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Supplementary Materials: Validation of U.S. Loss Estimates from Catastrophe Flood Models

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Sensitivity of Catastrophe Model AAL

The uncertainty surrounding the Verisk and KatRisk AAL are examined using the standard deviation of the AAL. We omit RMS from the exercise because RMS did not provide inland flood loss results. The standard deviation of the AAL is calculated using equation (S.1) where $E[L]$ is the AAL and $E[L^2]$ is the expected value of the squared loss which is calculated using the annual exceedance probability curve.

$$\sigma = \sqrt{E[L^2] - (E[L])^2} \ (S.1)$$

Inland and coastal standard deviations are calculated separately and then combined by taking the square root of the summed variances. This results in a standard deviation of annual loss of $5.39 billion for Verisk and $5.46 billion for KatRisk.

National Structure Inventory Validation

To ensure that the number of buildings in the NSI is reasonable, we compared the dataset to other published values. The total number of residential (1-4 units) buildings in the NSI is 107 million. The total number of housing units (several units are located in multifamily buildings) in the United States in Q4 of 2023 was 146 million (U.S. Census Bureau, 2024). In 2020, the total number of single-family and manufactured homes (does not include buildings with two to four units) was 101 million (Neal et al., 2020). The NSI estimate of 107 residential (1-4 units) buildings is highly similar to the estimate of single-family and manufactured homes presented by Neal et al., (2020). From these comparisons, we are confident that the NSI accurately represents the number of residential (1-4 units) buildings in the United States.

Depth-Damage Functions and Loss Rate Comparisons of the FCHLPM

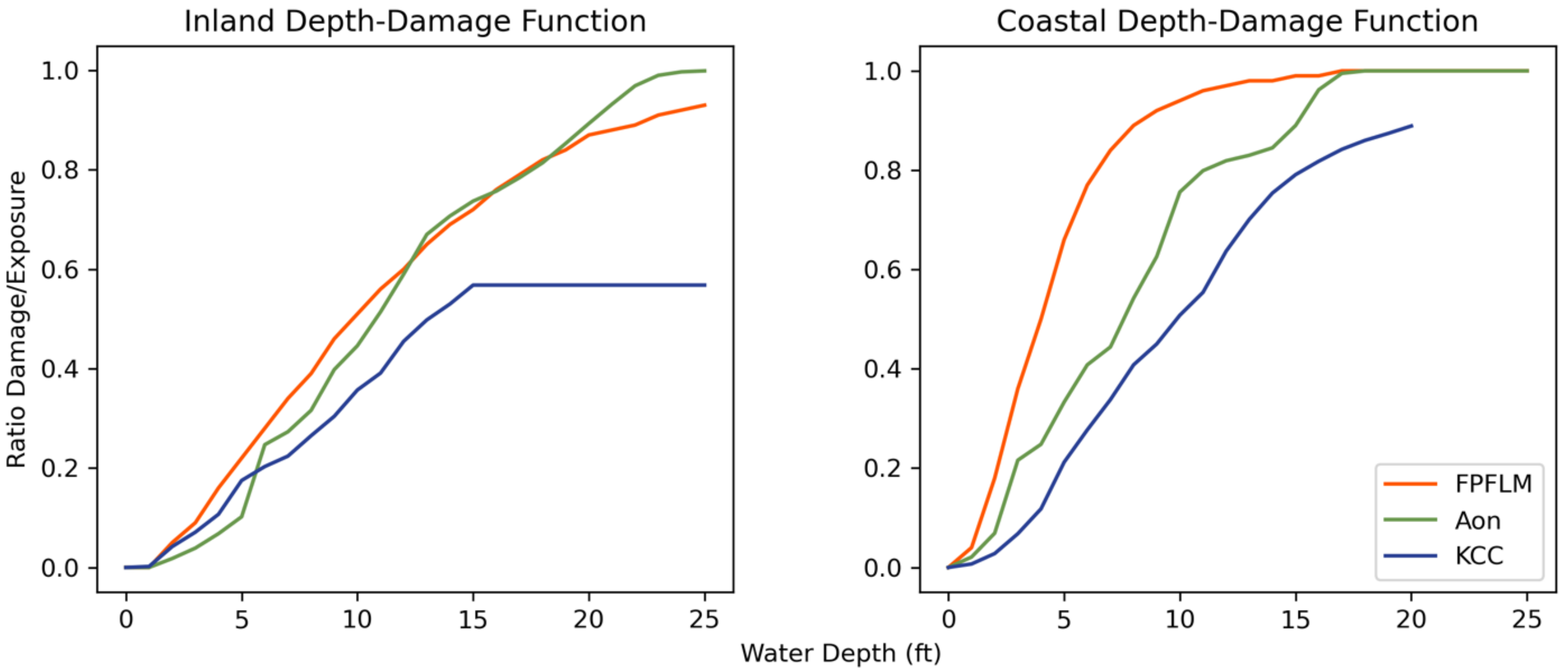

Figure S.1: *Depth-damage functions for inland (left) and coastal (right) for the Florida Public Flood Loss Model (FPFLM) (orange), Aon (green), and Karen Clark & Company (KCC) (blue) taken from each model's disclosure to the Florida Commission on Hurricane Loss Projection Methodology for 2021 (KCC, 2024 Aon, 2024; FIU, 2024).*

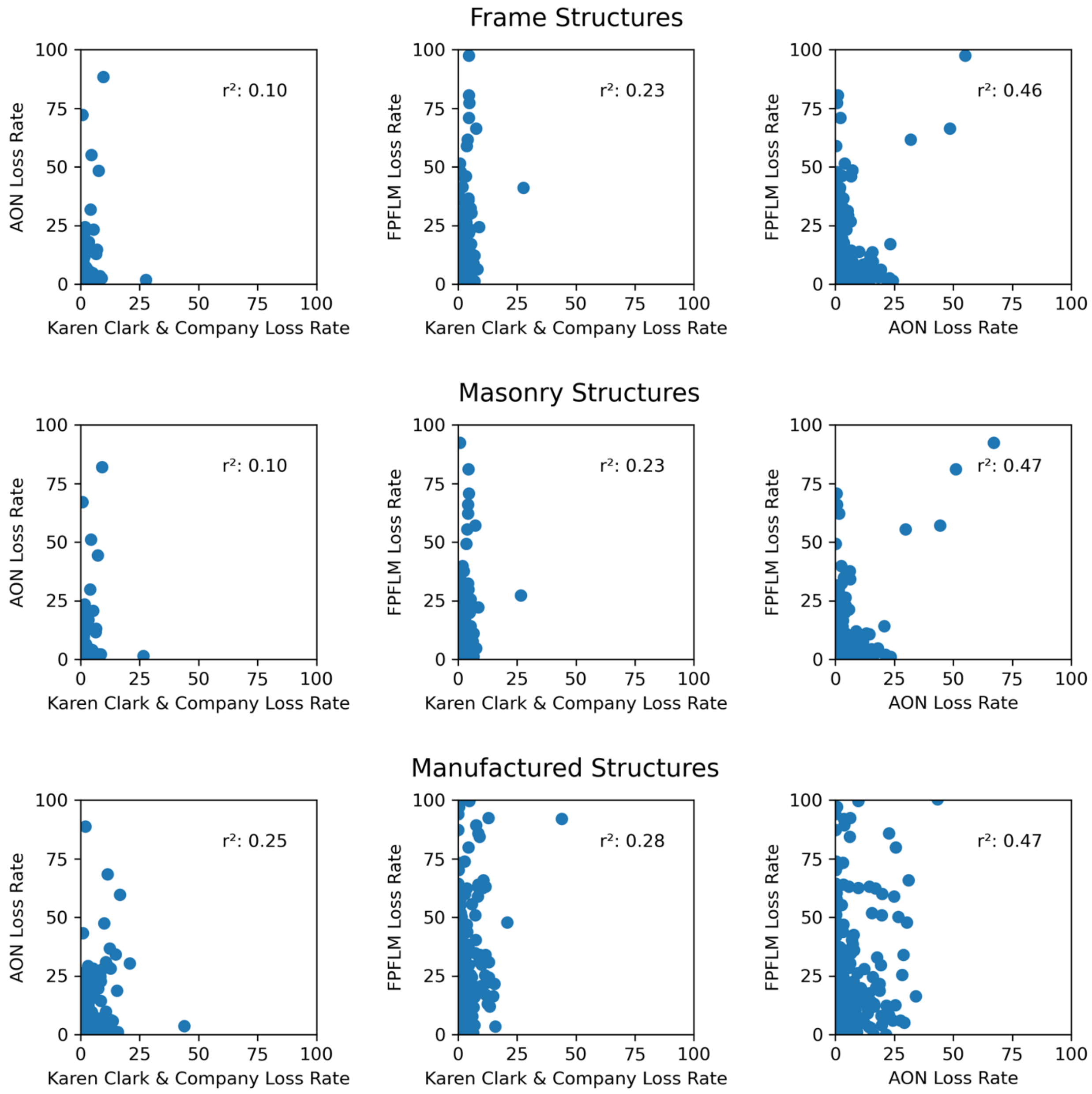

Figure S.2: *Scatter plots of loss rates for zip codes between FPFLM, Aon, and Karen Clark & Company for frame structures (top row), masonry structures (middle row), and manufactured structures (bottom row). Data is taken from each model's disclosure to the Florida Commission on Hurricane Loss Projection Methodology for 2021 (KCC, 2024 Aon, 2024; FIU, 2024).*

Caveats of Comparison Between First Street, Verisk, RMS, and KatRisk Burn Rate

While every effort has been made to make the burn rate comparison between the catastrophe models used by NFIP (i.e., KatRisk, Verisk, and RMS) and First Street as appropriate as possible, there are five caveats. In the aggregate, the caveats/methodological choices result in a conservative comparison since we have pushed the NFIP catastrophe models' burn rates closer to First Street's burn rate in this comparison exercise. Because of the limitations of publicly available data, these caveats are necessary but also give greater confidence to our result showing that First Street overestimates CONUS AAL. The first caveat is that the catastrophe models use actual cash value factors when calculating the AAL which will often result in a lower AAL versus an AAL calculated with the replacement cost value. It is unclear how First Street's Automated Value Model derived structure value compares to the actual cash value or replacement cost value. If we assume that the First Street structure value is based on replacement value, then the result would be a First Street burn rate that is higher than the catastrophe models' burn rates, all else equal.

Second, demand surge, defined as the increase in repair costs after a large-scale natural disaster, is included in the catastrophe model AAL. Demand surge can increase costs by 20% or more for individual events but is likely less for AAL values (Olsen and Porter, 2011). First Street does not mention demand surge in their AAL estimates so we assume it has been excluded which means the catastrophe models' burn rate should be higher, all else equal. Third, only residential building losses are included in the First Street estimate while residential, commercial, and content losses are included in the catastrophe models AAL. Contents exposure represents approximately 20% of total exposure according to the NFIP reinsurance placement data. This difference would mean that the catastrophe models' burn rate should be higher than the First Street burn rate, all else equal. Fourth, the First Street AAL represents ground up losses while the other catastrophe models' AAL represent gross losses. This difference would cause the First Street burn rate to be higher than the other models' burn rates, all else equal; however, we somewhat compensate for this by using the specified coverage amount below.

Finally, we assume a $250,000 coverage amount, the NFIP limit, for each building when calculating the First Street burn rate when in reality, many buildings have a replacement value of less than $250,000. In fact, the average structure value for all states listed in First Street (2021) is lower than $250,000 except for California. This methodology choice leads to an inflated total coverage amount for First Street and therefore, the burn rate of catastrophe models should be higher than First Street, all else equal. Three of these caveats would cause the First Street burn rates to be lower than the catastrophe models' metrics while two caveats causes the inverse. We cannot provide a quantitative measure of which caveats have the greatest impact on the results, but we estimate that the ground up vs gross losses, actual cash value vs replacement value, and coverage limit caveats play a more significant role than the demand surge and contents/commercial caveats. We have made these methodological choices to push the FEMA catastrophe modelers' burn rates closer to the First Street burn rate, and yet the First Street burn rate is still considerably higher than its catastrophe modeling peers. Therefore, this methodology gives us high confidence in our results showing that the First Street CONUS burn rate is overestimated.

Estimating the Highest Return Period of NFIP Annual Losses

Since the NFIP has only been in place for 47 years, it is not guaranteed that annual losses of the program are equivalent to the event catalogs of the catastrophe models that can reach tens of thousands of years in length. Therefore, to make a sound comparison between the NFIP losses and catastrophe models, we limit the AAL and burn rate calculation of the catastrophe models to the highest return period event that the NFIP has recorded, 152-year return period. This method of capping the aggregate exceedance probability curve to match the historical record for calculating the AAL has been previously done by RMS (2012) as well as Wing (2020). We determine the highest return period by fitting the 47 years of historical, loss trended NFIP losses to a Generalized Extreme Value (GEV) distribution using L-moments. The GEV, Gumbel, Pearson III, and Weibull distributions were tested for the best fit visually and with the Akaike Information Criterion (AIC). The AICs for the GEV, Gumbel, Pearson III, and Weibull distributions were 157.7, 207.1, infinity, and infinity, respectively. The GEV distribution was chosen since it visually represents the closest fit to the NFIP loss data and the AIC criterion is the lowest (a lower criterion is considered a closer fit) amongst the tested distributions. We then take the highest loss year and determine the return period of that event from the fitted GEV distribution. The histogram of NFIP annual losses and the fitted GEV, Gumbel, and Pearson III distributions is shown in Figure S.3. The 152-year loss for catastrophe models was estimated by fitting a logarithmic curve to the annual exceedance loss values of each catastrophe model for inland and storm surge flooding separately.

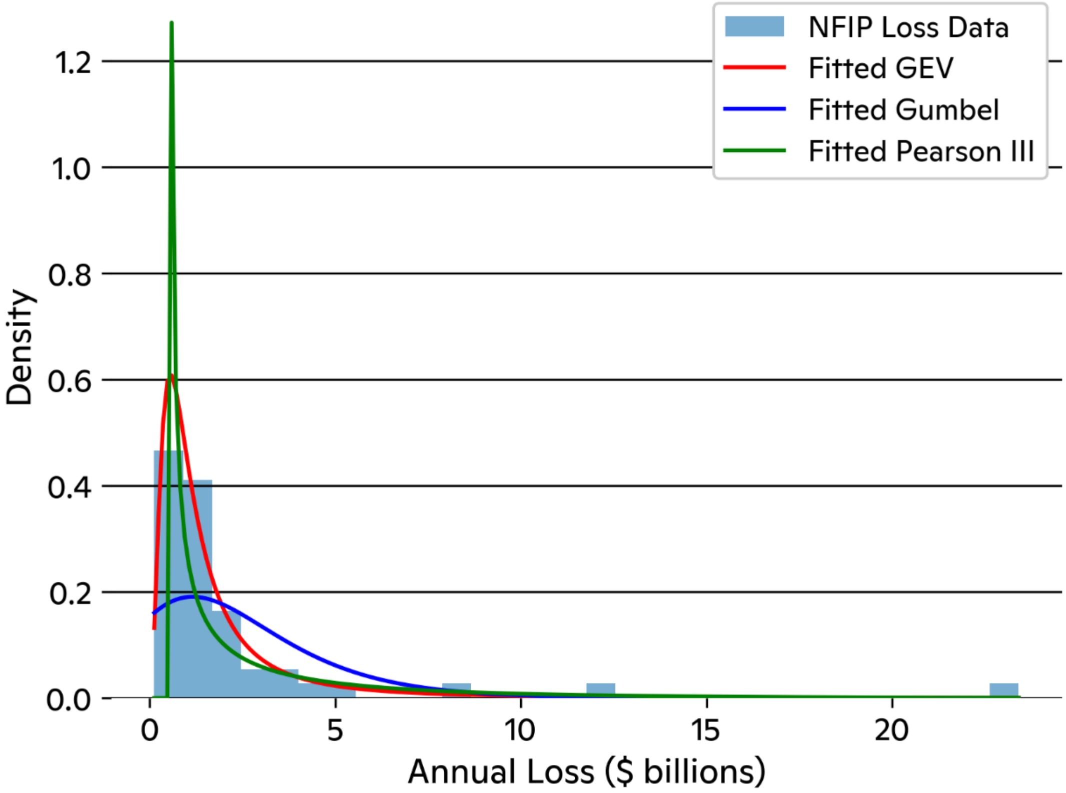

Figure S.3: *Histogram of NFIP annual losses and the fitted GEV, Gumbel, and Pearson III distributions generated from the NFIP data. The Weibull distribution is not plotted due to the highly unrealistic peak density.*

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