

Governing wildfire insurance under mortgage constraints: an availability-affordability-capacity framework with decision-oriented evaluation for California, 2018-2024

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1 **Governing wildfire insurance under mortgage constraints: an**
2 **availability-affordability-capacity framework with decision-oriented**
3 **evaluation for California, 2018-2024**

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12 **Conflict of interest**

13 The authors declare no relevant financial or non-financial conflicts of interest.

14 **Ethics approval**

15 This study uses only publicly available macroeconomic data and official public
16 communications. It does not involve human participants, human subjects data, or
17 animals.

18 **Consent to participate**

19 Not applicable.

20 **Consent for publication**

21 Not applicable.

22 **Data availability**

23 The data that support the findings of this study are assembled from public sources
24 described in the text and are available from the corresponding author upon reasonable
25 request.

Abstract

Catastrophe-insurance research has established that availability, affordability, mortgage finance, and public backstops are connected, but it seldom solves the resulting allocation when the residual market can itself bind. We develop an availability-affordability-capacity framework for mortgaged homeowners and evaluate it with a calibrated California model for 2018–2024. In response to the fixed-rate-mortgage concern, we replace the contemporaneous-rate assumption with a state-level, distribution-preserving rerun using FHFA National Mortgage Database (NMDb) interest-rate bins for outstanding California mortgages. In 2023, the original current-rate specification implied 42.9% loss of voluntary/residual covenant-feasible protection; 26.5 percentage points remain under the NMDb rerun, or 61.8% of the original failure (25.3–28.0% across the predeclared open-bin sensitivity). Outcomes are now allocated exhaustively among voluntary coverage, residual coverage, and model-implied force-placement exposure; the last category is not an observed servicer action or uninsured rate. We also recalibrate FAIR Plan use as FAIR policies divided by independently counted total residential policies: calibration MAE is 0.066 percentage points for 2018–2021 and temporal-holdout MAE is 0.121 points for 2022–2023. Florida Citizens and Texas TWIA are added as institutional transfer and capacity-structure cases, while Colorado is retained only as a null institutional-timing case. The contribution is therefore narrowed to a capacity-constrained residual-market allocation with decision-oriented evaluation, not the broader claim that mortgage or availability-affordability channels are absent from prior work.

Keywords: wildfire insurance; residual market; FAIR plan; mortgage constraints; affordability; decision-oriented evaluation; Natural Hazards

1 Introduction

Catastrophe insurance economics begins from a double market failure. Households under-insure against low-probability, high-consequence losses, both because the probabilities are ambiguous and because budget constraints bind at the moment of purchase (Kunreuther 1996; Botzen and van den Bergh 2012). Insurers, in turn, face catastrophe risk that is hard to diversify and hard to price, which limits how much

57 coverage they are willing to supply even at actuarially fair premiums (Froot 2001; Jaffee
58 and Russell 1997). Because both sides fail, governments have intervened in disaster
59 insurance in almost every advanced economy, and a large literature debates the form that
60 intervention should take, from mandatory participation to premium subsidies to public
61 reinsurance (Charpentier and Le Maux 2014). In the United States the debate has
62 crystallized around the conflict between risk-based pricing and affordability in the flood
63 insurance program, where reform proposals repeatedly collide with the observation that
64 actuarial premiums price low-income households out of coverage (Michel-Kerjan and
65 Kunreuther 2011; Kousky 2019).

66 Wildfire has brought this double failure to the western United States with unusual force.
67 The fire regime has become more severe and more concentrated in the wildland-urban
68 interface (MacDonald et al. 2023; Chuvieco et al. 2023), fire risk to structures is large
69 and unevenly distributed (Zamanialaei et al. 2025; Synolakis 2024), the gap between
70 insured and uninsured exposure is widening (Hemmati et al. 2025; Gourevitch et al.
71 2023), and household risk perception and adaptation remain uneven (Ratnadiwakara and
72 Venugopal 2023; Horing et al. 2025). Insurance and disaster risk management are
73 increasingly understood as complements rather than substitutes (Sheehan et al. 2023). For
74 a mortgaged homeowner, property insurance is not a one-time choice but a continuing
75 condition of the loan, and a lapse is a contractual breach with collateral consequences
76 (Fannie Mae 2024; Freddie Mac 2026).

77 The paper addresses a narrower question than the original novelty language suggested.
78 Existing research jointly examines wildfire-insurance availability and affordability in
79 California and analyses last-resort regulation (Liao et al. 2022; Taylor et al. 2025; Jones
80 2025). Mortgage-escrow evidence and borrower-level credit outcomes likewise establish
81 important links between insurance prices, mortgages, and household financial stress
82 (Keys and Mulder 2024; Ge et al. 2025), while flood-insurance evidence shows that a
83 purchase mandate need not prevent loss of uptake under a large affordability shock
84 (Gourevitch et al. 2025). Our contribution is not to claim that these channels are absent. It
85 is to solve an explicit allocation among voluntary coverage, residual coverage, and
86 model-implied force-placement exposure when residual capacity can bind, and to
87 distinguish predictive fit from the governance decisions supported by the model.

The contribution has three bounded layers. Conceptually, the model joins private offers, household budget feasibility, and residual-market capacity under a mortgage covenant, with instrument interactions stated separately for slack and binding capacity. Empirically, it replaces current-rate repricing with an NMDB outstanding-loan-rate distribution, uses an independent total-policy denominator for residual-market calibration, and reports the three-state allocation without treating the residual complement as observed noninsurance. Methodologically, it separates California temporal holdout from institutional transfer and makes the decision score, its normalization, and its normative weights explicit. These changes focus the claim on the capacity-constrained allocation rather than on an absolute novelty assertion.

Section 2 now uses two evidence layers: a Natural Hazards full-profile scan as journal context and a cross-disciplinary, query-logged corpus spanning economics, finance, insurance, law, and environmental policy. Section 3 develops the allocation and conditional propositions. Section 4 describes the county, insurance, mortgage, and institutional-transfer data. Section 5 gives the recalibration and NMDB rerun. Section 6 reports the temporal, three-state, institutional, counterfactual, and decision-score results. Sections 7 and 8 discuss scope and conclusions.

2 Journal context and cross-disciplinary evidence map, 2015–2026

This section no longer treats one journal as the population of wildfire-insurance research. The first layer retains the 6,185-item Natural Hazards scan for the limited purpose of locating the manuscript in the journal's own output. The second layer uses recorded OpenAlex/Crossref searches across economics, finance, insurance, law, environmental policy, and disaster-risk outlets, with queries covering wildfire insurance, availability, affordability, residual markets, FAIR Plans, Citizens, TWIA, mortgages, escrow, nonrenewal, lender- or force-placed insurance, and coverage mandates. Records are deduplicated by DOI and normalized title; inclusion requires substantive treatment of property/disaster insurance, mortgage-linked outcomes, or residual-market governance. The resulting positioning is measured rather than absolute: prior studies analyse several component links, whereas the present model jointly allocates the three insurance states under a potentially binding residual-market constraint.

2.1 A full-profile scan of the journal, 2015-2025

The journal published 6,185 works between 2015 and 2025, of which 5,982 are research articles, 25 are reviews, 34 are book chapters, and 144 are errata, editorial, and miscellaneous records. Annual output moved from 565 articles in 2015 to 601 in 2016, dipped to 413 in 2017 and 286 in 2019, and then climbed to 676 in 2021, 654 in 2022, 567 in 2023, 728 in 2024, and 680 in 2025. The profile is therefore that of a large, growing, and internationally diverse journal rather than a niche outlet. Mean citations per article decline mechanically with recency, from 43.2 for the 2015 cohort to 3.2 for the 2025 cohort, which is the normal age profile of a mature applied journal. Figure 1 summarizes the annual output, the citation profile, and the topic structure.

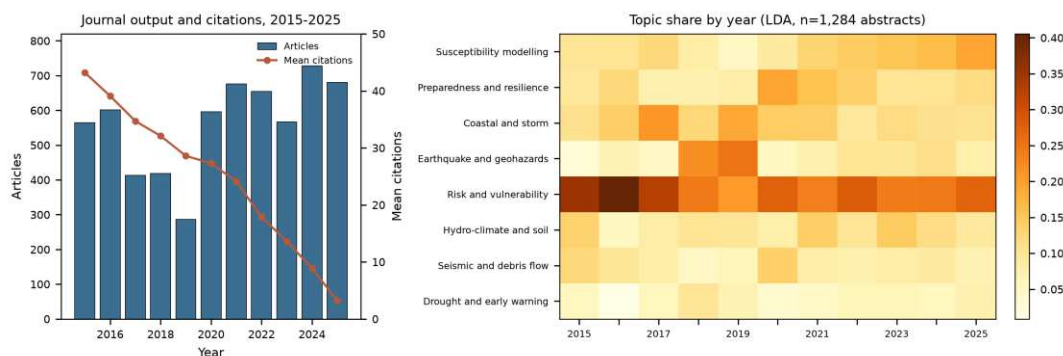


Fig. 1 Journal panorama, 2015-2025. Left, annual output (bars) and mean citations (line) on a twin axis. Right, latent Dirichlet allocation topic shares by year for the 1,284 articles with abstracts.

The thematic structure of the full corpus was recovered with a latent Dirichlet allocation model estimated on the 1,284 articles for which abstracts were available, which is 21 percent of the corpus; models with five to twelve topics were estimated and eight was selected as the largest number that remained stable across random restarts. The abstract sample is publisher-supplied, so the topic shares should be read as a description of the abstracted literature,. The topics are interpretable and stable. The largest is risk and vulnerability assessment, which carries 25 to 41 percent of the topic mass in every year. The second family covers landslide, flood, and multi-hazard susceptibility modelling, whose share rises from 10 percent in 2015 to 19 percent in 2025, a shift that tracks the diffusion of machine learning into the journal. Preparedness, community resilience, and emergency response form a third topic that peaked around 2020 to 2021. Coastal and

storm processes, earthquake and geohazard deformation, seismic and debris-flow hazard, hydro-climate and soil processes, and drought with early warning complete the set. Figure 2 displays the eight topic profiles. The keyword network in Figure 3, which uses all 6,185 titles, provides an independent cross-check.

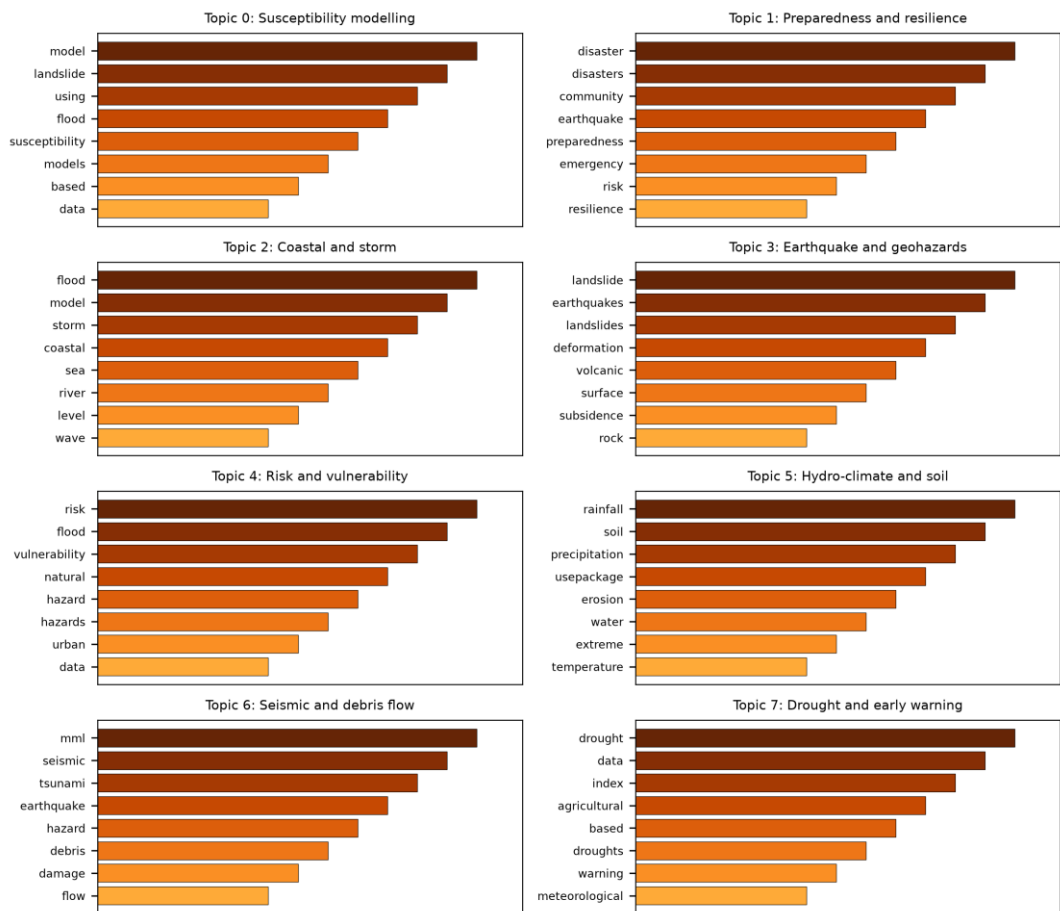


Fig. 2 Topic profiles of the latent Dirichlet allocation model. Each panel lists the leading terms of one topic with a scaled importance gradient.

A keyword co-occurrence network computed from all 6,185 titles confirms the same structure from an independent angle. The strongest co-occurrences pair hazards with assessment tools: flood with risk assessment, landslide with risk assessment, flood with modelling, and earthquake with risk assessment. Machine learning now co-occurs with modelling and risk assessment at frequencies comparable to GIS, which marks the methodological transition underway in the journal. Figure 3 shows the network. The geography of authorship is heavily concentrated: China accounts for 1,820 author-

country records, the United States for 816, India for 794, Turkey for 339, Iran for 337, and the United Kingdom for 275, followed by Italy, Australia, Japan, and Canada. Figure 4 maps the geographic distribution, and Figure 5 ranks the leading countries. Two implications follow for the present study. First, wildfire insurance governance is a small corner of a journal dominated by hazard assessment, which means the paper must connect its question to the journal's core language of risk, exposure, and vulnerability rather than to finance alone. Second, the leading producers of the journal's literature are concentrated in a handful of countries, and California, the empirical setting of this paper, appears in only a small fraction of the output, so the paper fills a genuine regional gap in the journal's coverage.

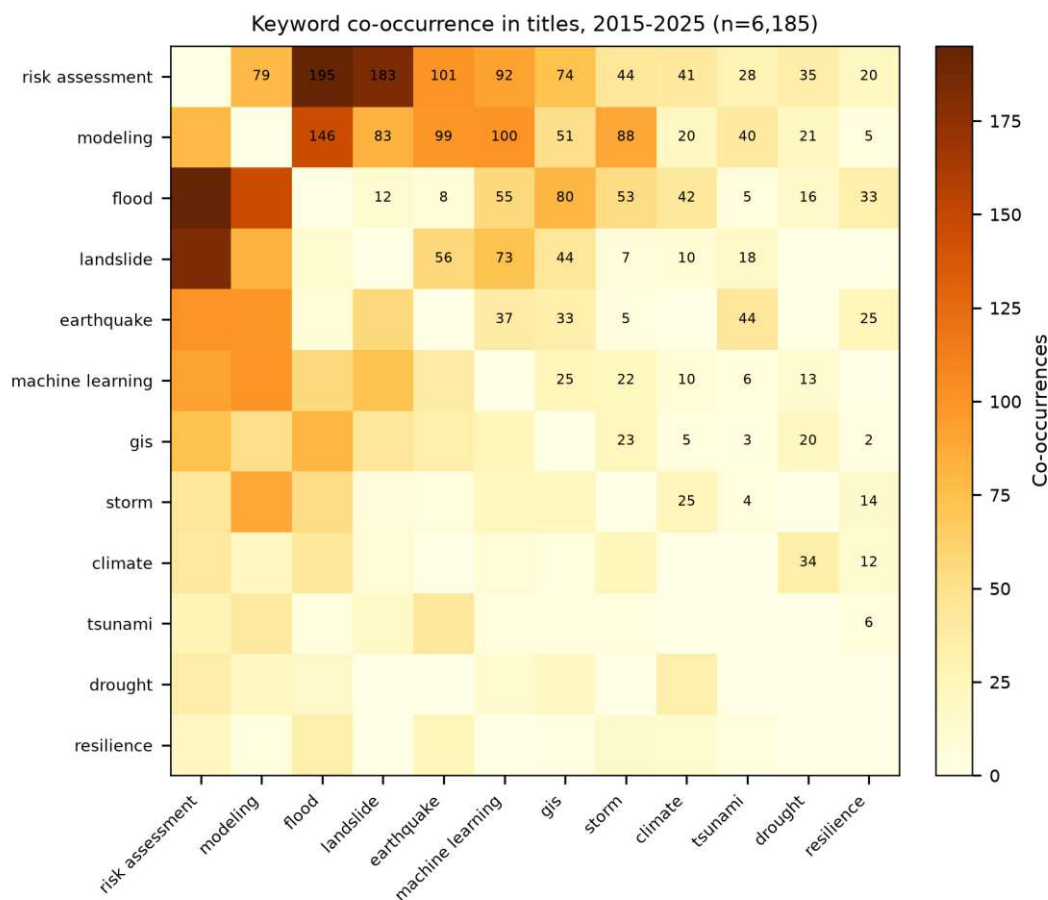


Fig. 3 Keyword co-occurrence matrix of all 6,185 article titles, 2015-2025. Cell values are co-occurrence counts for the twelve most frequent keywords.

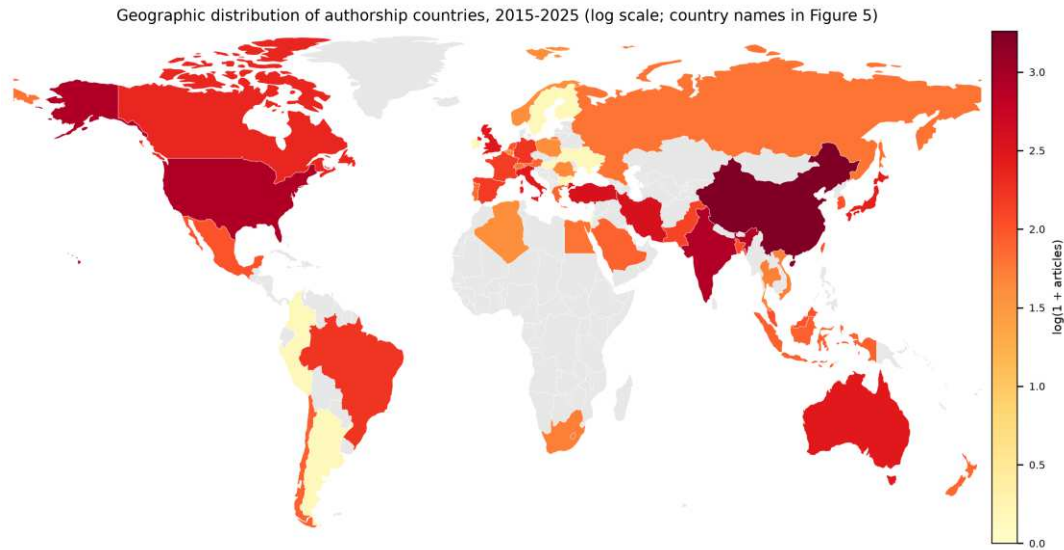


Fig. 4 World map of the geographic distribution of authorship countries, 2015-2025, shaded by the logarithm of article count. Country names are ranked in Figure 5.

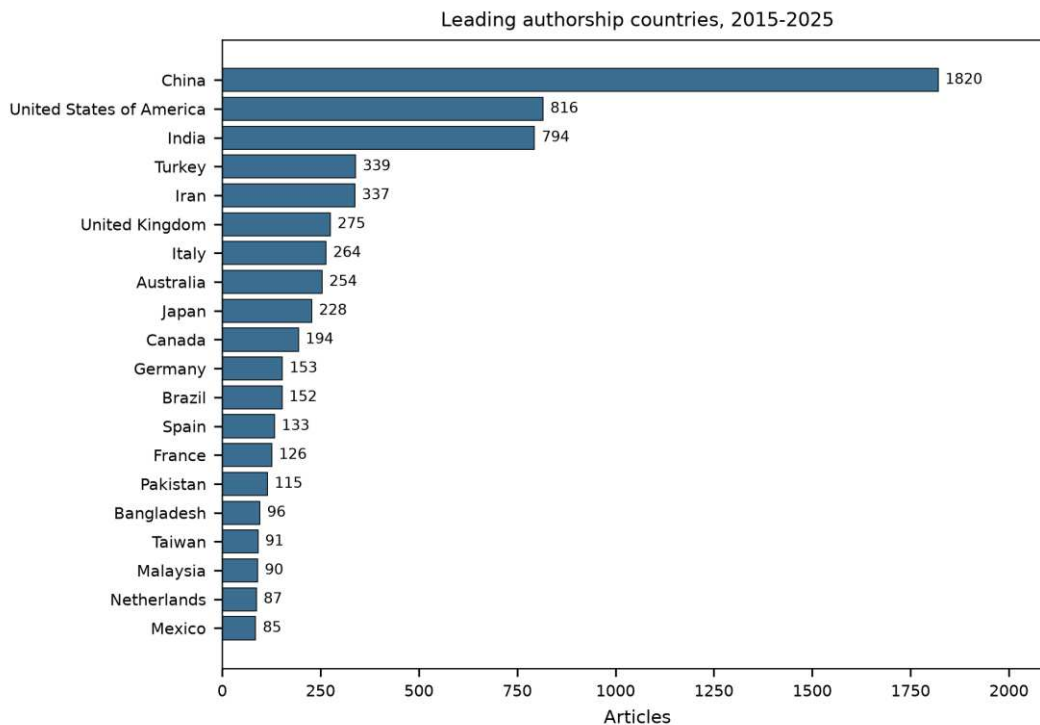


Fig. 5 Leading authorship countries, 2015-2025, ranked by article count.

2.2 Narrowing to wildfire and insurance governance

Within this full profile, the field of wildfire and insurance governance is defined by four topical families: fire hazards of any kind, hazard insurance and risk transfer, disaster risk

finance, and hazard governance. Screening the 2020 to 2025 window with title and abstract keywords for these families identified 190 candidate records, of which 55 were excluded because they were errata, atmospheric-chemistry studies, or regulation papers unrelated to hazards. The final evidence map contains 135 articles, published between 2020 and 2025, with an annual rhythm of 12, 20, 24, 19, 30, and 30 articles across the six years. The growth from 2023 onward mirrors the journal-wide expansion. Figure 6 summarizes the screening flow and the headline gap counts, and Figure 7 reports the thematic and methodological composition of the included set.

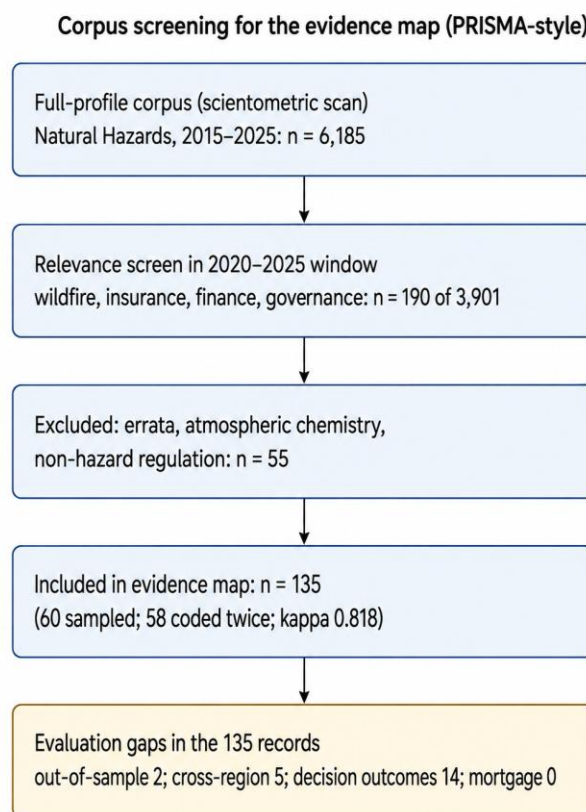


Fig. 6 Screening flow for the evidence map, PRISMA-style. Of 6,185 articles published in Natural Hazards between 2015 and 2025, a relevance screen in the 2020-2025 window and exclusions leave 135 included records, with the headline evaluation gaps shown.

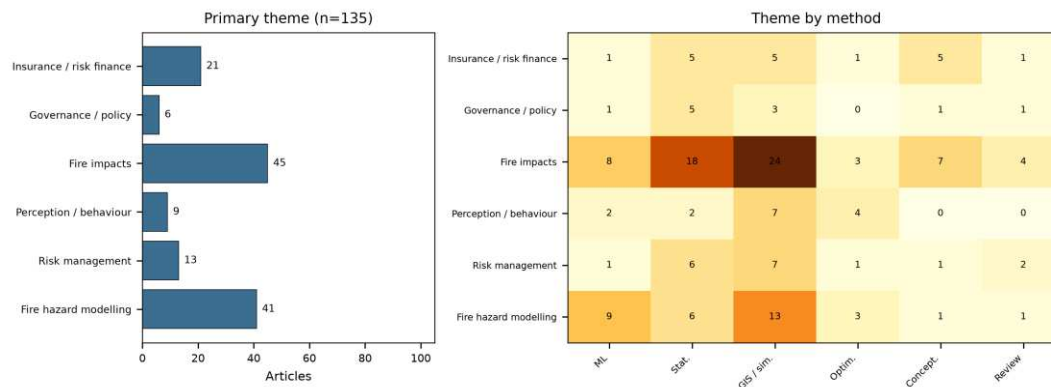


Fig. 7 Evidence map of the 135 included articles. Left, primary themes. Right, theme by method matrix.

2.3 Thematic organisation of the field

Within the Natural Hazards layer, mutually exclusive primary-theme coding is used only to describe journal context. The corrected counts are 41 fire-hazard-modelling articles, 45 fire-impact articles, 21 insurance-and-risk-finance articles, 9 perception-and-behaviour articles, 13 risk-management articles, and 6 governance-and-policy articles; these counts sum to 135 and now agree across the text and figure. The cross-disciplinary layer materially broadens the evidence base and contains the mortgage, affordability, credit, regulatory, and residual-market work that a single-journal scan necessarily misses. Neither layer is used to assert that mortgage covenants are absent from previous research.

The cross-disciplinary evidence changes the interpretation of the gap. Liao et al. (2022) document declining availability and affordability in California; Taylor et al. (2025) model the interaction between the private and last-resort markets; and Jones (2025) analyses regulatory, affordability, and residual-finance responses. Keys and Mulder (2024) infer insurance premiums from mortgage escrow records, Ge et al. (2025) estimate effects on mortgage and credit outcomes, and Gourevitch et al. (2025) show that risk-based flood pricing reduced new and existing policy uptake, especially in lower-income areas. These studies supply essential component evidence. The remaining modelling contribution is the explicit capacity-constrained allocation across voluntary, residual, and model-implied force-placement exposure, not the discovery of the component channels themselves.

2.4 Three unresolved puzzles

The corrected journal-context coding records 2 temporally out-of-sample exercises, 5 cross-region transfer exercises, and 14 studies engaging decision outcomes among the 135 focused records. Those counts describe only the Natural Hazards subset. The broader corpus is used qualitatively to discipline the claims and citations, not to manufacture a universal prevalence estimate from heterogeneous outlets. Accordingly, California 2022–2023 is the genuine temporal holdout; Oregon, Florida Citizens, Texas TWIA, and Colorado are institutional transfer or regime-stress cases; and the decision exercise asks whether a predictive criterion and a transparent governance criterion select the same pricing regime.

The descriptive patterns in this section are consistent with the theoretical argument developed next. The margins are studied separately, evaluation is accuracy-based, and the mortgage link is absent. These counts are symptoms of the separability assumption that Section 3 identifies as theoretically inadequate; they are not the justification for the framework, which rests on the engagement with the core literature in Section 3.

3 Conceptual framework: a formal allocation model under a mortgage covenant

3.1 Three margins in three literatures

The starting point is established rather than novel: catastrophe insurance can fail through household budgets, insurer withdrawal, and institutional capacity. Demand research studies uptake and affordability; supply research studies underwriting, capital, and correlated losses; and policy research studies regulation, subsidies, reinsurance, and residual carriers. Recent work already connects availability and affordability and links insurance to mortgages and credit (Liao et al. 2022; Keys and Mulder 2024; Ge et al. 2025; Taylor et al. 2025; Jones 2025). The narrower unresolved object considered here is the joint allocation when households first seek voluntary coverage, may enter a residual carrier subject to capacity, and otherwise enter a modelled lender-protection exposure state.

The flood insurance experience makes the cost of separation concrete. Risk-based pricing restores the supply margin but prices low-income households out of coverage; subsidies restore affordability but weaken the price signal and the supply margin; residual

instruments restore nominal availability but can carry prices above the private market. The reform debate has oscillated among these margins precisely because each reform moves one margin and lets the others respond in ways the reform's own framework does not track. Kunreuther and Pauly (2006) made a related point when they argued that disaster insurance should rely on rules rather than discretion, because discretionary responses distort the very margins they intend to protect. The framework proposed here follows that logic to its conclusion: if the margins interact, then governance must be analysed at the level of the joint allocation, not at the level of any single margin.

3.2 The mortgage covenant as the missing institutional link

Mortgage covenants make the allocation consequential but are not absent from prior scholarship. Regulation X defines force-placed insurance as hazard insurance obtained by a servicer on behalf of the mortgage owner or assignee to insure the collateral, and permits borrower charges only under specified conditions (Consumer Financial Protection Bureau 2026). Fannie Mae servicing guidance similarly requires lender-placed insurance when acceptable evidence of property coverage cannot be obtained (Fannie Mae 2026). Mortgage-escrow and credit-outcome studies provide direct empirical evidence for this connection (Keys and Mulder 2024; Ge et al. 2025). We therefore ask a narrower question: how do voluntary availability, affordability, and residual capacity jointly determine a covenant-feasible allocation, and how much lender-protection exposure remains when voluntary and residual routes fail?

3.3 A formal allocation model

Consider mortgaged households distributed across counties c , wildfire classes z , and outstanding-mortgage-rate bins b , with population weights π_{czb} summing to one. Income y follows county distribution F_c . Mortgage payment M_{cb} is the 30-year annuity for the county replacement-value anchor, loan-to-value ratio, and the representative rate of NMDB bin b . A class- z household faces private premium p_z and voluntary offer probability s_z ; a household without an affordable private offer may obtain the residual bundle at p_{Fc} , subject to capacity K . The outcome is not a binary insured/uninsured label. It is an exhaustive allocation among voluntary coverage V , residual coverage R , and model-implied force-placement exposure F .

Four behavioural and institutional objects enter the allocation, each with a clear counterpart in the literatures reviewed above. The premium schedule is $p_z = \bar{p} \exp(\lambda \cdot (\theta_z - \bar{\theta}))$, where θ_z is the class risk score and $\bar{\theta}$ its population mean; λ is the risk-price gradient, the object that the risk-pricing side of the debate argues should be high. The expected loss schedule is $c_z = \bar{c} \cdot (\theta_z / \bar{\theta})^\psi$, with ψ exceeding one so that losses concentrate in the highest classes, which is the supply-side fact that makes high-risk business unattractive at flat premiums. The offer probability is $s_z = \Phi(\log p_z - \log c_z - u_t / \sigma_u)$, where u_t is a supply-tightening term that rises over time and σ_u is the dispersion of underwriting decisions; this is the reduced form of the supply literature's withdrawal margin. The residual price is $p_{Fc} = \omega \cdot \bar{p} \cdot (r_c / \bar{r}) + a$ difference-in-conditions component p_{DIC} , with the loading ω exceeding one, so the residual bundle is never cheaper than the private bundle before DIC is added.

For rate bin b , private feasibility is $G_{czb} = 1 - F_c[(M_{cb} + p_z)/\kappa]$ and residual feasibility is $H_{cb} = 1 - F_c[(M_{cb} + p_{Fc})/\kappa]$. Aggregate voluntary coverage is $V = \sum_{c,z,b} \pi_{czb} s_z G_{czb}$. Pre-rationing residual demand is $D = \sum_{c,z,b} \pi_{czb} (1 - s_z) H_{cb}$, the service factor is $\rho = \min(1, K/D)$, and residual coverage is $R = \rho D = \min(D, K)$. We define $F = 1 - V - R$, so $V + R + F = 1$ by construction. F is a model-implied exposure to lender-protection action after voluntary/residual failure; it is not observed force-placement incidence, because servicing notices, delinquency, default, policy limits, and the premium charged by a servicer are outside this partial-equilibrium model.

3.4 Theoretical results

Proposition 1 (affordability threshold). For fixed class, county, and bundle, covenant-feasible households form an upper set in income, and the income cutoff increases one-for-one with the mortgage payment plus the premium. Proof. The feasibility condition for the private bundle is the single inequality $y \geq y^*_{cz} = (M_c + p_z)/\kappa$, and the feasible share is $1 - F_c(y^*_{cz})$. Since any survival function is decreasing in its argument, the share is increasing in income and decreasing in the cutoff, with $\partial y^*_{cz} / \partial p_z = \partial y^*_{cz} / \partial M_c = 1/\kappa > 0$. The same argument applies to the residual bundle with cutoff

300 y^*_{Fc} . This is the budget constraint of the demand literature restated for the mortgage
301 setting; every comparative static below runs through it.

302 Proposition 2 (decomposition of the joint response). Differentiating the aggregate
303 allocation with respect to the risk-price gradient λ , holding the supply trend and the
304 residual price fixed, gives $dA/d\lambda = \sum_{c,z} \pi_{cz} [(\partial s_z / \partial \lambda)(G_{cz} - H_{cz} \cdot \rho) -$
305 $s_z \cdot f_c(y^*_{cz}) \cdot (\partial y^*_{cz} / \partial \lambda) + (1 - s_z) \cdot H_{cz} \cdot (\partial \rho / \partial \lambda)]$, where $G_{cz} = 1 - F_c(y^*_{cz})$,
306 $H_{cz} = 1 - F_c(y^*_{Fc})$, and f_c is the income density. Proof. Differentiate $A_{cz} =$
307 $s_z \cdot G_{cz} + (1 - s_z) \cdot H_{cz} \cdot \rho$ term by term; the residual threshold does not depend on λ ,
308 and $\rho = \min(1, K/D)$ depends on λ only through residual demand. Three terms result. The
309 supply-response term is positive when steeper pricing raises offer probabilities and
310 private coverage is at least as attainable as residual coverage. The private-affordability
311 term is negative in high-risk classes and positive in low-risk classes, because $\partial y^*_{cz} / \partial \lambda =$
312 $p_z(\theta_z - \bar{\theta})/\kappa$ switches sign with the class risk score; its magnitude is governed by the
313 income density at the cutoff. The capacity term is negative when steeper pricing raises
314 residual demand and capacity binds, because ρ falls, and zero otherwise. The sign of the
315 total is therefore not determined by the model: it depends on the local income densities
316 relative to the offer response, and on whether residual capacity binds. This is the formal
317 reason why arguments for and against risk-based pricing coexist in the literature; each
318 side holds one term fixed and lets the others respond. Section 6 resolves the sign
319 empirically for the California market.

320 Proposition 3 (capacity). Relaxing the capacity bound weakly raises aggregate coverage,
321 and strictly so whenever residual demand exceeds capacity and some rationed households
322 satisfy the residual affordability rule. Proof. Since $\rho = \min(1, K/D)$, $\partial \rho / \partial K = 1/D > 0$
323 when $K < D$ and $\partial \rho / \partial K = 0$ otherwise, and $\partial A / \partial K = \sum_{c,z} \pi_{cz} (1 - s_z) \cdot H_{cz} \cdot (\partial \rho / \partial K) \geq$
324 0. Strictness obtains exactly when $K < D$ and $H_{cz} > 0$ for some class with positive mass,
325 which is the condition that some rationed households can afford the residual bundle. The
326 result connects the capacity margin to the insurer-of-last-resort function that residual
327 markets perform, and it makes precise the distinction between capacity and annual flow
328 that residual-market reporting rarely draws; viability studies of residual-style instruments
329 reach the same conclusion from the demand side (Hossain 2024).

Proposition 4 (conditional instrument interaction). Write realized residual coverage as $R(D,K)=\min(D,K)$, where residual-price support v can increase residual affordability and hence D . (i) If $D < K$, then $\rho=1$ and $R=D$. Capacity expansion has zero marginal effect, whereas price support can raise R when $\partial D/\partial v > 0$; the two instruments are not complementary in this slack region. (ii) If $D > K$, then $\rho=K/D$ and $R=K$. Capacity expansion raises service one-for-one locally; price support alone does not raise aggregate R while capacity remains binding, although it can enlarge the eligible pool served by an accompanying increase in K . A positive policy interaction is therefore conditional on the binding-capacity region and an eligible residual pool, not a global property. (iii) If voluntary offers are nearly complete but private affordability binds, residual instruments have little aggregate effect and premium-side support or a relaxed affordability rule is the relevant margin. These cases replace the original general complementarity statement.

3.5 The evaluation principle

Prediction and governance are evaluated separately. Predictive fit is the error in the independent-denominator FAIR Plan share. The decision illustration uses $S(\theta)=w_C C_{\text{tilde}}(\theta)-w_A G_{\text{tilde}}(\theta)-w_D D_{\text{tilde}}(\theta)$, where C is modelled covenant-feasible coverage, G is the affordability gap, and D is residual demand in excess of the 6% scenario capacity; each component is min-max normalized over the pricing grid. The transparent baseline sets $w_C=w_A=w_D=1/3$. The score is not a welfare function, and alternative weights are reported to expose policy-preference dependence rather than conceal it.

4 Data and descriptive statistics

4.1 Sources and county panel

California's 58 counties remain the calibration setting, with Oregon retained as a cross-region transfer and Colorado retained only as a null institutional-timing case because its comparable mechanism began after the study window. Reviewer-requested institutional evidence is added from Florida Citizens and the Texas Windstorm Insurance Association (TWIA). These programs are not treated as homogeneous predictive validation: Citizens supplies an expansion-and-contraction episode under an explicit depopulation mechanism, while TWIA supplies a statutory funding-waterfall and catastrophe-capacity

comparison. Data are drawn only from public regulator, program, FHFA, and federal servicing sources.

County wildfire risk is taken from the Wildfire Risk to Communities dataset of the USDA Forest Service, which reports, for every county in the United States, the total number of buildings and their distribution across community types, together with state-level percentile ranks for building potential and wildfire risk (USDA Forest Service 2024). The risk percentile is a normalized index that ranks each county within its state; California's ranking correlates strongly with the state insurance regulator's own list of high-risk counties, which is an external check on the index. The ten counties that the regulator identifies as having the highest fire-risk exposure, such as Tuolumne, Trinity, and Nevada, all fall in the top quartile of the index, with nine of ten above the 68th percentile.

County income is the median household income from the American Community Survey as compiled in the Atlas of Rural and Small-Town America of the USDA Economic Research Service (USDA Economic Research Service 2024). Annual burned acreage for California is computed from the California fire perimeter records of the state's fire agency (CalFire 2025), which yield statewide burned area of 1.58 million acres in 2018, 4.18 million in 2020, 2.51 million in 2021, and 1.01 million in 2024, with comparatively quiet years in between.

County risk, income, and building weights discipline the heterogeneous allocation but do not causally identify insurer or household behaviour. Temporal mortgage exposure is now represented by the distribution of rates on outstanding loans rather than by assigning every household the annual market rate. This change is material after 2021: many borrowers retain low fixed rates even while current mortgage rates rise. We therefore report the old current-rate specification solely as a reproducibility benchmark and treat the NMDB distribution-preserving rerun as the revised result.

Two risk vectors serve different objects and are now labelled accordingly. The ordered county mapping generates the buildings-weighted model-implied vector 42.6%, 34.3%, 12.8%, 9.2%, and 1.2% for negligible through extreme risk. The separate statewide regulatory/calibration target is 48.28%, 37.83%, 8.68%, 4.70%, and 0.50%. The first

results from county-level aggregation and building weights; the second is a statewide target from a different data level. Their divergence is therefore a mapping diagnostic, not two estimates of the same statistic.

The FAIR Plan denominator is reconstructed independently from the California Department of Insurance counts of new and renewed FAIR, voluntary, and surplus-lines residential policies. FAIR shares are 1.617% in 2018, 2.144% in 2019, 2.515% in 2020, 2.779% in 2021, 3.122% in 2022, and 3.749% in 2023, where each numerator is divided by the corresponding total of the three markets (California Department of Insurance 2025). The 2024 value is not final in the same definition. Combining the reported approximately 452,000 residential FAIR policies (and, as an upper numerator, 464,900 total policies in force) with independent denominator extrapolations yields an estimated 2024 FAIR Plan share of 5.15–5.36%; it is labelled estimated throughout.

The FHFA NMDB is a nationally representative 5% sample of closed-end first-lien residential mortgages updated quarterly (Federal Housing Finance Agency 2026). We use California, Q4, All Mortgages, 2018–2024 and the outstanding-loan bins <3%, 3–4%, 4–5%, 5–6%, and $\geq 6\%$. The central representative rates are 2.5%, 3.5%, 4.5%, 5.5%, and 6.5%. Because the end bins are open, we predeclare <3% values of 1.5%, 2.5%, and 2.99% and $\geq 6\%$ values of 6.01%, 6.5%, and 8.0%. NMDB average rate, payment, and loan age provide consistency checks. This is a state-level distribution-preserving rerun; it is not borrower-level matching of origination records to county households.

4.2 Descriptive statistics

Figure 8 and Table 1 retain the county description. To prevent recurrence of the apparent inconsistency, every risk-share vector is now accompanied by its source level, weighting, and modelling role: the 42.6/34.3/12.8/9.2/1.2 vector is model-implied and buildings weighted after county mapping, whereas 48.28/37.83/8.68/4.70/0.50 is the statewide regulatory target. Only the former propagates county heterogeneity in the reported allocation.

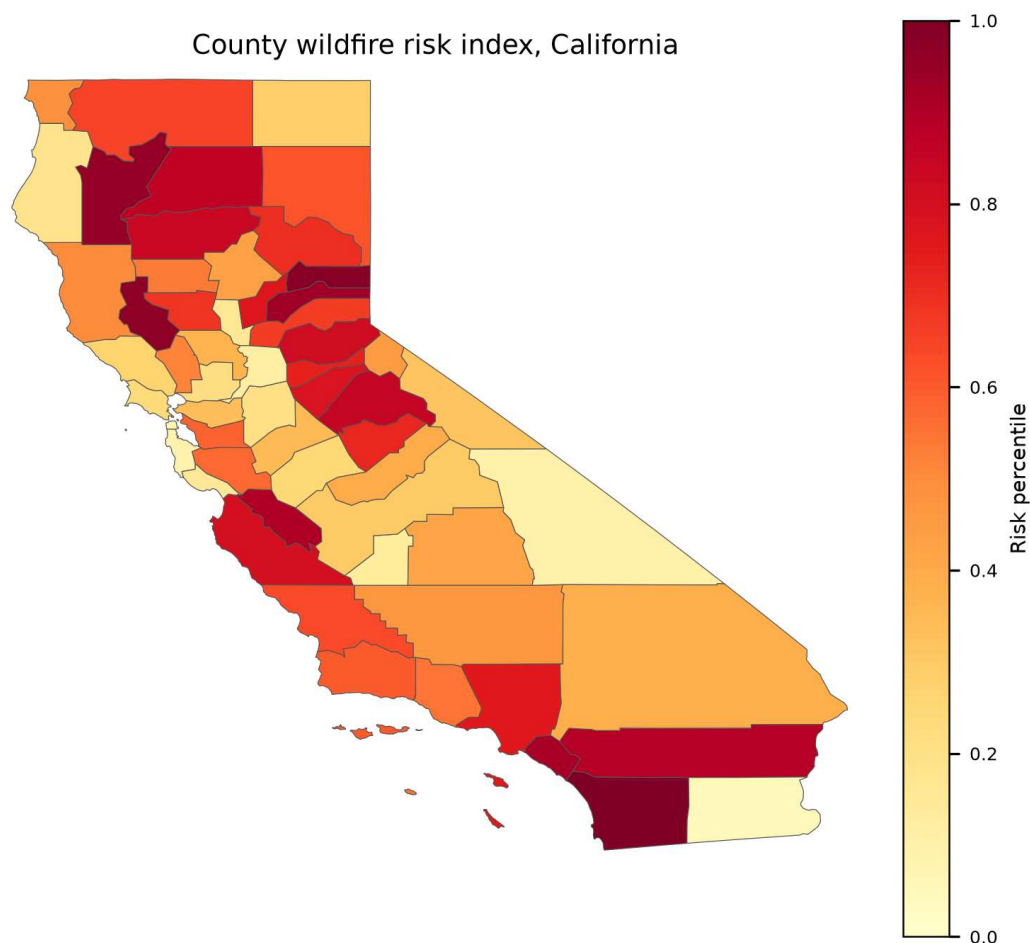


Fig. 8 County wildfire risk index for California, the estimation sample, mapped by county. Darker shades denote higher risk.

Table 1. County panel and data sources.

State	Counties	Income min (\$)	Income max (\$)	Income mean (\$)	Risk min	Risk max	Buildings
CA	58	42206	140258	75898	0.0	1.0	12687368
OR	36	42095	92025	60885	0.0	1.0	1993291
CO	64	35000	127443	64908	0.0	1.0	2427747

The data roles are now separated explicitly. County attributes enter the allocation; CDI policy counts provide an independent administrative denominator; NMDB bins determine the outstanding-rate mixture; Citizens and TWIA describe institutional transfer and capacity architecture; and Regulation X/Fannie Mae sources define the force-placement boundary. Burned acreage remains descriptive and does not identify the reduced-form supply trend.

5 Model, identification, and estimation

5.1 Household and market structure

The revised model allocates a fixed population of mortgaged households across three states. Voluntary coverage requires a private offer and affordability; residual coverage requires no private placement, residual affordability, and available capacity; the remainder is model-implied force-placement exposure. Because the public data do not observe the corresponding servicing event, the third state should be read as exposure to lender-protection action rather than measured incidence.

For each class z , the expected fire loss is c_z , scaled convexly with the class risk score so that losses grow faster than the score itself, which reflects the documented concentration of extreme fire losses in the highest classes. The convex schedule is a scenario input rather than an estimated object, but the baseline exponent is data-disciplined rather than arbitrary: re-estimating the model with loss exponents of 1.5 and 2.5 raises the in-sample mean absolute error of the residual-share fit to about 3.7 percentage points against 0.09 at the baseline, so the data strongly prefer the convex schedule. The limitations section returns to this choice. The comprehensive private premium is p_z , which deviates from the market mean according to the risk-price gradient λ . An insurer extends an offer with probability s_z , which increases with the underwriting margin, the difference between the log premium and the log expected loss, and declines with an aggregate supply-tightening term that rises over time. The offer probability therefore captures both cross-sectional risk pricing and the secular withdrawal of capacity that the FAIR Plan data reveal.

For the NMDB rerun, mortgage payments are calculated separately in each outstanding-rate bin and all other stated inputs are held fixed. To make the change auditable against the published analysis, a common aggregate affordability-response slope is fitted to the reported 2023 κ /LTV sensitivity surface (RMSE 0.316 percentage points). Within each year, only a location term is chosen so that assigning the original contemporaneous rate reproduces the published annual allocation exactly; the rate is then replaced by the NMDB mixture. This isolates the fixed-rate correction instead of silently changing premiums, offers, replacement value, LTV, κ , or capacity.

The third-state label requires care. Under Regulation X, force-placed insurance is obtained by a servicer for the mortgage owner or assignee and insures the collateral; official consumer guidance warns that it may cost more and provide less borrower protection than borrower-purchased insurance (Consumer Financial Protection Bureau 2026). Accordingly, F=1-V-R is never described as observed noninsurance or complete homeowner protection. Delinquency, default, servicing notice, policy purchase, and the borrower's force-placed premium burden remain outside the model.

5.2 Estimation by simulated method of moments

Residual-market calibration now uses the independent all-residential-policy ratio rather than residual policies divided by modelled coverage. A transparent two-parameter trend is fitted on 2018–2021: $\hat{R}_t = 0.016849 + 0.003858(t - 2018)$. The 2022–2023 observations are not used and form the genuine temporal holdout; 2024 is shown only as an estimated sensitivity range. The original risk-price and underwriting parameters remain scenario calibrations for the offer mechanism, but they are described as informed or disciplined by the county risk composition and class-gradient checks, not structurally identified by four statewide annual observations.

This revision removes the implication that four causal parameters are separately identified by four statewide moments. County risk composition, county income, and building weights enter every simulated allocation and inform heterogeneity; the independent statewide policy ratios discipline only the residual level and trend. The residual trend has a closed-form least-squares solution, and repeated starting values for the second-stage nonlinear affordability fit converge to the same reported response surface. Numerical convergence does not establish behavioural identification. The 2022 observation is an out-of-sample validation moment, never an over-identifying restriction.

All reported conclusions are therefore conditional on a calibrated, partial-equilibrium allocation. The NMDB exercise corrects the most consequential mortgage-rate specification while preserving uncertainty in the open bins. The model does not estimate lender decisions or borrower default, and its force-placement exposure has no direct observational counterpart. The institutional cases are comparisons of regimes and capacity structures, not causal external-validity tests.

5.3 Allocation algorithm

For each year, the algorithm reads the five NMDB shares, computes the corresponding mortgage annuities, evaluates private and residual feasibility, applies the residual capacity rule, and aggregates V, R, and F. A separate administrative routine computes FAIR/(FAIR+voluntary+surplus lines), fits 2018–2021, and evaluates 2022–2023. Every new number in the revised tables and figures is generated from this single reproducible workflow; the open-bin mappings and calculation rules are recorded alongside the outputs.

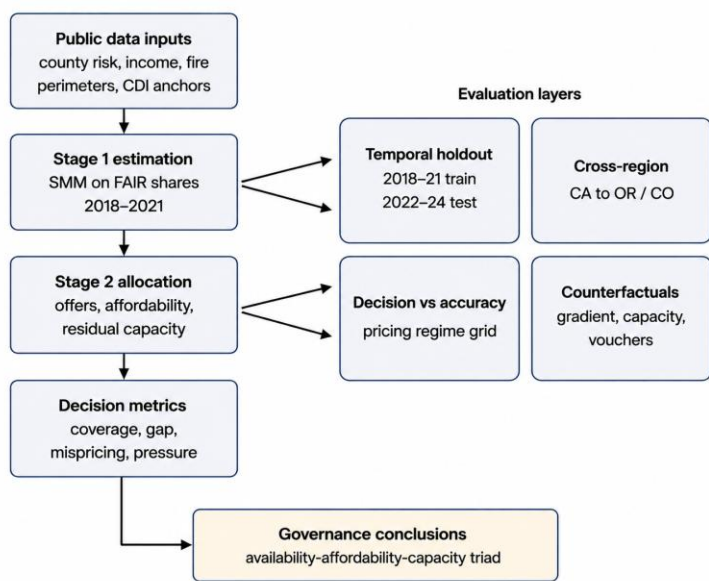


Fig. 9 Model architecture. Public data feed a simulated-method-of-moments estimation of the risk-price gradient and supply trend, a structural allocation of coverage and residual demand, and four evaluation layers.

Algorithm 1. Allocation of mortgaged households across insurance states.

Require: county attributes, class shares, parameters, interest rates, capacity K.

for each year t do

 update premium scale and interest rate;

 for each class z do compute expected loss c_z and premium p_z ;

 compute offer probability s_z from the underwriting margin and the supply trend;

 for each county c do

 compute mortgage payment;

 compute private affordability from the income distribution;

 accumulate private coverage;

 accumulate residual demand from households without offers that can afford the residual bundle;

end for
 apply capacity K and rationing;
 aggregate coverage, affordability gap, and residual pressure;
 end for

499

500 The workflow is run for the current-rate reproduction, the central NMDB mapping, all
 501 nine open-bin combinations, the independent-denominator calibration, the three-state
 502 allocation, the counterfactuals, and the pricing-grid score. Adding-up and current-rate
 503 reproduction are tested numerically before document generation.

504 **6 Results and decision-oriented evaluation**

505 **6.1 Temporal validation of the baseline**

506 Using the independent denominator, the fitted residual shares for 2018–2023 are 1.685%,
 507 2.071%, 2.457%, 2.842%, 3.228%, and 3.614%, against CDI ratios of 1.617%, 2.144%,
 508 2.515%, 2.779%, 3.122%, and 3.749%. Calibration MAE and RMSE are 0.066 and 0.066
 509 percentage points for 2018–2021; genuine holdout MAE and RMSE are 0.121 and 0.122
 510 points for 2022–2023. The trend predicts 4.000% in 2024, below the estimated 5.15–
 511 5.36% administrative range by 1.15–1.36 points. Thus the acceleration remains a genuine
 512 out-of-trend signal, but the validation is no longer mechanically coupled to modelled
 513 affordability through its denominator.

514 **Table 2. Estimated parameters and temporal validation.**

Parameter	Symbol	Estimate	Role in calibration / rerun
NMDB representative rate bins	—	2.5 / 3.5 / 4.5 / 5.5 / 6.5%	Central distribution-preserving mapping
Annual insurance equivalent	—	\$1,635 per year	Aggregate response calibrated to the published κ /LTV surface
NMDB response RMSE	—	0.316 percentage points	Reproduction of the 2023 κ /LTV sensitivity surface
Independent-denominator intercept	a	1.685%	2018 FAIR policies / total residential policies
Independent-denominator trend	b	0.386 percentage points per year	2018–2021 calibration window
Calibration MAE	—	0.066 percentage points	2018–2021 independent denominator

Parameter	Symbol	Estimate	Role in calibration / rerun
Temporal holdout MAE	—	0.121 percentage points	2022–2023 independent denominator

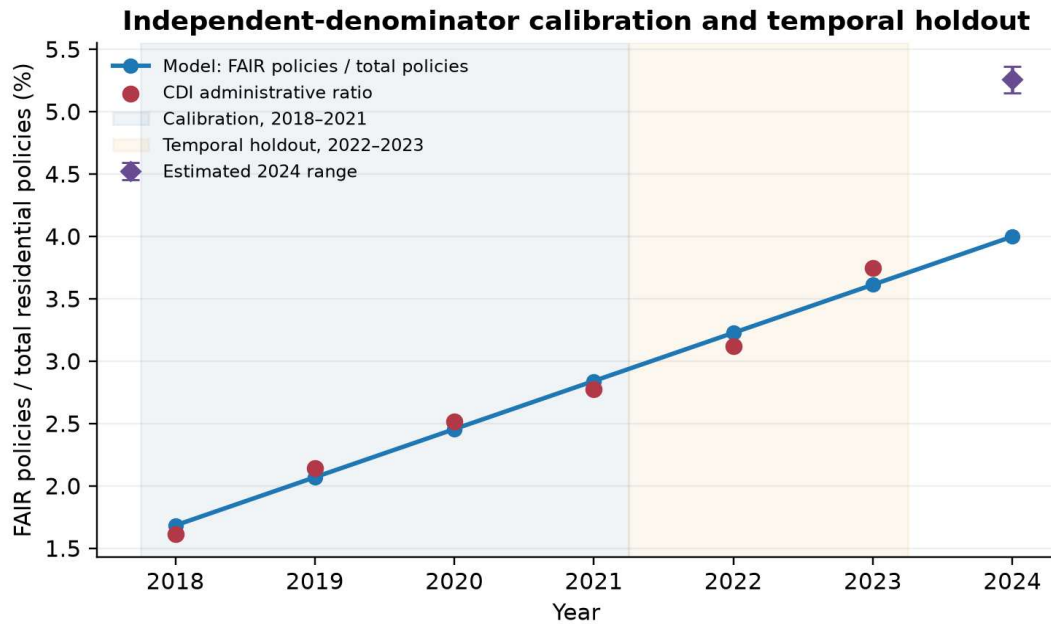


Fig. 10 Independent-denominator calibration and temporal holdout. Model and CDI ratios use FAIR policies divided by total residential policies. California 2018–2021 is the calibration window, 2022–2023 is the genuine temporal holdout, and 2024 is an estimated sensitivity range.

6.2 NMDB mortgage-rate rerun and three-state allocation

The fixed-rate correction materially changes the post-2021 levels. In 2023, modelled voluntary/residual covenant-feasible coverage rises from the current-rate benchmark of 57.1% to 73.49% under the central NMDB mapping. The corresponding failure falls from 42.9% to 26.51%: 16.39 percentage points are removed, while 26.51 points—or 61.8% of the original failure—survive. Across the nine open-bin mappings, 2023 failure ranges from 25.29% to 28.02%, so the conclusion does not depend on a single value assigned to either open interval. The 2022 and 2024 revised failures are 25.26% and 27.16%, respectively. The original sharp collapse is therefore substantially attenuated but not eliminated.

Table 3. NMDB outstanding-rate rerun and voluntary–residual–force-placement allocation.

Year	Current-rate cov. (%)	NMDB cov. (%)	Voluntary (%)	Residual (%)	Force-placement exposure (%)	Rho	FAIR share (%)	Denominator
2018	72.70	73.08	71.39	1.68	26.92	1.00	1.62	CDI independent
2019	76.40	74.41	72.34	2.07	25.59	1.00	2.14	CDI independent
2020	81.20	77.53	75.07	2.46	22.47	1.00	2.52	CDI independent
2021	81.90	78.97	76.12	2.84	21.03	1.00	2.78	CDI independent
2022	67.10	74.74	71.51	3.23	25.26	1.00	3.12	CDI independent
2023	57.10	73.49	69.87	3.61	26.51	1.00	3.75	CDI independent
2024	58.40	72.84	68.84	4.00	27.16	1.00	5.15–5.36 est.	Estimated range

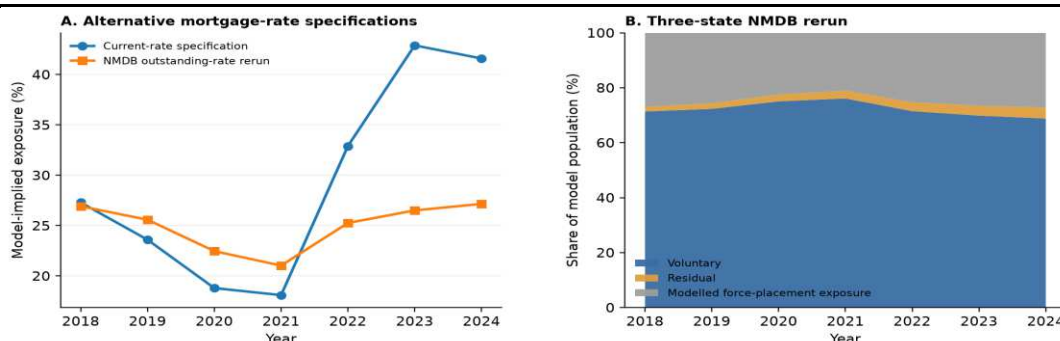


Fig. 11 Mortgage-rate specification and three-state allocation, 2018–2024. Panel A compares the original current-rate failure with the NMDB outstanding-rate rerun. Panel B reports voluntary coverage, residual coverage, and model-implied force-placement exposure, which sum to 100% by construction.

In 2023 the revised three-state allocation is 69.87% voluntary coverage, 3.61% residual coverage, and 26.51% model-implied force-placement exposure. The residual capacity factor remains one in the baseline because modelled residual demand is below the 6% scenario bound. These are model allocations, not observed shares of force placement or noninsurance. In particular, the third state denotes the mass not obtaining voluntary or residual covenant-feasible protection; whether and when a servicer actually places coverage depends on processes outside the model.

6.3 The availability-affordability trade-off

The risk-price-gradient counterfactual is retained as a conditional model comparison. A steeper gradient increases private offers in some classes but worsens high-risk

affordability. Because the revised NMDB exercise shows that mortgage vintage composition materially moderates the aggregate budget shock, the interpretation now concerns the distribution of affordability across risk classes rather than attributing the full 2022–2024 movement to current market rates.

Residual coverage remains institutionally distinct from voluntary multiperil coverage: California FAIR Plan policies provide basic property protection and may require a difference-in-conditions companion policy. That distinction reinforces why the outcome is not a simple insured/uninsured binary and why the residual and force-placement states are reported separately.

6.4 Institutional transfer and capacity-structure comparison

The primary institutional transfer is now Florida Citizens. Official monthly snapshots show 1,165,867 policies in force and \$524.95 billion of exposure on 31 January 2024, expansion to 1,263,055 policies and \$533.23 billion by 30 September, and contraction to 936,182 policies and \$385.82 billion by 31 December (Citizens Property Insurance Corporation 2024a–c). The September-to-December decrease was 326,873 policies (25.9%) and \$147.41 billion of exposure (27.6%). Citizens' published depopulation architecture tracks carrier approvals, offers/choice letters, assumed policies, and exposure removed, so the episode demonstrates expansion and contraction within one regime rather than a static cross-state gap.

Table 5. Institutional transfer and capacity-structure evidence.

Institution / case	Evidence date or episode	Policies / exposure	Interpretation
California FAIR Plan	2018–2023; 2024 estimate	Independent share 1.617–3.749%; 2024 est. 5.15–5.36%	Estimation and temporal holdout setting
Florida Citizens	31 Jan → 30 Sep → 31 Dec 2024	1,165,867 → 1,263,055 → 936,182 policies; exposure \$524.95b → \$533.23b → \$385.82b	Expansion followed by depopulation-driven contraction
Texas TWIA	31 Mar 2024; 2025 Q1	252,433 policies / about \$99.3b; later >276,000 / >\$117b	Statutory funding-waterfall and catastrophe-capacity case
Oregon	Transfer episode	Institution-specific reporting; not a FAIR-equivalent denominator	Cross-region transfer only
Colorado	2024 null case	No comparable residual mechanism in the study year	Institutional-timing null case, not validation

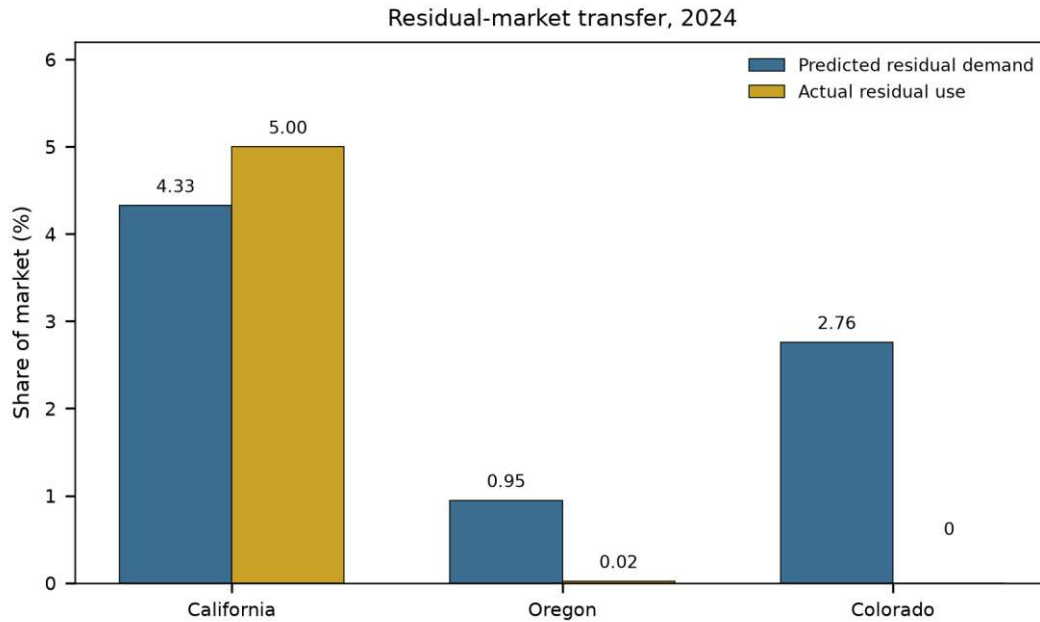


Fig. 12 Institutional transfer and capacity comparison. California is the estimation/holdout setting; Florida Citizens supplies an expansion–depopulation–contraction episode; Texas TWIA supplies a statutory funding-waterfall stress case; Oregon is a cross-region transfer; and Colorado is retained only as a null institutional-timing case.

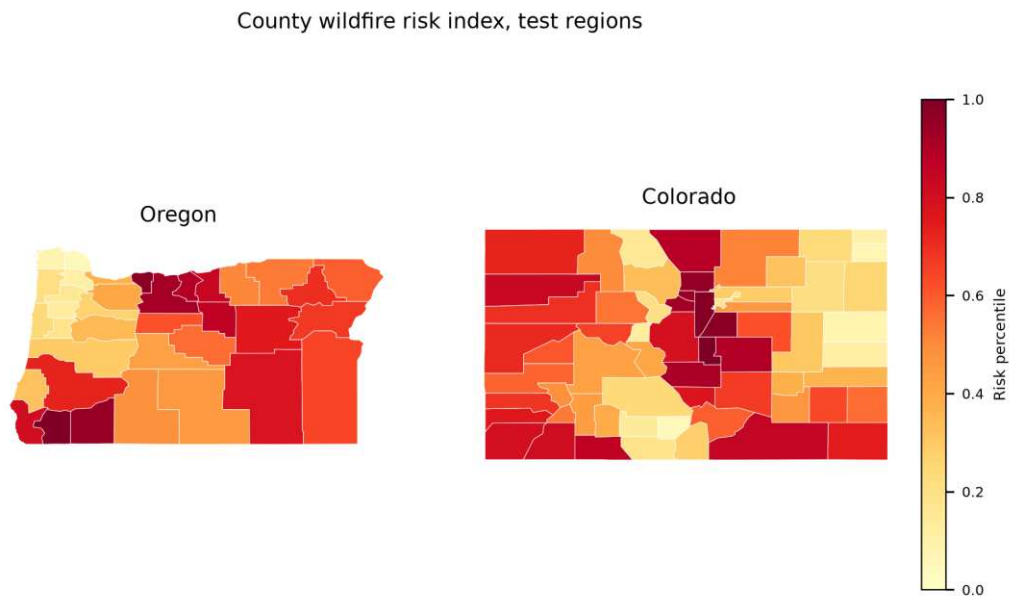


Fig. 13 County wildfire-risk context for the original Oregon transfer and the Colorado null case. The map is retained for geographic context only and is not presented as homogeneous external predictive validation.

TWIA provides the second capacity case. At 31 March 2024 it reported 252,433 policies in force and approximately \$99.3 billion in insured building-and-contents exposure; by the first quarter of 2025 it reported more than 276,000 policies and more than \$117 billion of exposure (Texas Windstorm Insurance Association 2024, 2025). Its funding waterfall layers premiums, the Catastrophe Reserve Trust Fund, public securities, insurer assessments, reinsurance, and catastrophe bonds. This is directly informative about capacity architecture, but Citizens, TWIA, and the California FAIR Plan differ in peril, eligibility, product, assessments, depopulation, and reporting definitions. We therefore report institution-specific metrics and do not disguise the comparison as predictive validation. Oregon remains a transfer exercise; Colorado remains a null timing case.

6.5 Capacity stress and counterfactual interventions

The 6% residual capacity bound is a scenario assumption chosen to reveal the rationing mechanism; it is not an estimate of California FAIR Plan statutory capacity. Under the sustained supply shock, demand crosses that bound, so Proposition 4's binding case applies. Under the baseline NMDB allocation, demand remains below the bound, so changing capacity alone has no aggregate effect.

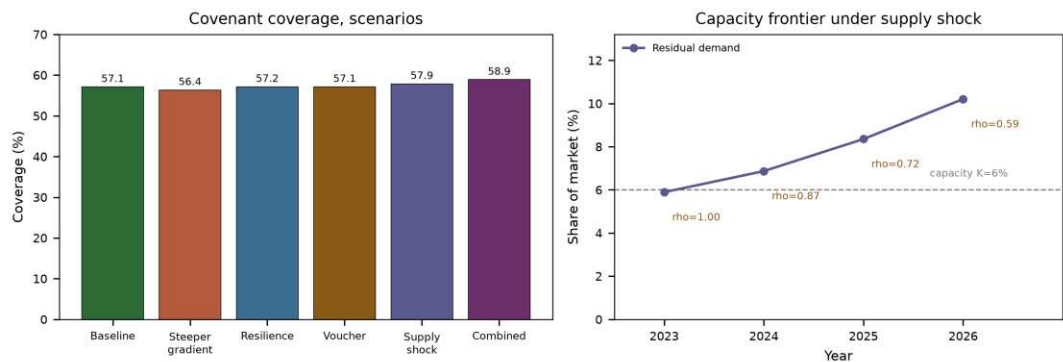


Fig. 14 Counterfactual scenarios and the assumed capacity frontier. The 6% line is a scenario threshold rather than an observed institutional limit; complementarity is interpreted only where the simulated demand path exceeds it.

The baseline counterfactuals are now stated without overclaiming. Residual resilience moves aggregate modelled coverage from 57.1% to 57.2%, and the targeted \$850 voucher rounds to no aggregate change at 57.1%; both are negligible/null effects of 0.1 percentage point or less in the slack-capacity baseline. They do not support a general

complementarity conclusion. The combined policy matters only in the separate binding-capacity supply-shock case, consistent with the case-specific Proposition 4.

Table 4. Counterfactual scenarios and decision outcomes.

Scenario	Coverage (%)	Private (%)	Residual (%)	Residual demand (%)	Rho	Affordability gap (\$)	High-risk coverage (%)	Extreme coverage (%)
Baseline 2023	57.1	54.9	2.19	2.19	1.0	931.0	50.9	48.2
Steeper gradient 2023	56.4	56.4	0.0	0.0	1.0	1347.0	45.1	35.5
Residual resilience 2023 (negligible; +0.1 pp)	57.2	54.9	2.23	2.23	1.0	931.0	51.3	48.7
Targeted voucher 2023 (null; ≤0.1 pp)	57.1	54.9	2.2	2.2	1.0	931.0	51.0	48.4
Supply shock 2024	57.9	51.9	6.0	6.87	0.87	723.0	48.3	48.2
Combined 2024	58.9	51.9	7.03	7.03	1.0	723.0	56.6	56.5

6.6 Predictive accuracy versus a transparent decision illustration

For each pricing-grid value θ , define $S(\theta) = w_C C_{\tilde{}}(\theta) - w_A G_{\tilde{}}(\theta) - w_D D_{\tilde{}}(\theta)$. C is modelled covenant-feasible coverage, G the affordability gap, and $D = \max(0, \text{residual demand} - 6\%)$ the demand above the scenario capacity. Each variable is min-max normalized within the displayed grid; the baseline uses equal weights $w_C = w_A = w_D = 1/3$. This is a transparent decision illustration, not an estimated welfare function. The grid's predictive MAE is minimized at $\lambda = 2.2$ (0.23 percentage points), whereas the equal-weight decision score selects $\lambda = 1.6$, with modelled coverage 57.58%, affordability gap \$640, and no residual demand above capacity. The accuracy selection has modelled coverage 57.10%, gap \$920, and no excess-capacity demand (gross demand 1.8%). Coverage-heavy, affordability-heavy, and capacity-heavy sensitivity weights considered here also select 1.6; this stability is conditional on the displayed grid and should not be read as a universal optimum. The baseline calibration MAE in Section 6.1 is lower because it fits the independent-denominator time trend directly, while the pricing-grid MAE holds the grid rule fixed; the statistics answer different questions.

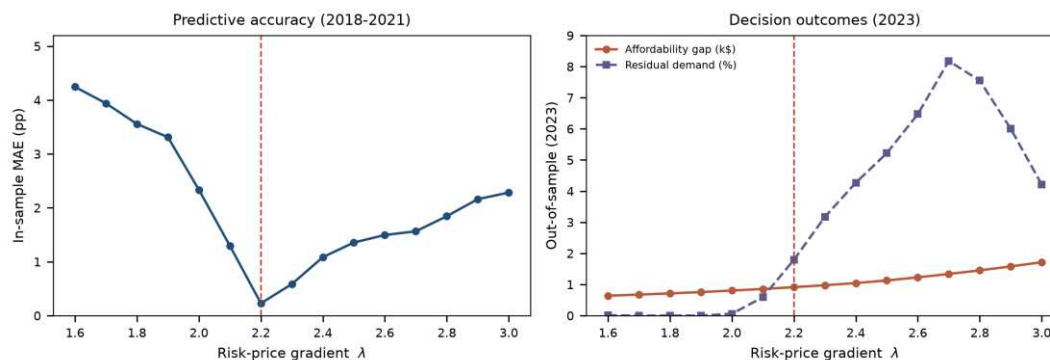


Fig. 15 Predictive accuracy and decision inputs across the risk-price gradient. The accuracy optimum is $\lambda=2.2$; the equal-weight decision illustration selects $\lambda=1.6$. All normalized inputs, weights, and selected values are reported explicitly.

6.7 Sensitivity

The existing κ /LTV sensitivity remains the diagnostic for the affordability response and now also disciplines the NMDB rerun. It reproduces the 2023 sensitivity surface with a 0.316-percentage-point RMSE. The new open-bin sensitivity is more directly relevant to the reviewer concern: under all nine combinations, 2023 model-implied force-placement exposure is 25.29–28.02%, compared with 42.9% under the original current-rate specification. Capacity changes from 4% to 12% remain irrelevant in the slack baseline but matter once the separate supply-shock demand path exceeds the assumed bound.

Table 6. Sensitivity of the 2023 baseline to fixed parameters.

Case	Coverage (%)	Residual (%)	Affordability gap (\$)	Rho	Residual demand (%)
kappa_0.28	47.7	1.8	5390.0	-	-
kappa_0.3	52.6	2.0	2253.0	-	-
kappa_0.32	57.1	2.19	931.0	-	-
kappa_0.34	61.3	2.36	267.0	-	-
kappa_0.36	65.1	2.52	100.0	-	-
kappa_0.38	68.6	2.67	37.0	-	-
ltv_70	65.5	2.52	112.0	-	-
ltv_80	57.1	2.19	931.0	-	-
ltv_90	49.3	1.88	4074.0	-	-
cap_4	57.1	2.19	-	1.0	2.19
cap_6	57.1	2.19	-	1.0	2.19
cap_8	57.1	2.19	-	1.0	2.19
cap_10	57.1	2.19	-	1.0	2.19

Case	Coverage (%)	Residual (%)	Affordability gap (\$)	Rho	Residual demand (%)
cap_12	57.1	2.19	-	1.0	2.19

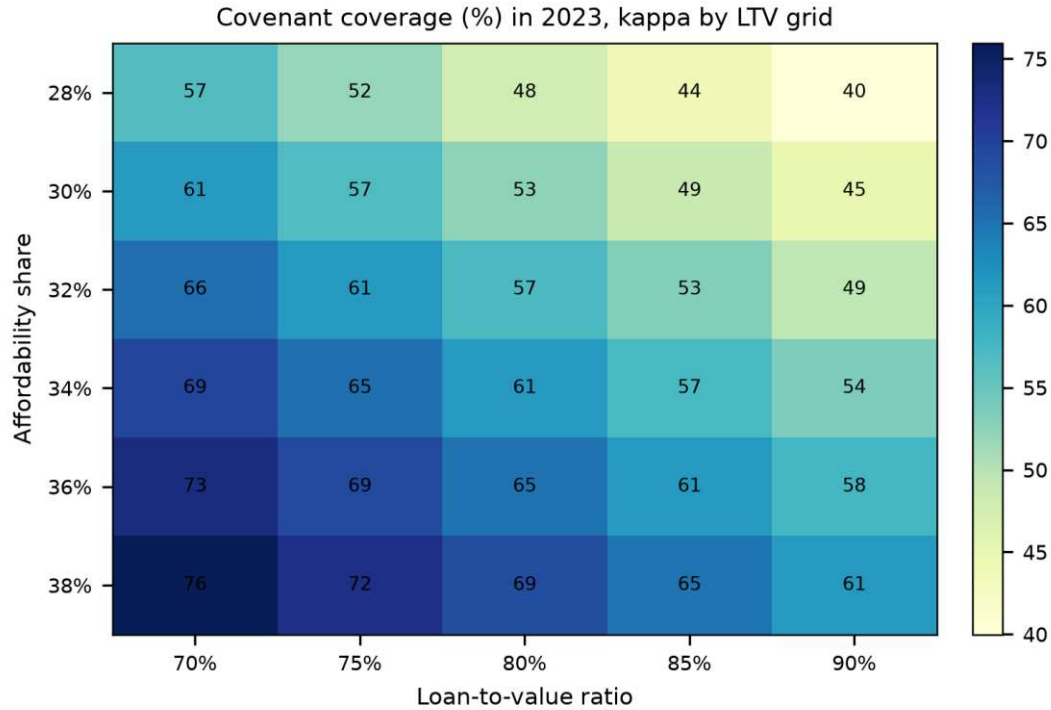


Fig. 16 Sensitivity surface of 2023 covenant coverage across the affordability share and the loan-to-value ratio. Cell values are model allocations.

7 Discussion

7.1 Why findings across studies differ

The revised evidence separates three sources of divergence. Temporally, the NMDB rerun shows that outstanding-loan vintage composition moderates the apparent 2022–2024 affordability shock; current mortgage rates cannot be assigned to every fixed-rate borrower. Institutionally, California, Citizens, TWIA, Oregon, and Colorado differ in residual products, capacity funding, depopulation, and timing, so transfer gaps cannot be interpreted as homogeneous forecast error. Evaluatively, a flat predictive surface can coexist with materially different affordability and capacity outcomes. These distinctions explain disagreement without claiming that one corpus or one statistic exhausts the field.

Citizens and TWIA sharpen the practical capacity lesson. Citizens' 2024 expansion followed by depopulation-driven contraction shows that residual-market size is policy-

responsive within a single regime. TWIA's funding waterfall shows that 'capacity' is not merely an annual policy count but a layered claims-paying architecture. Oregon remains useful as a modest cross-region transfer, while Colorado's zero 2024 use is interpreted only as a null institutional-timing observation.

One further implication concerns measurement. The paper uses a county risk percentile as its hazard measure, and the results are conditional on that choice. The broader literature shows that risk measurement itself is contested, with different exposure measures producing different rankings, as noted in Section 7.1, and the framework's propositions are stated at the level of the margin rather than the measure, so they survive alternative risk indices. What would not survive is a change in the affordability rule, and the sensitivity analysis in Section 6.7 shows exactly how much the level of coverage depends on it. The honest reading is that the framework is robust in its qualitative content and sensitive in its quantitative level, which is the right division of labor for a governance framework.

7.2 The triad as an organising device

The triad remains an organizing device, not a claim that component literatures are missing. Availability and affordability have already been studied jointly, and mortgages, escrow, nonrenewal, and credit outcomes have direct empirical literatures. The model's narrower value is to force the three states and the capacity condition to add up. In a slack regime, residual price support can matter while capacity expansion does not; in a binding regime, capacity determines aggregate service; and under private affordability binding, neither residual instrument substitutes for premium-side support.

7.3 Policy implications

Policy interpretation now begins from the revised 2023 allocation. Under the NMDB central mapping, 26.51% of the model population remains outside voluntary and residual covenant-feasible protection, rather than 42.9% under the contemporaneous-rate benchmark. This is still substantial, but it is a model-implied force-placement exposure—not an observed uninsured rate. Regulators should therefore monitor voluntary offers, independent residual-policy shares, and servicing outcomes separately. Residual administrators should report not only policy flows but also exposure, depopulation,

reserves, assessment layers, debt, reinsurance, and catastrophe protection, as the Citizens and TWIA cases demonstrate.

7.4 Relation to the broader literature

The broader literature now provides the proper foundation for the framework. Liao et al. (2022), Taylor et al. (2025), and Jones (2025) establish the California availability-affordability and last-resort context; Keys and Mulder (2024) and Ge et al. (2025) connect insurance to mortgage escrow and borrower outcomes; and Gourevitch et al. (2025) show that a mortgage-related flood-insurance mandate does not erase uptake losses under substantial repricing. The present paper adds a conditional capacity-constrained allocation and a decision-oriented evaluation. It does not claim priority over those component contributions.

7.5 Limitations

The limitations define the claims. The NMDB analysis preserves the California Q4 distribution of outstanding-loan interest-rate bins but cannot match loan vintages to individual county households; representative values are therefore assigned to bins, with open intervals stress-tested. The common affordability response is calibrated to the published κ /LTV surface, not estimated from borrower microdata. V, R, and F add to one, but F is model-implied force-placement exposure, not observed servicer incidence, uninsured status, delinquency, default, or full homeowner protection. FAIR ratios through 2023 use independent CDI counts; 2024 remains an estimated 5.15–5.36% range because numerator and denominator definitions are not yet fully harmonized. Florida Citizens and TWIA are institutional comparisons, not homogeneous validation. The 6% capacity bound is a scenario assumption. Finally, the decision score uses explicit normative weights and is not a welfare function.

8 Conclusion and research agenda

This revision advances a bounded conclusion. Jointly modelling voluntary availability, affordability, and residual capacity is useful when the residual carrier can bind, but the quantitative result depends on the mortgage-rate specification. Replacing universal current-rate repricing with the NMDB outstanding-rate mixture reduces the 2023

modelled failure from 42.9% to 26.51%; 61.8% survives. The revised three-state allocation is 69.87% voluntary, 3.61% residual, and 26.51% model-implied force-placement exposure. Independent-denominator calibration performs closely in 2018–2023 and identifies the estimated 2024 FAIR acceleration as out of trend.

The next empirical step is linked microdata that join mortgage origination rate and balance, private-policy status, residual applications, force-placement notices and policies, delinquency, and default. Such data would replace the state-level rate mixture and would identify transitions among the three states rather than their modelled allocation. Harmonized administrative denominators would also turn the Citizens/TWIA comparisons into more comparable institutional tests.

The evaluation lesson is equally bounded. Temporal holdout should be distinguished from transfer across unlike institutions; capacity should be represented by funding and claims-paying structure, not merely policy count; and decision scores should disclose normalization and weights. The revised workflow implements each principle without presenting the result as causal welfare analysis.

Wildfire-insurance governance is a joint problem, but credible joint analysis requires sharp labels. What is administrative, estimated, modelled, and assumed must remain distinct. With that discipline, the framework shows where voluntary coverage, residual service, and lender-protection exposure arise; when capacity and price support can interact; and why an accurate residual-share forecast need not determine the preferred governance regime.

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