0	0.0	0.0	0.7	26.0	241.2
Hurricane Wind	81.4	3.8	4.4	0.0	0.0	12.5	15.8	3.2	10.7	0.0	0.0	0.0	1.4	19.2	54.2
Wildfire	82.9	0.7	0.9	0.0	0.0	0.7	0.9	1.1	6.5	0.0	0.0	0.0	0.1	4.3	21.8
All	80.9	10.1	11.2	0.9	0.0	43.7	54.5	12.5	58.4	0.0	0.1	1.0	4.6	47.1	251.6
Hurricane Wind & Wildfire	81.3	4.5	5.3	0.4	0.0	13.4	16.8	4.2	12.2	0.0	0.0	0.5	2.4	23.6	59.0

(b) Summary Statistics (USD)

	Count SFRs	*AAL*						*Absolute Difference in AAL*							
Peril	**(millions)**	**CL Mean**	**FSF Mean**	**CL Median**	**FSF Median**	**CL SD**	**FSF SD**	**Mean**	**SD**	**p10**	**p25**	**Median**	**p75**	**p95**	**p99**
Flood	81.6	130	149	1	0	1,098	1,880	222	1,989	0	0	1	15	582	4,986
Hurricane Wind	81.4	98	128	0	0	575	731	88	501	0	0	0	29	423	1,560
Wildfire	82.9	27	28	0	0	216	248	38	274	0	0	0	4	131	755
All	80.9	256	308	21	0	1,349	2,127	322	2,086	0	1	23	114	1,184	5,604
Hurricane Wind & Wildfire	81.3	125	157	9	0	613	770	122	564	0	0	11	58	603	1,824

Table 2: Correlation of Risk Estimates at Different Levels of Aggregation

This table presents the correlation of the modelers' average annual loss (AAL) estimates at different levels of aggregation in Panel (a) and the results from a multi-level regression model that decomposes the within-area and between-area components of the relationship in Panel (b). AALs are expressed as basis points of replacement cost. Properties in tracts where estimates are not available for at least 30 properties in tract are excluded. t-statistics shown in parentheses reflect heteroskedasticity-robust standard errors clustered at the respective area levels (e.g., tract or county). *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic and First Street Foundation.

(a) AAL Correlations

	AAL Correlation		
Peril	*Property-level*	*Tract-level*	*County-level*
Hurricane Wind	0.71	0.85	0.81
Wildfire	0.31	0.52	0.54
Flood	0.20	0.34	0.53
All	0.28	0.53	0.60
Hurricane Wind & Wildfire	0.65	0.83	0.74

(b) Multi-level Regression Results

	Tract		**County**	
Peril	β_{within}	$\beta_{between}$	β_{within}	$\beta_{between}$
Hurricane Wind	0.05***	1.16***	0.22***	1.27***
	(14.8)	(49.1)	(4.9)	(11.3)
Wildfire	0.13***	0.56***	0.25***	0.66***
	(12.9)	(21.7)	(7.7)	(10.4)
Flood	0.19***	0.60***	0.23***	0.59***
	(45.0)	(19.8)	(18.7)	(5.2)
All	0.19***	0.83***	0.24***	0.91***
	(44.7)	(36.9)	(17.8)	(9.3)
Hurricane Wind & Wildfire	0.07***	1.10***	0.22***	1.24***
	(17.1)	(52.5)	(6.8)	(11.2)

Table 3: Tract Characteristics by Absolute Difference in AAL

This table presents census tract characteristics sorted by a quintile of model risk, defined as the absolute difference in average annual loss (AAL) estimates for hurricane wind, wildfire, and flood. AALs are expressed as basis points of replacement cost. Model risk is calculated at the property level and then aggregated up to tract level. Census tracts where estimates are not available for at least 30 properties in tract are excluded. Demographic data are collected from the ACS. All values are winsorized at the 1st and 99th percentiles within quintiles. Data source: CoreLogic, First Street Foundation, and Census American Community Survey (2019-2023 5-Year).

	Mean (Standard Error) *Tract Average Wildfire + Hurricane Wind + Flood AAL Absolute Difference*				
Variable	**Quintile 1**	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**
Absolute Diff AAL	0.83	2.32	4.42	9.58	42.58
	(0.004)	(0.004)	(0.007)	(0.023)	(0.324)
Average CL AAL	0.67	2.00	3.97	8.59	35.29
	(0.004)	(0.011)	(0.023)	(0.057)	(0.331)
Average FSF AAL	0.30	0.99	2.38	6.11	43.11
	(0.003)	(0.011)	(0.025)	(0.062)	(0.437)
Median Home Value	380,018	383,733	391,841	354,353	325,466
	(2,819)	(2,587)	(2,629)	(2,526)	(2,333)
Median Household Income	85,479	90,009	90,962	85,246	76,789
	(351)	(352)	(354)	(336)	(293)
Percent White	54.9	57.0	61.0	63.3	64.1
	(0.3)	(0.3)	(0.2)	(0.2)	(0.3)
Percent Black or Non-White Hispanic	28.4	27.4	24	22.8	23.5
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Percent Bachelor's Degree	35.1	34.5	34.5	31.2	28.6
	(0.2)	(0.2)	(0.2)	(0.2)	(0.1)
Percent Owner Occupied	60.1	65.5	67.4	70.1	70.2
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Percent Mortgaged	38.1	41.2	41.2	40.4	36.6
	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
Percent Population 65+	15.6	16.7	17.4	18.6	21
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Population Density (per sq mi)	5,203	5,255	4,653	2,830	2,487
	(44)	(77)	(76)	(45)	(38)
Total Population	4,410	4,782	4,815	4,731	4,374
	(19)	(20)	(20)	(21)	(21)
Number of Tracts	12,908	12,908	12,908	12,908	12,907

Table 4: Premium Regressions

This table presents Poisson regression results from models where a homeowner's insurance premium (USD) is regressed onto various measures of physical risk and model risk. The AALs include hurricane wind and wildfire risk; flood risk is not included because it is not covered under a standard homeowner's insurance policy. AALs are expressed as basis points of replacement cost. Other insurable perils include severe convective storm, and winter storm, which are all covered under a standard homeowner's insurance policy. Risk from these perils is produced only by CL. Control variables include deductible amount, coverage amount, property value, and credit score at origination. ZIP code, policy year-month, and insurer fixed effects are included in all specifications. All values are winsorized at 1st and 99th percentiles. t-statistics are shown in parentheses. Heteroskedasticity-robust standard errors are clustered on ZIP code. *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic, First Street Foundation, and ICE, McDash.

	Dependent Variable: Monthly Homeowner's Insurance Premium ($)			
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Absolute Difference in AAL	-0.00386***			
	(-19.98)			
Average of CL and FSF AALs	0.0144***			0.00741***
	(23.40)			(15.00)
(Average of CL and FSF AALs)^2	-0.0000852***			-0.0000144*
	(-10.93)			(-2.02)
CL AAL		0.00710***	0.0129***	
		(35.82)	(23.59)	
FSF AAL		0.000810***	0.00143***	
		(5.49)	(4.18)	
(CL AAL)^2			-0.000110***	
			(-12.76)	
(FSF AAL)^2			-0.00000779*	
			(-2.18)	
$\mathbb{1}$(FSF AAL > CL AAL + 1 bps)				-0.0145***
				(-6.74)
$\mathbb{1}$(CL AAL > FSF AAL + 1 bps)				0.0181***
				(9.76)
CL AAL from Other Insurable Perils	0.00987***	0.00188***	0.00720***	0.0108***
	(19.37)	(12.93)	(14.00)	(20.30)
(CL AAL from Other Insurable Perils)^2	-0.000233***		-0.000172***	-0.000261***
	(-15.70)		(-11.72)	(-16.71)
Control Variables	Y	Y	Y	Y
N	9,518,106	9,518,106	9,518,106	9,518,106
Pseudo R-squared	0.62	0.62	0.62	0.62

Table 5: Migration Regressions

This table presents regressions of average tract-level net migration rates from 2015 to 2024 on measures of tract-level model risk. The net migration rate is defined as the net number of migrants (derived from FRBNY Consumer Credit Panel/Equifax Data) normalized by the tract's 2015 population (ACS), presented in percentage points. Model risk is calculated at property-level and then aggregated up to tract-level. Model risk is examined separately for hurricane wind (HW) and wildfire (WF) and flood. The HW+WF AAL and Flood AAL are the average of the CL and FSF AALs provided for the property. AALs are expressed as basis points of replacement cost. Other perils include severe convective storm, winter storm, and earthquake. Risk from these perils is produced only by CL. Tracts where AAL estimates are not available for at least 30 properties in the tract are excluded. All values winsorized at the 1^{st} and 99^{th} percentiles within full sample of tracts. t-statistics are presented in parentheses. Heteroskedasticity-robust standard errors are clustered on county. *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic, First Street Foundation, FRBNY Consumer Credit Panel/Equifax Data, and Census American Community Survey (2011-2015 5-Year).

	Dependent Variable: Tract Net Migration (% of 2015 Pop)			
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Tract Average Absolute Difference in HW+WF AAL	0.17667***	0.40323***	0.37172***	0.30814***
	(2.71945)	(6.24972)	(5.78254)	(5.98247)
Tract Average Absolute Difference in Flood AAL	0.01475	0.03981	0.02193	0.01875
	(1.59942)	(1.38957)	(0.58648)	(1.00567)
Tract Average HW+WF AAL		-0.20100***	-0.09807	-0.20240***
		(-2.70342)	(-1.36750)	(-3.10748)
Tract Average Flood AAL		-0.02578	0.00901	-0.00485
		(-0.53090)	(0.14434)	(-0.17812)
Tract Average Other Perils AAL		-0.12734***	-0.11188***	-0.23876***
		(-3.71263)	(-2.81029)	(-4.81589)
(Tract Average HW+WF AAL)^2			-0.00106**	0.00015
			(-2.45240)	(0.84161)
(Tract Average Flood AAL)^2			-0.00002**	-0.00002*
			(-2.35605)	(-1.65042)
(Tract Average Other Perils AAL)^2			-0.00022	0.00032
			(-0.54969)	(0.90820)
County FE				Y
N	65,541	65,541	65,541	65,541
Adjusted R-squared	0.013	0.023	0.026	0.215

Online Appendix: Model Risk in Physical Risk Models

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Table A1: Summary Statistics for Premium Regression Variables

This table presents the summary statistics for variables used in the premium regressions shown in Table 4. AALs shown here include hurricane wind and wildfire risk; flood risk is not included because it is not covered under a standard homeowner's insurance policy. AALs are expressed as basis points of replacement cost. Other insurable perils include severe convective storm, winter storm, and earthquake, which are all covered under a standard homeowner's insurance policy. Sale amount is appraisal amount in the case of refinances. All values winsorized at 1st and 99th percentiles. Data source: CoreLogic, First Street Foundation, and ICE, McDash.

	N	**Mean**	**SD**	**Min**	**Max**
Absolute Difference in AAL (Model Risk)	9,518,106	3.73	9.24	0	55.25
CL AAL	9,518,106	3.68	8.84	0	54.16
FSF AAL	9,518,106	4.99	14.47	0	82.07
Mean CL/FSF AAL	9,518,106	4.36	11.08	0	64.33
Indicator FSF > CL + 1bp	9,518,106	0.15	0.65	0	1
Indicator CL > FSF + 1bp	9,518,106	0.23	0.42	0	1
CL AAL from Other Insurable Perils	9,518,106	6.49	5.87	0.01	29.08
Monthly Premium ($)	9,518,106	184	124	46	735
Deductible ($)	9,518,106	1,949	1,723	500	10,000
Coverage Amount ($)	9,518,106	454,900	276,600	108,200	1,849,000
Credit Score at Origination	9,518,106	740	60	525	819
Sale Amount ($)	9,518,106	410,500	350,800	66,600	2,180,000

Table A2: Summary Statistics for Migration Regression Variables

This table presents the summary statistics for variables used in the migration regressions shown in Table 5. Net migration rate is defined as the net number of migrants (derived from FRBNY Consumer Credit Panel/Equifax Data) normalized by the tract's 2015 population (ACS), presented in percentage points. AAL-related variables are presented in basis points of replacement values. HW = Hurricane Wind; WF = Wildfire. Data source: CoreLogic, First Street Foundation, FRBNY Consumer Credit Panel/Equifax Data, and Census American Community Survey (2011-2015 5-Year).

	N	**Mean**	**SD**	**Min**	**Max**
Tract Net Migration (%)	65,541	-0.42	14.23	-32.06	58.54
Tract Absolute Difference in HW+WF AAL (bps)	65,541	3.78	8.68	0.00	50.57
Tract Average HW+WF AAL (bps)	65,541	4.58	12.47	0.00	74.05
Tract Absolute Difference in Flood AAL (bps)	65,541	8.70	18.71	0.07	128.88
Tract Average Flood AAL (bps)	65,541	5.56	13.05	0.03	91.97
Tract Average Other Perils AAL (bps)	65,541	10.85	7.92	1.24	41.57