Flood Insurance-Pricing, Coverage, and Distributional Impacts for Underserved Communities

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1. Background

Since 1968, FEMA's National Flood Insurance Program (NFIP) has played a role in fostering community resilience in the face of increasing flood risks. Beyond insuring households and businesses against flood damage, NFIP requires participating communities to meet flood plain management practices, awards discounts to the residents of communities that adopt further mitigation practices and offers lower premiums to homeowners for structural elevation and/or floodproofing. In addition, NFIP helps cover expenses associated with meeting current floodplain building regulations during post-storm rebuilding through its Increase Cost of Compliance program.

Nonetheless, the NFIP has met with considerable criticism over the past few decades as increasing flood events have contributed to the agency's rapidly growing debt. At the same time, Congress has objected to rate hikes that would affect their constituents and the market value of their property in flood risk areas. In the fall of 2021, FEMA produced a completely new pricing scheme that largely eliminated an array of subsidies and a complex of rate mechanisms that changed every six months, replacing it with an impenetrable algorithm which calculates risk and subsequent insurance premiums at the individual property-specific level. The existence of NFIP's various programs is now being threatened, adding uncertainty that may end in an increased role for state and local governments.

Against this confusing policy backdrop, homeowners must make their own decisions – the type and level of coverage, the amount of deductible, and whether to purchase flood insurance at all. Coverage is important in disaster recovery and thus resilience. According to a report from the Department of Housing and Urban Development analyzing recovery after Hurricane Katrina, they found that homes with coverage were 37% more likely to be rebuilt.[1] In a report from 2006, RAND estimates that coverage for flood damage exists on only about half of single-family homes at a high risk of flooding in the US, 49% in NFIP, and 1% with private insurance.[2]

Decisions are constrained if the homeowner holds a federally backed loan (e.g. a mortgage) on their property as mortgaged structures in Special Flood Hazard Areas (SFHA)[3] are required to be insured against flooding. However, even for these policyholders, if costs become too great,

[1] https://www.huduser.gov/publications/pdf/gulfcoast_phase2.pdf

[2] https://www.rand.org/content/dam/rand/pubs/technical_reports/2006/RAND_TR300.pdf

[3] FEMA defines the SFHA as areas that will be inundated by the flood event having a 1-percent chance of being equaled or exceeded in any given year. Loosely defined, 'V' and 'A' zone properties are, respectively coastal and inland. Non-SFHA zones are labeled 'X" (or sometimes divided into 'B' and 'C' zones) but have historically been responsible 40% of claims since 2015. Ref: Understand the differences between FEMA flood zones – First Street™

flood insurance premiums can be avoided by selling the house. Prior studies have found evidence that households' decisions related to flood insurance uptake are affected by a combination of individual, property, and contextual factors, including hazard exposure, regulatory requirements, neighborhood characteristics, policy tenure, and households' socio-economic vulnerability. (Fu & Wang, 2014; Arteya, 2015; Kousky et. al., 2020; Rufat et.al., 2023; Rieger-Fels, 2024).

In this project we are particularly concerned with the plight of low-income householders as they attempt to navigate the complex and increasingly expensive flood insurance landscape. Even though they may hold the least valuable assets, poorer households are often the most vulnerable to flood damage as their house may often be their only substantial asset. They may also face relatively high insurance costs because disadvantaged populations are often relegated to undesirable, risky locations. These are the households that have no resources to adopt cost-saving mitigations and cannot undertake substantial renovations without being required to elevate their homes.

The analysis in this report examines policyholders' decisions regarding their participation in National Flood Insurance Program and makes a preliminary attempt at determining how those decisions might differ for lower income households. We also discuss how homeowner choices affect overall program effectiveness. Hazard models are the statistical means by which we attempt to capture the timings and likelihood of changes in policy status across different policyholders and block group characteristics.

2. Data assembly

2.1. Constructing the flood insurance policy database

The data analyzed in this project is somewhat unique. It stems from FEMA's recently established on-line Open Access Policy Database (OAPD) which is essentially a computerized data 'dump' of flood insurance policy transactions from 2009 onwards[4]. We begin the construction process by selecting transaction records from the OAPD for the community of interest. The three key identifying fields to assign records to a community (*National Flood Insurance Program (NFIP) community name*, *NFIP community number*, and *census tract and block group numbers*) exhibit occasional missing values and inconsistencies, but a combination of these fields, relying heavily on the census tract number, yields a reasonably reliable community identifier that also supports connection with census demographic data.

Our analysis relates specifically to single family houses, as it is the decisions of independent economic agents that are of interest. Records associated with condominiums, non-

[4] According to FEMA's FAQs "The data released via OpenFEMA represents the best accounting of NFIP policies for as long as the program has had complete data. Due to data retention policies in place prior to 2009, FEMA does not have access to complete policy records from before this time."

profits, businesses, farms, and government agencies are deleted, as are all structures other than the primary living quarters of the policy holder. Each record is a description of a policy of one-year duration. Given that addresses are redacted, there is no clear way of identifying records belonging to the same policy over time. The database construction process aims to link renewals of the same policy over time, thus creating an unbalanced panel dataset made up of each policy holder's original flood insurance purchase[5] and all subsequent renewals of that policy until the policy is abandoned or the end of the study period is reached. To our knowledge, no prior work has constructed the data in this manner.

The appendix to this report describes the extensive and tedious process of creating the links between records to form the policy history – a difficult task given the absence of addresses, the limited location data available, and occasional missing data and/or revision of key variables. The process begins by assigning a preliminary identifier – a concatenation of house construction date, policy origination date and census block group number. For the most part, policies are renewed each year on the anniversary of their origination. Subsequent data refinement separates multiple or overlapping independent policies that happen to have the same preliminary identifier. An iterative process follows that provides additions to existing policy histories that were initially missed because of revisions in construction or policy origination dates.

Some of the variables included in the OAPD appear to be extracted from flood insurance applications[6] and others, in particular the elements of cost calculations, are supplied by FEMA. The transaction records include policy cost as well as data elements that enter the calculation of these costs. Combining these elements with information from FEMA's periodically released rate manuals provides enough information for us to recalculate, on our own, the final policy cost. Recreating these calculations provides a check on our understanding of how flood insurance costs are derived and also provides a check on possible errors in the data. It meets an additional need, as well.

To evaluate policyholder decisions, we need to estimate the counterfactual cost. This is particularly important for evaluating decision-making through the lens of environmental justice. Policyholders facing affordability challenges may have responded to rising costs by exiting the program, reducing coverage, or increasing deductibles. Understanding this "price signal" is central to our analysis. For example, if a policyholder chooses to abandon his flood insurance policy, we want to know what policy cost he was facing when that decision was made, as there will be no transaction record in the data set to provide this key information. Recreating the reported policy cost calculations teaches us how to calculate these unobservable policy costs.

[5] Policies originating before 2009 can only be observed in 'mid-life', but in most cases the origination date, if not the historical descriptive information, can be recovered.

[6] FEMA relies on its "Write Your Own" program through which independent insurance agents help homeowners submit applications for flood insurance by reporting property attributes and choices of coverage and deductible levels for the structure and, where desired, the contents of the home.

FEMA flood insurance policy costs are made up of two parts – a premium and a set of fees that have been added on and, for the most part, increased over time. Most of the information necessary for calculating policy costs is reported in FEMA rate manuals. Over our study period (January 2009 through March 2022) 28 rate manuals have been published, reporting changes in rates and/or fees over time. These manuals contain a wide range of actuarial tables depending on the rate methods used. For the majority of the policies, the Standard Rate method applies. Under this method, the premium part of policy cost is calculated based on a combination of base rates per $100 of insurance coverage, deductible levels, increased cost of compliance (ICC) premiums, and Community Rating System (CRS) discounts for those towns having earned CRS status. These inputs vary by structure type, location, flood zone, and building features such as basements, enclosures, or elevation. Furthermore, different rate tables are used for 'Pre-FIRM' (or 'subsidized') and 'Post-FIRM' (or 'full risk rate') status. Fees include a reserve fund assessment applied as a percent of the premium, initiated in 2012 as part of the Biggert-Waters legislation and increasing substantially over years of our study period. In 2014, the Homeowner Flood Insurance Affordability Act (HFIAA) surcharge was added as a compromise when the increased basic rates proposed in the Biggert-Waters were reversed. The HFIAA surcharge has remained constant at $25 for all primary residents but penalizes owners insuring second homes with a fee of $250 per year. Finally, the modest administrative federal policy fee is added to complete the policy cost calculation.

In anticipation of our *analysis* of policy abandonment decisions, we need to predict the policy cost that would have been paid had the policyholder chosen to renew the 'existing' (i.e. same coverage and deductible choices and same primary residence status) policy. The relevant rates and fees to be extracted from FEMA rate manuals are conditional on property factors such as structural features, rated flood zone, and PreFIRM subsidized vs Full Risk Rate, factors not reliably reported in the OAP data. Our solution is to work backwards from the reported policy costs and associated cost elements present in the last transaction record to deduce these property factors. This reverse-engineering required digitizing over 200 pages of FEMA's rate manuals which are only available in PDF format. We scraped and compiled all relevant tables, including basic and additional rate factors, and merged them with OAPD policy records. This allowed us to construct the unobserved "price signal" for each renewal decision.

2.2. Appending supplemental data

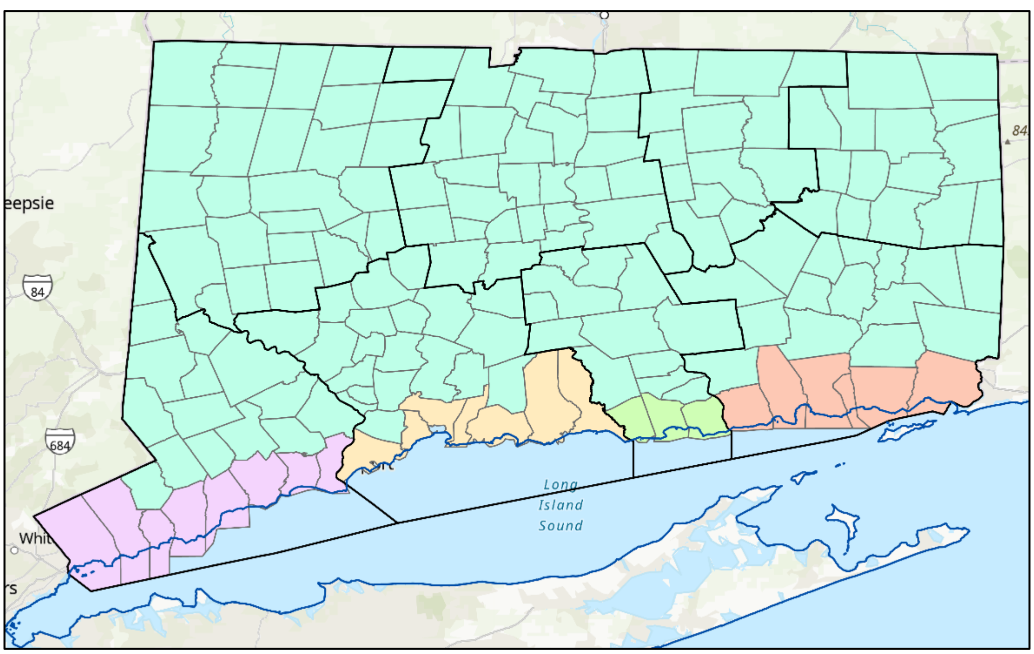
The OAP data includes neither socio-economic information about the policy holder nor appraised value of the insured structure, making it difficult to evaluate how different financial circumstances affect behavior. The lowest level of geographic differentiation in the OAPD is the Census block group and so it is at this level that we assemble and incorporate additional data to supplement the analysis. Data on mortgage coverage rates, average assessed property values and number of total single-family homes are obtained from CoreLogic.

Socio-economic indicators are drawn from the US Decennial Census 2010 and the 2006-2010 American Community Survey (ACS) and are used to construct a block group level 'Social Disadvantage Index'. The index combines three key block group level indicators: *the percentage of households living below poverty line*, *the share of adults with less than 4 years of college education* and *the percentage of non-white residents*. Distinguishing individual impacts is quite difficult because these variables are highly correlated. We combined these variables into a single index, rescaled to a range of 1 to 100. Higher values of the index indicate greater socio-economic disadvantage.

2.3. Defining the study area

The data description process described above is replicable for all towns in Connecticut. At this point we have completed data processing and preliminary analysis for 24 shoreline NFIP communities, which together account for approximately 75% of flood insurance policies statewide. These communities include a substantial number of residences in SFHA. Fairfield and New Haven counties account for the largest numbers of flood insurance policies in the state. The locations of these communities are pictured in Figure 1.

Figure 1: Study Area



3. Summary Statistics

Table 1A presents descriptive statistics calculated by policy (where each policy includes a series of transaction records over time). The statistics are further disaggregated by county to highlight variation in policy characteristics across the study area.

Across all policies, the average number of renewals is 6.7. Secondary home ownership is more common in Middlesex coastal communities (40%) and least common in Fairfield (18%). Though the majority of policies fall within Special Flood Hazard Areas (particularly A-Zone), the distribution varies by county. Fairfield has the largest share of policies in A-Zones (66%) and least share in V-Zones (2%). On the other hand, New London stands out with the largest share of policies in X-Zones (54%), where flood risk is considered lower. The average annual increase in policy cost is approximately $137 and average policy cost is $1630, from January 2009 to March 2022.

Table 1A: Summary Statistics in Shoreline Communities (Policy Level)

Variable	**Mean (SD) Total Sample**	**Mean(SD) Fairfield**	**Mean(SD) New Haven**	**Mean(SD) Middlesex**	**Mean(SD) New London**
Average Renewals	6.7 (3.1)	6.6 (3.1)	6.7 (3.1)	6.9 (3.1)	6.7 (3.0)
Secondary Home (%)	24.6 (43.1)	17.6 (38.1)	25.6 (43.6)	39.7 (48.9)	33.5 (47.2)
Zone A (%)	59.2 (49.2)	65.7 (47.5)	60.9 (48.8)	53.0 (49.9)	39.9 (49.0)
Zone V (%)	4.1 (19.9)	2.1 (14.4)	6.3 (24.3)	5.5 (22.8)	5.8 (23.3)
Zone X (%)	36.7 (48.2)	32.1 (46.7)	32.8 (47.0)	41.5 (49.3)	54.4 (49.8)
Annual Policy Cost Change ($)	136.5 (293.0)	120.0 (273.1)	139.4 (293.6)	177.8 (332.2)	152.0 (315.8)
Avg Policy Cost ($)	1630.7 (1509.8)	1621.0 (1351.5)	1593.8 (1583.4)	1727.7 (1725.2)	1651.5 (1666.2)
Total Policies (N)	**28,214**	**13,389**	**7,389**	**3,265**	**4,171**

Table 1B: Summary Statistics in Shoreline Communities (Block Group Level)

Variable	**Mean (SD) Total Sample**	**Mean(SD) Fairfield**	**Mean(SD) New Haven**	**Mean(SD) Middlesex**	**Mean(SD) New London**
Median Home Value ($)	343641.7 (379891.4)	486298.8 (473563.5)	178755.2 (87371.4)	215998.3 (46125.5)	187460.2 (76113.4)
Homes with Mortgages (%)	77.1 (9.3)	80.2(6.9)	78.2 (6.5)	75.0 (10.0)	61.4 (9.1)
<4 Years College (%)	57.6 (22.4)	51.6 (23.7)	65.4 (20.5)	62.5 (11.6)	61.9 (15.9)
Non-White Population (%)	21.7 (21.4)	23.4 (21.2)	23.5 (24.0)	5.8 (2.1)	14.2 (13.5)
Below Poverty Line (%)	7.6 (9.7)	7.4 (10.0)	9.2 (10.6)	4.4 (3.6)	5.6 (6.4)
Social Disadvantage Index (1 – 100 Scale)	38.4 (25.0)	36.7 (26.4)	43.9 (25.4)	28.7 (7.2)	34.2 (17.0)
Block Groups (N)	**639**	**337**	**202**	**24**	**76**

Table 1B presents block group level characteristics. On average, 77% of single-family homes have mortgages. The median assessed value is about $344,000, but it varies widely across counties; from just $179,000 in New Haven to over $486,000 in Fairfield. Educational attainment also differs notably across counties: 65% of adults in New Haven have less than 4 years of college education; the number dropped to 52% in Fairfield. Around 8% of households live below the poverty line. Though the share in New Haven (9.2%) is more than twice that of Middlesex (4.4%). The average Social Disadvantage Index score is 38, ranging from 29 in Middlesex to 44 in New Haven. Overall, Middlesex suggests the most well-off county in the current study area and New Haven has the greatest socioeconomic disadvantage.

Figure 2a: Social Disadvantage by Quartile

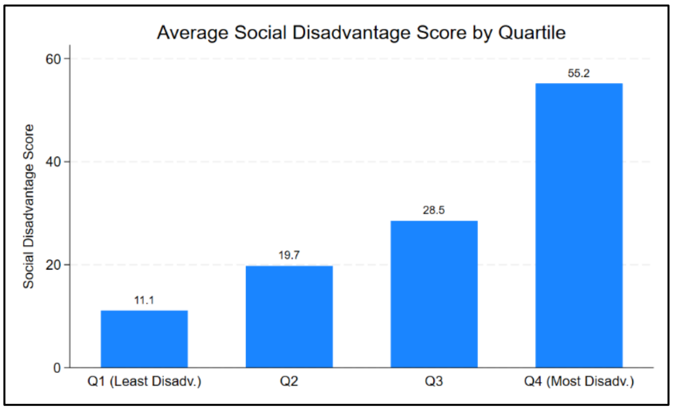


Figure 2b: Home Assessed Value by Quartile

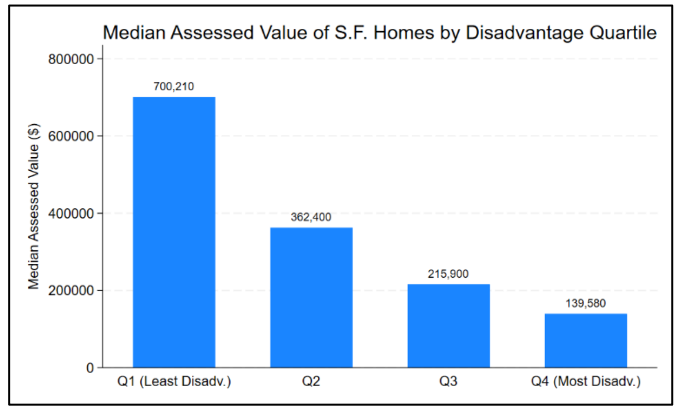
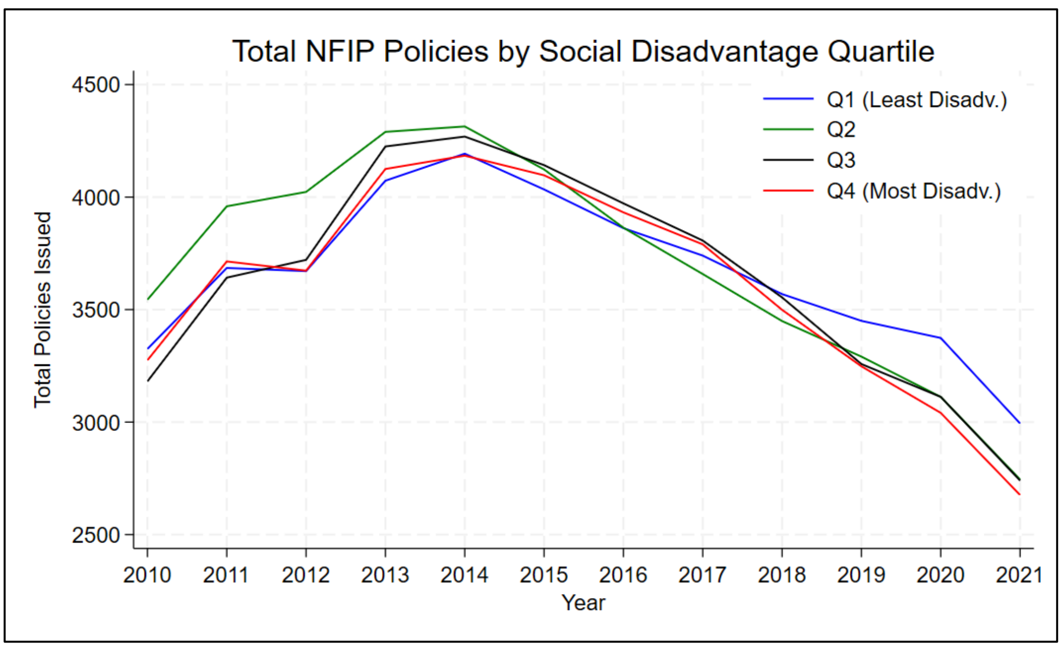


Figure 3: Total NFIP Policies by Disadvantage Quartile (2010–2021)



We also explore, descriptively, how NFIP policy coverage varies across socio-economic groups. To do that, we divided all Block Groups into four quartiles based on their Social Disadvantage Index. Figure 2a shows that average disadvantage scores increase sharply from Q1

(11.1) to Q4 (55.2), reflecting clear socioeconomic differences across four quartiles. Correspondingly Figure 2b highlights how more socioeconomically disadvantaged areas have lower property values. Finally, Figure 3 shows trends in total NFIP policies issued between 2010 and 2021. The figure suggests that participation in NFIP is broadly similar across 4 quartiles, yet the most troubling trend might be the decline across all quartiles after 2014.

4. Hazard Model Approach

We analyze the household decisions to drop their insurance coverage from NFIP using what is commonly called failure, duration, or hazard modeling. The defining characteristic of this modeling approach is that the subject is in a "current state" (working, status quo) until the subject "fails". Definition of failing depends on the researcher and runs the gamut of engineering – analyzing mechanical failures or famously light bulb failures, to social science – land use conversion decisions being a prime example. We utilize hazard models to estimate how various factors influence policyholders' decisions, regarding if and what type of coverage they maintain over time.

We are interested in the annual renewal of flood insurance policies, because this is the time when the household will receive the premium quote to maintain their current coverage levels. Thus, we choose to define our failure event in the following way:

- **Non-Renewal of Insurance Policy** – The event/outcome measures the decision of policyholders who exit the program entirely by choosing not to renew their insurance coverage.

It is important to note that mortgage companies require NFIP coverage on all houses in the FEMA flood zones (V and A zones). This is a restriction on the decision to drop coverage, but the option to terminate coverage by selling their house is still open to the mortgaged homeowner. This fact also makes all findings, at best, lower bounds.

4.1. Non-parametric Cox Model

An exhaustive review of the concepts of duration models is not possible here. Still, we briefly summarize the basics to present the proposed empirical model. Suppose one is concerned with a random variable t, the time until an event, and one wishes to know the influence of specific covariates x on t. An application of least squares to this type of problem suffers from three major problems: it requires data aggregation that will drop time-varying covariates, it cannot handle censored observations (observations that do not experience the 'event'), and it might predict meaningless negative durations (event occurrence before time zero).

Duration models were developed to address these limitations. Observations (spells) are realizations of an underlying random process which can be characterized by the probability density function (pdf)

$$f(t) = \Pr(t \leq T < t + dt)$$

And the corresponding cumulative density,

$$F(t) = \int_0^t f(s)ds = \Pr(T \leq t)\,, t \geq 0,$$

Where $T \geq 0$ denotes the duration until failure and t denotes a particular value of T. The survivor function $S(t) = 1 - F(t)$, is the complement of the cumulative distribution function and is the mathematical representation of the likelihood of surviving until time t. For those observations that survive, they contribute S(t) to the likelihood function in estimation. Those that fail contribute the value of the pdf to the likelihood function. Since these models do not aggregate data over time, they are ideal to model time-varying independent variables in a straightforward fashion.

There are two additional functions of interest: the hazard function, $\lambda(t)$, and the integrated hazard, $\Lambda(t)$. The hazard function is the instantaneous probability of failure in the interval dt assuming survival up to time t:

$$\lambda(t) = \Pr(t \leq T < t + dt | T \geq t) = \frac{f(t)}{S(t)}$$

To facilitate estimation, it is necessary to incorporate covariates. This is typically accomplished by specifying the individual hazard as

$$\lambda(t) = \lambda_0(t)\kappa(X)$$

Where $\kappa(X)$ is the systematic part typically specified as exp $(X_i\beta)$ and $\lambda_0(t)$ is the baseline hazard common to all observations. This general form is called the proportional hazards specification because the effect of covariates is to shift the hazard proportionally. It is, by far, the most popular model utilized in this literature.

If priori theoretical or empirical reasoning implies a relationship for the baseline hazard, a parametric function for $\lambda_0(t)$ can be imposed. However, when no relationship can be assumed to exist, it is appropriate to utilize a non-parametric baseline model, where the focus is only on the impacts of covariates. A method developed by Cox (1959) using a partial likelihood approach is appropriate. The common baseline hazard is treated as a nuisance parameter and factored out of the likelihood function.

$$\frac{\lambda_i(t)}{\lambda_j(t)} = \frac{\lambda_0(t)}{\lambda_0(t)} \exp\{(x_{i1} - x_{j1})\beta_1 + ... + (x_{ik} - x_{jk})\beta_k\}$$

To see this, note that for any two observations, i and j, and the baseline hazard, being the same for everyone, cancels out. Estimation is accomplished using the 'partial' likelihood function, where the term 'partial' denotes the fact that estimation of the baseline is not attempted. This method is based on the assumption that the intervals between successive duration times (failure times) contributes no information regarding the relationship between the covariates and the hazard rate (Collett, 1994). It is the order of the failure times, not the interval between failure times, which contributes information to the partial likelihood function.

Consider a data set in which there are N observations, of which Nf fail during the study period, and N-Nf are censored. The likelihood function for the Cox model is the product of Nf terms – one for each failure, in which the contribution of the ith failure is given by:

$$\Pr(t_i = T_i \mid R(t_i)) = \frac{\exp(X_i\beta)}{\sum_{j\in R(t_i)}\exp(X_j\beta)}$$

where ti is defined as the time period of the ith failure and the set R(i) is the set of all observations still at risk at time ti. This equation is the probability that, given that a failure occurs in period ti, it is the observation i among the set of observations still at risk that is the one that fails. Taking the product of these conditional probabilities yields the partial likelihood function:

$$L_p = \prod_{i=1}^{N}\left[\frac{\exp(\beta' X_i)}{\sum_{j\in R(t_i)}\exp(\beta' X_j)}\right]^{d_i},$$

where di=1 if the observation is uncensored and di=0 if it is right-censored (i.e. the observation does not 'fail' during the study period and remains in the risk set). This is a conditional logit likelihood function which is often referred to as a fixed effects model, where the "effect" that is "fixed" is the risk period. Note that the likelihood function does not include an explicit term for the censored observations, although they are represented repeatedly in the denominator as they remain in the risk set throughout.

The model is well-suited for our study because of the nature of our data. Through our stacking process, we can track the same policies over multiple renewal periods and capture how policyholders respond to regulatory, risk-related conditions, and aggregate socio-economic conditions.

In the models,

- A hazard ratio greater than 1 means a higher likelihood that the event occurs sooner (for instance, a policyholder is more likely to drop out earlier);
- On the other hand, a hazard ratio of less than 1 means that the event is less likely to occur quickly (for instance, longer policy retention).

5. Results

In this section, we present results for one key choice outcomes of NFIP policyholders: non-renewal of insurance policies. We test a series of hypotheses. These hypotheses are based on prior literature and NFIP requirements.

> **H1: Price Sensitivity:** Increases in policy cost are positively associated with the likelihood of exiting the program.
>
> **H2: Being in SFHA:** Policyholders located in V, and A Zones are more likely to stay in insurance coverage because of the mortgage requirement associated with Special Flood Hazard Areas.
>
> **H3: Socio-Economic Disadvantage:** Socio-economically disadvantaged households are more cost-constrained, but are they more likely to exit the program if they are not in A and V Zones where insurance is required due to mortgage obligations?
>
> **H4: Past Adjustments as Predictors**: Households that previously reduced coverage (e.g., dropped contents or increased deductibles) are more likely to eventually leave the program entirely. The past adjustment may signal that policyholders are facing difficulty keeping full coverage. This may be possibly due to financial pressure or perceive less risk. They may start by cutting costs and eventually decide to leave the program altogether.

These hypotheses have implications for any changes in the role of FEMA with NFIP to encourage resilience via flood coverage.

5.1. Hazard of Policy Dropped

In this subsection, we examine policy holders' decision of whether to discontinue their policy or not. In Figure 4, we presented Kaplan – Meier survival curves which plot the probability of retaining coverage over time, non-parametrically. The curves are disaggregated by whether the household is a primary or secondary residence, whether it is located within a SFHA, whether it is located in a better socio-economic neighborhood, and whether the household has previously made changes to its coverage.

Though descriptive in nature, the curves reveal distinct differences in survival patterns. In each of these figures, one must keep in mind the mortgage requirement for insurance is pivotal. It showed that secondary homes policy holders tend to drop policies earlier than those on primary residences likely from an ability to get out of mortgage debt and thus unlock the choice to drop coverage. In the X zone, where there is less risk and no mortgage requirement, properties have shorter policy durations. Households that have previously dropped contents coverage are also more likely to discontinue their policies earlier than those that have never dropped contents coverage. In addition, socially disadvantaged communities tend to keep their insurance, whereas, in wealthier areas, homeowners may have more flexibility to choose whether or not to maintain coverage, again due to the mortgage requirement. However, as shown in Figure 4, these differences are relatively small.

While these figures provide valuable initial insights, they do not control for other covariates that could also influence policy duration. To evaluate such relations, we estimate a series of hazard models, which are presented in Table 2.

The table shows that we have 28,214 unique policies, of which 17,741 policies ultimately dropped. Each column of the tables introduces a new explanatory variable, which tests the consistency of estimated hazard ratios in a stepwise fashion. Across specifications, we find that the hazard ratio dollar change in policy cost is 1.025 and 1.035. This suggests that for every $100 increase in policy cost from the previous renewal, the likelihood of a policyholder dropping out of the NFIP rises by around 3% increase in the hazard rate. Even though the effects are modest in size, it supports hypothesis 1, households are demonstrating price sensitivity.

Policies that are located in A and Non-Special Hazard Areas are substantially more likely to drop compared to policies in V-Zones. This is because V-Zone properties are usually adjacent to the coast. Furthermore, the large and significant coefficient of non-SFHA policies reinforces the idea that in the absence of a mortgage requirement, policyholders tend to drop out of the NFIP program at a faster rate. The result is consistent with Hypothesis 2.

It is important to note that being outside the SFHA does not imply the absence of flood risk. Our Analysis of FEMA Open Access Claims data from 2009 to 2023 shows that, in Connecticut, 18% of all NFIP claims from single-family homes during this period occurred in X Zones, compared to 73% in A Zones and 9% in V Zones.

We also find that policyholders who previously increased their deductibles or dropped contents coverage are more likely to drop their policies. This supports Hypothesis 4, which suggests that past adjustments may signal that policyholders are facing difficulty keeping full coverage; they initially start by cutting costs and eventually decide to leave the program altogether. This is an interesting result because it suggests that these households "want" coverage but seem to give it up eventually. Also, our preliminary results provide weak evidence that second home residents are more likely to drop the policy.

Furthermore, we do not find statistically significant evidence that the Social Disadvantage Index is associated with flood insurance retention. While the estimated coefficients are directionally consistent with the hypothesized role of mortgage requirements and financial constraints, these patterns should not be interpreted as conclusive. Future work incorporating additional covariates and alternative empirical strategies may help clarify these relationships.

Figure 4: Survival of NFIP Policies by Key Household, Property, and Location Factors

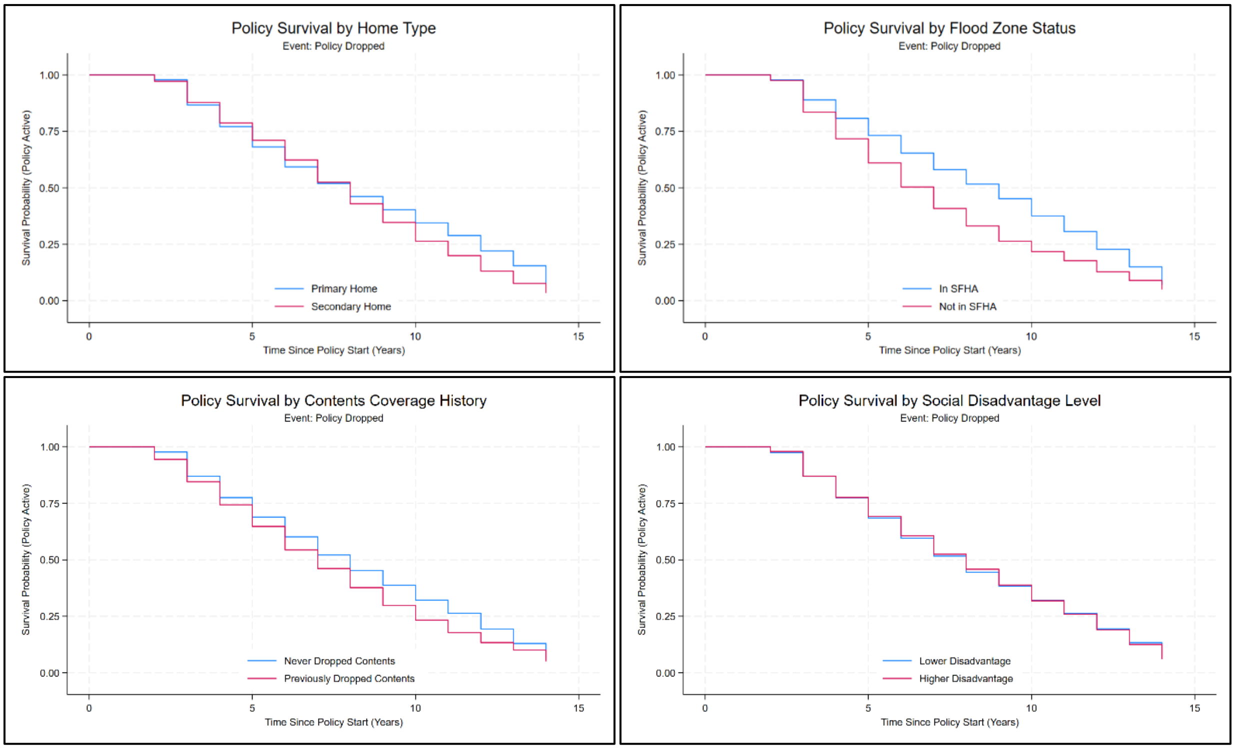


Table 2 – Event: Non-Renewal; Total Policies: 28214; Failed to Renew: 17741

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dollar	1.028***	1.035***	1.035***	1.035***	1.035***	1.035***	1.025***	1.026***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Not in SFHA		2.380***	2.388***	2.386***	2.337***	2.456***	2.201***	2.158***
		(0.218)	(0.217)	(0.217)	(0.218)	(0.227)	(0.206)	(0.204)
A - Zone		1.539***	1.543***	1.536***	1.539***	1.544***	1.329***	1.204*
		(0.149)	(0.149)	(0.148)	(0.149)	(0.151)	(0.136)	(0.118)
Second Home			1.038*	1.045**	1.045**	1.048**	1.018	0.988
			(0.022)	(0.022)	(0.022)	(0.022)	(0.020)	(0.020)
One Minus – Percentage Mortgage in BG				0.999	0.998	0.999	0.999	0.995***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Median Assessed (in, 000)					1.000	1.000	1.000*	1.000
					(0.000)	(0.000)	(0.000)	(0.000)
Social Disadvantage Index					1.000	1.000	1.000	1.002
					(0.001)	(0.001)	(0.001)	(0.001)
Not in SFHA x Social Disadvantaged Index					1.001	1.001	1.001	1.000
					(0.001)	(0.001)	(0.001)	(0.001)
Increase in Building Deductibles Cumulative						0.868***	0.872***	0.815***
						(0.014)	(0.014)	(0.012)
Contents Dropped						1.342***	1.350***	1.290***
						(0.066)	(0.066)	(0.062)
A Zone x Dollar							1.021***	1.019***
							(0.004)	(0.004)
Not in SFHA x Dollar							1.001	1.000
							(0.005)	(0.005)
Year and Tract Fixed Effects	No	No	No	No	No	No	No	Yes
N	160,734	160,734	160,734	160,734	160,734	160,734	160,734	160,734

Standard errors clustered at the Block Group level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

6. Discussion regarding Risk Rating 2.0

Under the new pricing structure of Risk Rating 2.0 (RR2.0) there are two major changes in determining your policy's cost,

1. Your property's location in the flood map no longer matters, and
2. Your property's specific individual risk does matter.

Regarding point 1, FEMA is responsible for continually maintaining flood maps, as they serve as the basis for mandatory coverage, community discount calculations, and local building codes. However, on one account, the current maps are woefully inadequate as 75% of them are out of date, with some 11% dating back to the 1970s and 80s. Even when the maps are current, they utilize historical flow data and tidal gauges making them unprepared for future environmental changes.[7]

Further, there are uncertainties surrounding the future configuration of FEMA as an executive agency. In January of 2025, a FEMA Review Council was established to, among other considerations, conduct "An evaluation of whether FEMA can serve its functions as a support agency, providing supplemental Federal assistance, to the States rather than supplanting State control of disaster relief"[8]. In short, the future of the responsibility of flood mapping is uncertain, and as our results show the mandatory requirements imposed using the flood maps are a driving force behind the amount of insurance coverage in effect in communities.

Regarding point 2, rates for the state have changed to under RR2.0. Figure 5 shows the national expectations produced by FEMA compared to the observed Connecticut changes from our sample. The figure shows that more policies will have rate increases than expected nationally. Only 4% of FEMA calculations are increases of $20 or more a month whereas our sample shows 16%, and more troubling is that increases greater than $10 a month are expected in only 11% of FEMA's estimates but are 56% in our data.

Further, Figure 6 shows how the distribution of rate increases spans the designated flood zones. Here Zone X sees the most increases and Zones A and V have a large portion of the price decreases.

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[7] https://help.firststreet.org/hc/en-us/articles/360048256493-Understand-the-differences-between-FEMA-flood-zones

[8] https://www.whitehouse.gov/presidential-actions/2025/01/council-to-assess-the-federal-emergency-management-agency/

Figure 5: National FEMA Projections vs. Connecticut Actual Changes

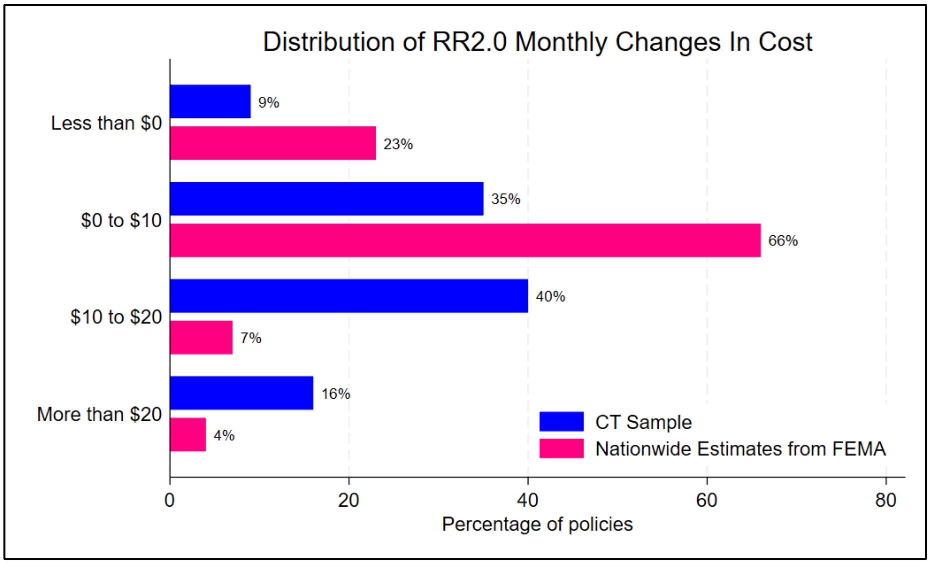
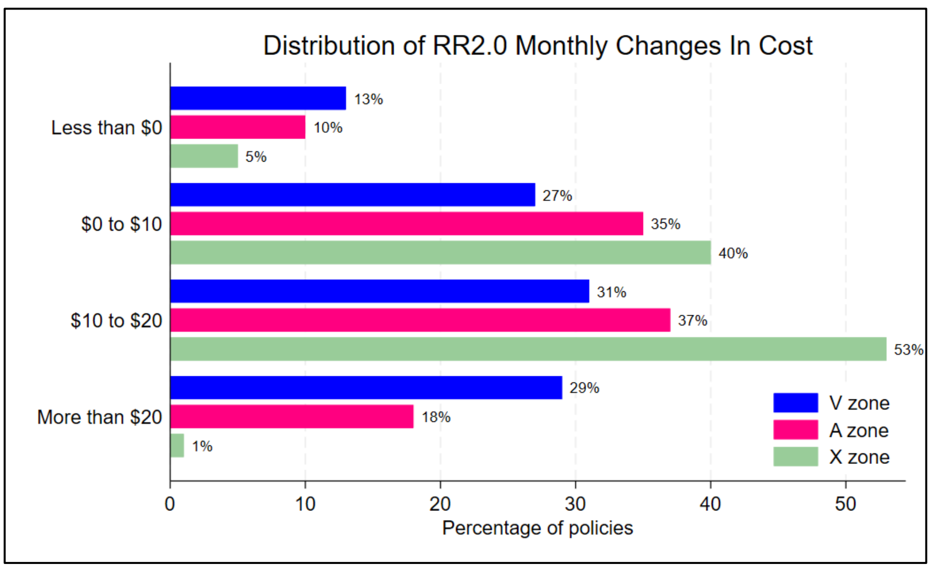


Figure 6: Distribution of Rate Increases Across Designated Flood Zones



Our hazard model results show that there is a strong pull to drop insurance coverage when the opportunity presents itself and all models show especially strong sensitivity to price increases.

If the calculations shown in Figure 6 hold true across the broader landscape of Connecticut precisely the wrong households, those in the X zone, are likely to flee to market in response to their price adjustment. In light of the fact that a disproportionate amount of flood insurance damage claims arises from the X zone this is an unfortunate byproduct of the new more risk precise RR2.0. Regarding impacts across disadvantaged groups, the current evidence does not provide clear support for the notion that these households are systematically more burdened by mortgage requirements in a way that translates into higher insurance retention. While mortgage mandates may mechanically increase observed coverage persistence, the results do not allow us to conclude that this mechanism differentially constrains disadvantaged households relative to wealthier ones.