When Insurers Exit: Climate Losses, Fragile Insurers, and Mortgage Markets

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Abstract

Despite growing climate losses, Americans continue to move into high risk areas. This paper uses a range of natural experiments to show how mispricing of climate risk in mortgages and property insurance creates large taxpayer exposures and leads to excess credit flows to risky areas. Our central finding is that the government-sponsored enterprises' (GSEs) policies for evaluating property insurers are a crucial source of this mispricing. We assemble a comprehensive new dataset on both mortgages and insurance to analyze these dynamics in Florida from 2009-2018. We begin by documenting a breakdown in the quality of insurance provision, with new under-capitalized and under-diversified insurers dominating insurance markets. These fragile insurers have high rates of insolvency, which we show causally increases mortgage defaults after natural disasters. We find that the GSEs' reliance on third-party ratings of insurers leads them to accept insurance from companies at high risk of insolvency without pricing for it. This creates large taxpayer exposures, with an estimated 31% of the GSEs' expected losses in Florida coming from insurance fragility. Most starkly, we show that private lenders strategically respond to the GSE mispricing. Mortgage denial rates are sensitive to insurance quality in the jumbo segment where loans are retained, but not in conforming segment where loans are offloaded to the GSEs. Our estimates imply that 1 in 5 GSE-eligible conforming mortgages would not have been originated by private lenders if they internalized insurance fragility risk at origination.

Keywords: Climate Risk, Insurance, GSEs, Lenders, Mortgages, Rating Agencies, Housing.

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The last few decades have seen an unprecedented growth in property damage from natural disasters in the United States. Forecasters expect losses to accelerate further as climate change brings an increase in the frequency and intensity of natural disasters (IPCC, 2023). At the same time, a number of reports document that Americans are increasingly moving towards high climate risk areas.[1] For example, the *Financial Times* writes that "Six states prone to severe weather, including California and Texas, accounted for half of the country's population growth in the 2010s."[2] This raises the important question: why do people continue to move in the way of danger?

This paper focuses on two key financial contracts that influence household location choices: mortgages and homeowners insurance. Financial contracts help determine how expensive it is to live in one place relative to another. A mispricing in these contracts means that households may not internalize the full cost of living in high risk areas. By unintentionally *subsidizing* high risk areas, mispricing can create a misallocation of people, with too many individuals in high risk areas. This leads to an even greater increase in climate losses, irrespective of other fundamental changes in climate systems due to climate change.

Pricing of climate risk in mortgages is different from other types of spatial risks in the literature (Hurst et al., 2016). Mortgage lenders have limited need to price climate risk when property insurance markets are well-functioning. Insurance is required for all mortgages, with nearly all households having homeowners insurance. Insurance provides a first line of defense against climate losses by helping households rebuild after natural disasters.[3] Insurance therefore helps preserve collateral values for lenders and limits households' default incentives after natural disasters. From the perspective of the lender, climate events become most relevant when there are large disruptions in insurance markets at the same time as natural disasters. In particular, if a large disaster precipitates insurer insolvency, both households and lenders are left exposed to the direct effects of the climate event. Mortgage borrowers may end up defaulting, leaving lenders with damaged properties as collateral. Insurer insolvency is not just a theoretical concern– since 2009, 15 insurers have become insolvent in Florida alone. Therefore, it is important for lenders to monitor insurer solvency risk, particularly for mortgages in high climate risk areas. This becomes of heightened importance as climate change places increasing stress on insurers' financial stability.

In this paper, we show that the eligibility criteria used by the government-sponsored enterprises (GSEs) to screen property insurers is insufficiently sensitive to their insolvency

[1] See, for e.g., Scheutz (2024); Redfin, "More people are moving in than out of areas facing high risk from climate change."; New York Times, "Where Americans Have Been Moving Into Disaster-Prone Areas."; CBS News, "Americans are flocking to U.S. regions most threatened by climate change."

[2] Smith, Ian. "US Home Insurers Suffer Worst Loss This Century." *Financial Times*. July 28, 2024.

[3] Swiss Re, "How big is the protection gap from natural catastrophes where you are?", October 2023.

risk, which in turn creates a mispricing of climate risk. Specifically, the GSEs Fannie Mae and Freddie Mac require that insurers have a rating that exceeds a minimum threshold, with these ratings being provided by third-party rating agencies. While these ratings are supposed to assess long-term solvency of insurers, we show that there are many insurers at high risk of insolvency ("fragile insurers") which nevertheless secure high enough ratings to meet GSE eligibility. Furthermore, the GSEs do not adjust the fees they charge for mortgages backed by fragile insurers, even though we show that such mortgages are at substantially higher risk of defaulting after disasters. This creates an implicit transfer with large taxpayer exposures through the GSEs. Our evidence points to this pattern being driven in part by private lenders strategically offloading these high risk mortgages to the GSEs. Most starkly, we find distortions in credit supply at origination. Private lenders internalize insurer fragility risk by denying loans or charging higher rates for the jumbo mortgages they must retain. However, they exhibit significantly more lax screening standards for the conforming mortgages that can be sold to the GSEs. As a result, we conclude that there is excess credit supply in the GSE segment relative to the jumbo segment.

Historically, these dynamics were hard to study because of limited granular data on property insurance that can be linked to data on mortgages. While mortgages can be studied at the loan-level, insurance is most often studied at the state-level, the level at which the regulatory filings are available. We address this gap by combining loan-level mortgage data with a novel county-level insurance underwriting dataset covering the state of Florida from 2009-2018. Ideally, we would have liked to study insurance at the individual level. However, there is no systematic collection of homeowners insurance underwriting at the individual policy level by any state, as far as we are aware. While policymakers at the Federal Insurance Office have been trying to assemble micro-data for years, these efforts have stalled because of opposition from insurers and state regulators.[4] In fact, Florida, one of the very few states that had collected county-level data, stopped systematically doing so after 2018. As a result, our analysis stops in 2018 and our insurance analysis is limited to the county level. That said, even our county level data allows us to provide some of the first evidence on the joint dynamics of homeowners insurance and mortgage markets.

In the first part of the paper, we document a dramatic rise in the market share of financially fragile insurers at high risk of insolvency in Florida. There is a large decline in the market share of insurers rated by traditional rating agencies S&P and AM Best (traditional insurers henceforth), driven by policy cancellations and limited new underwriting. This gap

[4]See, e.g., New York Times. "National Plan to Look Into Homeowners Insurers Hits a Hurdle". March 21, 2024.: "Each state regulator can decide whether to participate in the data call, and some of the states (...) may either share limited data or opt out of the program entirely."

is primarily filled by insurers rated by an emerging rating agency called Demotech (Demotech insurers henceforth), whose market share has grown to over 50% by 2018. Demotech insurers face lax insurance regulation even though they are of significantly lower quality. We show they operate in riskier areas, have lower risk-based capital ratios, are less diversified, and have less reliable reinsurance. Most starkly, nearly 20% of Demotech insurers entered insolvency proceedings in the past decade, while none of the traditional insurers did.

Despite being riskier, Demotech insurers uniformly secure just high enough financial strength ratings to meet GSE eligibility for securitization. Using standard methodologies that are widely used in the literature (Koijen and Yogo, 2016), we construct a counterfactual AM Best rating of Demotech insurers, and find that the majority would not have met GSE eligibility with these counterfactual ratings. We externally validate our approach by comparing the insolvency rates reported to the Securities and Exchange Commission (SEC) by the rating agencies. The SEC reports show that insurers which meet GSE eligibility with ratings from Demotech have almost a 25 times higher insolvency rate than those that meet eligibility through AM Best. Even those that are ineligible through AM Best have lower insolvency rates than those that are eligible through Demotech. This suggests that the GSEs' ratings thresholds for evaluating insurers are miscalibrated. This is particularly important because the GSEs do not adjust the fees that they charge lenders to guarantee the mortgage default risk ("guarantee fees") based on insurer fragility risks.

In the second part of the paper, we show that Demotech insurers dominate the conforming segment, which are loans below the conforming loan limit (CLL) and eligible for GSE securitization. In contrast, jumbo loans, that are ineligible because they are above the CLL, are significantly less likely to have Demotech insurance. There are two potential explanations for this market segmentation. The first is that lenders strategically offload loans backed by Demotech insurers to the GSEs to reduce their exposure to fragile insurers. The second is that the segmentation is driven by negative borrower selection. That is, lenders simply reduce exposure to high risk borrowers by selling loans to the GSEs, with, high risk borrowers being more likely to obtain insurance from Demotech insurers.

We show that lenders strategically offload insurance fragility risk to the GSEs by exploiting a natural experiment that provides quasi-exogenous variation in insurer quality while keeping borrower risk fixed. The state of Florida periodically runs a "Depopulation" program, which transfers existing policies of Citizens, the state-run insurer-of-last-resort, to private insurers. Demotech insurers account for over 95% of the participating insurers in the program, taking over nearly 850,000 policies between 2009-2018. Importantly, the timing of the depopulation is set by the state and unrelated to borrower characteristics. Furthermore, we show that the structure of the program leaves limited scope for negative selection in which borrowers are depopulated. We evaluate securitization outcomes of borrowers whose insurance policies are transferred from the arguably safer state-run Citizens to the more risky Demotech insurers due to the depopulation. We focus on seasoned conforming mortgages that private lenders had previously chosen to retain on their balance sheet, testing whether these mortgages are more likely to be sold to the GSEs when there is a quasi-exogenous switch in the insurer as a result of depopulation. We estimate that lenders sell roughly 27 out of every 100 previously retained depopulated mortgages to the GSEs due to a deterioration in insurer risk.

The third part of our paper shows that fragile insurers cause a 150% increase in conforming mortgage defaults after natural disasters, explaining why lenders offload loans backed by Demotech insurers to the GSEs. Our empirical strategy exploits the landfall of Hurricane Irma, which led to several Demotech insurers becoming distressed and insolvent. We argue that Irma creates quasi-exogenous variation in insurance fragility across counties and over time that is unrelated to borrower and climate risks. The main idea rests on the following logic. The path of the hurricane is random, with Hurricane Irma hitting some counties but not others. This would lead to stress for those insurers which happen to be exposed to the hit counties. Because many high hurricane-risk counties of Florida were not hit by this particular storm, there are other high risk Demotech insurers, who also tend to operate in risky counties and cater to risky borrowers, which do not go insolvent. As a result, the hurricane exogenously causes some Demotech insurers to go insolvent but not others. We can therefore look at how mortgage defaults vary after Hurricane Irma by a county's ex-ante exposure to insolvent insurers using a standard continuous-treatment difference-in-differences framework. We provide evidence supporting the three key identifying assumptions: (a) that counties with both high and low exposure to insolvent insurers have similar ex-ante hurricane risk exposures, (b) have similar borrower characteristics, and (c) that there are no pre-trends of mortgage defaults.

We are able to separately identify the causal effect of insurance fragility from the direct effect of the storm using several approaches. First, we estimate a triple difference-in-differences design that shows that insurance insolvency matters even after holding fixed the intensity of the storm, as measured by actual property damages from Irma. Second, we exploit the differential effects on conforming vs. jumbo loans within a narrow band of the CLL. Jumbos provide a good placebo test because they are far less likely to have fragile Demotech insurance but are no less likely to experience property damage in the storm. If the storm has an effect on mortgage defaults through channels other than insurance fragility, then jumbos and conforming should have similar default outcomes. However, if insurance fragility matters then conforming loans, who are more exposed, should default more than jumbos, who are less exposed, after the storm. This test relies on the identifying assumption that the treatment effect of the storm is homogenous for both jumbo and conforming borrowers, after conditioning on observable borrower characteristics. This assumption is consistent with evidence from the literature which finds limited selection on *unobservables* within narrow bands of the CLL (Hurst et al., 2016).

We estimate that insurance fragility causes mortgage default to increase by 71 basis points (bps) for conforming loans, which represents a 150% increase over the pre-period baseline. We find no increase in defaults for jumbo loans, suggesting that the storm causes higher mortgage defaults only if insurance provision is poor. The sizeable increase in defaults in the conforming segment implies an implicit transfer from taxpayers to the state of Florida via the GSEs, because the GSEs bear default risks which they do not price. We provide a back-of-the-envelope estimation of the size of the implicit transfer, extrapolating from our default estimates and using standard assumptions for lender recovery rates. We find that close to 31% of the GSEs expected losses in Florida are due to insurance fragility, with losses from Hurricane Irma accounting for 16% of the GSEs total pre-Irma capital.

In the last part of the paper, we ask whether the GSEs' mispricing changes lender credit supply. The fact that lenders can offload insurer counterparty risk to the GSEs without any charge may distort their incentives to screen for this risk for conforming loans. In contrast, lender behavior in the jumbo segment reflects how they would screen for insurance fragility risks when they retain the full risks of originating the mortgage. Therefore, any divergence in lenders' screening in conforming relative to jumbos quantifies the excess credit being originated in the conforming segment due to the GSEs' mispricing.

Causally identifying a divergence in lenders screening of insurance fragility risk requires two sources of exogenous variation. First, we require variation in the availability of high quality insurance for new loans. The ideal experiment would evaluate whether a lender would be more likely to deny a loan for the same borrower if she were randomly assigned to a Demotech insurer instead of a traditional insurer. Second, we require variation in lenders' ability to securitize a loan. That is, we would like to know whether the denial rate would change if the same mortgage borrower randomly becomes GSE-eligible. We combine two natural experiments in a continuous treatment difference-in-differences design to make progress. The first component of the test again exploits the landfall of Hurricane Irma. We show that the insolvencies triggered by Irma lead to a withdrawal by traditional insurers which is unrelated to underlying borrower characteristics or climate risks. This creates a shock to the availability of high quality insurance for new mortgages in the counties exposed to insolvent insurers after Irma. The second component of the test exploits narrow bands of the CLL and controls for borrower credit risk. This gives us variation in the ability to securitize the mortgage while holding differences in borrower risk fixed.

Using this empirical test, we find that lenders significantly restrict new credit and increase mortgage interest rates after the storm for jumbo borrowers due to insurance fragility. However, they do not screen for insurance fragility in conforming loans. At the same time, Demotech share of new policies significantly increases in the conforming segment, but decreases in the jumbo segment. Taken together, the results suggest that lenders either limit the choices of jumbo borrowers to traditional insurers, or they deny jumbo loans that have a high probability of being insured by Demotech insurers. In a counterfactual scenario where lenders fully internalized fragility risks in conforming loans, it is likely that both Demotech shares and credit supply in Florida would have been lower. We estimate that lenders would have originated 450,000 fewer conforming loans, or ∼\$95 billion in originated volume, had the GSEs priced insurance fragility risk. This represents over 20% of the originated volume of conforming mortgages in Florida between 2009-2018.

We conclude by discussing the policy implications of our work. It is well-known that the GSEs shy away from risk-based pricing. Part of this choice is rooted in the belief that uniform pricing provides inter-regional risk-sharing, creating a source of insurance against region-specific idiosyncratic shocks (Elenev et al., 2016, Asdrubali et al., 1996). This belief likely led the GSEs to accept Demotech ratings in the 1990s to support Florida's housing market after Hurricane Andrew in 1992. However, uniform pricing becomes problematic when risks are persistently high in certain areas, turning into a subsidy for high-risk regions.

In this vein, Hurst et al. (2016) show that uniform pricing creates large inter-regional transfers because predictable default risks are not priced. We similarly document an implicit transfer from low to high risk areas. However, in addition, we also identify a moral hazard channel (Ehrlich and Becker, 1972) stemming from GSE mispricing because lenders' adjustments also happen through credit rationing. This causes excess mortgage origination in high risk areas, which in turn leads to an increase in overall climate risk exposures for the broader economy, putting both households and taxpayers at risk.

We argue that a guarantee fee adjustment would help lenders internalize the costs associated with low-quality insurers. This would compensate taxpayers for bearing the additional default risk as well as help provide accurate signals to households about insurer and climate risks. Our estimates suggest that the GSEs would need to increase guarantee fees in Florida by 31% to match the expected losses due to insurance fragility. Pricing this risk will only grow in importance, given that climate losses and the footprint of fragile insurers are growing across a number of states.

Related Literature: We make three contributions. First, this paper contributes to the growing literature on the impact of climate change on mortgage markets. Our novel contribution is to emphasize how climate risks interact with existing agency frictions in financial markets, with miscalibrated GSE policy and the unraveling in homeowners insurance market playing a central role. The literature that studies the impact of climate risk on mortgages has mostly focused on the direct effects of climate shocks, without systematically examining the role of insurance markets.[5] To the extent that insurance is studied, the literature has primarily focused on flood insurance, which is provided by the government and therefore does not exhibit the type of unraveling we study in this paper.[6] Unlike flood insurance, homeowners insurance is required for all mortgages and is mostly provided by private companies, which elevates the importance of how insurance companies are screened. This is particularly relevant given the dramatic decline in insurance quality we document, driven by the exit of high quality insurers and the expansion of low quality ones. Furthermore, insurance insolvency is a central channel through which climate shocks lead to mortgage defaults. In this sense, our work also contributes to the very large literature on the drivers of mortgage default (e.g., Foster and Van Order (1984), Ganong and Noel (2020, 2023)) by emphasizing the role played by insurance insolvency, which has not been previously explored.

Second, we add to the large literature on GSE pricing and securitization in mortgages. Our contribution to this literature are threefold. First, we document a new source of GSE mispricing which stems from insurer risk.[7] Our second contribution is in studying the effects of this mispricing. In particular, we provide evidence of how GSE mispricing creates a type of *ex-ante moral hazard* in the spirit of Ehrlich and Becker (1972): GSE mispricing leads to excess mortgage origination in high risk areas. This regional aspect is different from the literature on credit expansion to low FICO or high-LTV borrowers during the financial crisis, because the *same* household with the same mortgage contract receives a higher subsidy in a higher risk area. This not only induces a redistributive transfer through subsidized interest rates as in Hurst et al. (2016), but as we show, incentivizes excess mortgage *origination* in high risk regions. Mortgage contracts have been shown to impact household mobility and location choice (Quigley, 1987, Fonseca and Liu, 2024), explaining why credit expansions could impact building and population growth in high climate risk areas. Lastly, consistent

[5] For example, Gallagher and Hartley (2017), Kousky et al. (2020), Billings et al. (2019), Issler et al. (2019), An et al. (2023), Biswas et al. (2023), Ouazad and Kahn (2021), Lacour-Little et al. (2023) study the impact of various disaster shocks on mortgage defaults, prepayments, and securitization.

[6] This literature thus far has focused primarily on government-provided flood insurance, such as how flood insurance market distortions affect mortgage lending (Sastry, 2022, Santos and Blickle, 2022), how subsidized flood premiums impact real estate prices (Ge et al., 2023), how lack of flood insurance take-up can impact mortgage default (Kousky et al., 2020), and why flood insurance take-up is low (Wagner, 2022).

[7] Elenev et al. (2016) show the GSEs' guarantee fees under-price credit risks like FICO and LTV.

with the literature, we also find significant evidence of adverse selection in what lenders sell to the GSEs following a depopulation.[8]

Finally, our paper contributes to a new literature studying the supply-side of insurance contracts. The handful of papers on homeowners insurance have focused on the determinants of insurance pricing and claims payments, including the role played by state-level price regulations (Oh et al., 2023), informational asymmetries (Boomhower et al., 2023), capital market frictions (Froot and O'Connell, 1999, Jaffee and Russell, 1997), and trust and claims' validity (Gennaioli et al., 2022). There is also a broader literature on other types of insurance contracts which has extensively studied the role of demand-side (e.g., adverse selection) and supply-side (e.g., financing frictions).[9] Our novel contribution to these literature is to show how agency frictions in mortgage markets, specifically those coming from the GSEs' requirements and lenders' origination incentives, spill over to homeowners insurance markets. We highlight that mortgage lenders and the GSEs are the natural monitors of homeowners insurance companies, and that loose monitoring induces changes in the quality and I/O of insurance markets. To our knowledge, we are the first to point out that homeowners insurance and mortgage contracts are inextricably linked, and the developments in one market have far-reaching implications for the other.

1. Institutional Background

Mortgage markets bring a range of different financial institutions together in complex institutional arrangements. Households use mortgages to purchase homes. Banks and non-banks originate loans. The government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac directly own or guarantee a large portion of the $12 trillion US mortgage market. Households buy property (homeowners) insurance which pays out a claim in response to a covered loss event. Each of these agents may bear some exposure to physical losses to the property.

The distribution of climate risk: Households are exposed to climate-related physical losses, e.g., hurricanes and wildfires, through their homes. At the same time, households rely on property insurance to hedge climate losses, with insurance claims helping households rebuild in case of physical damages to the home. The U.S. property insurance market is large, with insurers selling over $15 trillion in multi-peril insurance coverage annually to

[8] Several papers focusing on the 2008 financial crisis show that the ability to offload risks through securitization creates adverse selection in what lenders sell to the GSEs and their incentives to monitor mortgages (see, e.g., Downing et al. (2009), Keys et al. (2010), Demyanyk and Van Hemert (2011), Adelino et al. (2013, 2016), Bhutta and Keys (2022)).

[9] See, e.g., Yaari (1965), Rothschild and Stiglitz (1976) for demand-side, and Koijen and Yogo (2015, 2016, 2022), Ellul et al. (2015, 2022), Ge (2022), Sen and Humphry (2018), Sen (2021), Sen and Sharma (2020), Barbu (2021), Tang (2023), Tenekedjieva (2021), Oh (2020), Egan et al. (2021) for supply-side.

almost 95% of all U.S. homeowners with a mortgage (Jeziorski et al., 2021). The standard contract is annual and covers damages from most climate-related disasters, except flood.[10]

Losses from property damage may be borne by lenders and the ultimate mortgage owners (e.g., the GSEs) if households default following climate events and depending on insurance payouts. From the mortgage lender's standpoint, repairs financed by insurance claims help to preserve the collateral value of the property, and potentially also lower households' incentive to default on their mortgage. In other words, insurance directly reduces risks for lenders and the ultimate mortgage owners as both households and lenders are named beneficiaries of the insurance policy. Unsurprisingly, lenders *require* property insurance at mortgage origination and through the life of the loan, and the GSEs only purchase loans backed by high quality insurers.[11] The quality of insurance provision determines whether losses are borne by insurance markets, or whether some losses spill over to households, lenders, and the GSEs. Figure C.1 summarizes these relationships.

1.1. GSEs' Insurance Requirements and Pricing

The GSEs have two margins to adjust for risk, generally: screening and pricing. Our paper considers both approaches.

(a) Insurer Screening Criteria. To be eligible to be sold to the GSEs, a mortgage must meet the GSEs' eligibility criteria. The most well-known criteria are the conforming loan limit, which limit mortgages based on the size of the loan balance at origination, and the FICO credit score criteria (Keys et al., 2010, 2012). Less well known are the GSEs' requirement that property insurers backing the mortgage meet a minimum quality threshold.

The GSEs are exposed to the risk that households default due to the insurer becoming insolvent at the same time as there are claims to be paid for a natural disaster. To address this concern, the GSEs require that the property insurer backing the mortgage meets a minimum financial strength rating (FSR) threshold. The FSR measures an insurer's solvency and ability to make timely payments on its policyholder claims. It therefore serves as an indicator of the counterparty risk that an insurer poses to mortgage owners, lenders, and households. The GSEs do not accept mortgages backed by insurers classified as too risky, i.e. insurers whose FSRs are too low. To be eligible, insurers therefore seek FSRs from third party rating agencies, in exchange for paying the agencies a fee.

[10] Flood insurance is mostly sold by the federal government through the National Flood Insurance Program.

[11] Insurance requirements are monitored by mortgage servicers on behalf of the ultimate mortgage owner. Servicers face a cost for being out of compliance through "put-back risk" risk–that is, if a mortgage becomes delinquent and the GSEs discover violations of the servicing guide, the servicer is required to repurchase the deficient mortgage.

The main rating agencies accepted by the GSEs include AM Best, S&P Global, and Demotech.[12] Table 1 shows some key facts on the three agencies and the minimum FSR thresholds. AM Best and S&P have longer histories, rate multi-state insurers across the U.S., and have been monitored by the U.S. Securities & Exchange Commission (SEC) since 2007. Demotech is relatively new, having started in the 1990s around when the GSEs started accepting Demotech ratings, largely rates small single-state insurers operating in coastal states, and came under the SEC's purview recently in 2022.

Notably, the GSEs' insurer FSR thresholds vary by the issuing rating agency. For example, Fannie Mae sets out that insurers with AM Best ratings of B+ or better meet their eligibility. For Demotech they accept ratings of A or better.[13] It is important to note that as long as an insurer meets eligibility through any one of the rating agencies, it meets the GSEs' eligibility requirements.[14]

(b) GSE pricing. The GSEs price risks by charging a "guarantee fee" to cover the credit risk and other costs they incur when they acquire mortgages from lenders. There is a baseline fee with some adjustments made for borrower risk based on their FICO credit score and loan-to-value (LTV) ratio, as well as the maturity of the loan (FHFA, 2019).[15] The theoretical calculation of the guarantee fee suggests that, all else equal, the fee should rise to match increases in expected losses (Goodman et al., 2014). However, in practice, the guarantee fees do not vary with a number of key features of default risk, including local house price risk (Hurst et al., 2016), as well as insurance fragility risk. In other words, despite the wide disparity in the ex-ante quality of property insurers, even among those that meet the GSEs' FSR requirements, differences in insurers' risk are not priced in the GSEs' guarantee fees. That is, lenders are not charged additional fees to sell mortgages backed by properties that are insured by risky property insurers.

1.2. Property Insurance Market

Insurers' insolvencies. Property insurance is primarily sold by private insurers who can periodically experience financial distress, often after facing large climate-related losses. While insolvencies are relatively rare, their occurrence are on the rise, particularly in states facing

[12] Kroll Bond Rating Agency (KBRA) was also added to this list for Fannie Mae in 2018, and for Freddie Mac in 2023. We focus on AM Best, S&P, and Demotech as they accounted for most of the market share during the time frame of our study (2009-2018).

[13] For more details see Fannie Mae's and Freddie Mac's origination and servicing guides.

[14] State-run insurance of last resort plans are exempt from the financial strength requirement, so mortgages backed by them meet the GSEs' property insurance eligibility requirements.

[15] The GSEs refer to the LTV and FICO adjustments as a loan-level pricing adjustment (LLPA). See, e.g., Fannie Mae's Pricing Matrix.

elevated climate-related risks. For example, 15 insurers have become insolvent in the state of Florida alone between 2009 and 2022.

Households and lenders have some protections against their insurer becoming insolvent, but these are imperfect and incomplete. Typically, once an insurer is declared insolvent, the state-run Florida Insurance Guaranty Association (FIGA) would take over the remaining claims, paying for them from the estates of the insolvent insurer, investment income, and assessments levied on the remaining solvent insurers. However, several factors indicate that households are not fully compensated despite FIGA payouts.

First, insolvency is a long-drawn process (often 2-3 years) with FIGA payouts occurring only after the bankruptcy proceedings are finalized in courts. During this time insurers often delay paying claims, and as a result, households face lengthy delays, leaving them to bear any immediate costs of rebuilding on their own.[16] Second, FIGA caps the maximum payment to $300,000, which can be potentially below the cost of repair. Third, insurance claims are often not paid in full.[17] These factors imply that insurers' insolvencies may turn out to be costly for households, lenders, and the GSEs.

Monitoring insurers' financial solvency and ability to pay claims is under the purview of state insurance regulators. We consider the key aspects of state regulation but relegate these details to Appendix A.1 because our primary focus is to study how the GSEs' monitoring affects the quality of insurance provision and mortgage market outcomes.

Insurer-of-last-resort (Citizens). A growing issue, following the rise in climate losses and the subsequent crisis in property insurance, is the growth of "insurer-of-last-resort" (residual) markets, which provide insurance to homeowners who cannot otherwise obtain a policy through the private market. Indeed, Florida was one of the first states to experience a rapid rise in losses and insurer exits after Hurricane Andrew in 1992. The insurance market crisis led to the creation of a state-run insurance provider Citizens Property Insurance Corporation (Citizens) in 2002, with liabilities fully backed by the state.

Citizens market share ebbs and flows through time. The growth in Citizens' size indicates a lack of private insurance availability as households can only access Citizens if they are unable to find private coverage. At its peak in 2011, Citizens market share grew to 23%, then it gradually dropped to 4% in 2019, and has been rising again recently. As we discuss in Section 4.2, this large drop in policies can be largely explained by Citizens periodic strategy to reduce its exposures through the "Depopulation" program, which encourages private insurers, mostly the ones rated by Demotech, to take out its policies. We exploit this

[16] A Bloomberg article reveals an anecdote where a household's claim for a damage due to Hurricane Irma in 2017 was still unresolved by FIGA as of 2024.

[17] A legal note lists several strategies employed by FIGA to underpay claimants.

policy to study how lenders respond to a switch in the insurer backing a given loan.

2. Data

We combine data from a number of sources to obtain a comprehensive view of insurance and mortgage markets. Insurance data include underwriting information at the county level, financial statements, financial strength rating histories, insolvencies data, and consumer complaints and regulatory exams data. Mortgage data include information on mortgage origination, securitization, performance, and pricing.

2.1. Insurance Data

Insurers' county-level underwriting data in Florida. We exploit novel county-level insurance underwriting data for Florida. All property insurers that operate in the state were required to report underwriting information to the Florida Office of Insurance Regulation (FLOIR) at a county-level, which we access through FLOIR's Quarterly and Supplemental Reporting System (QUASR) database. Insurers report total premiums, number of policies, total coverage written, policies cancelled, as well as, policies transferred to and assumed from other insurers. The data are available at a quarterly frequency. We bring it to the annual level to match the frequency of our mortgage data by using fourth-quarter data for stock variables (e.g., total premiums, number of policies), and sum across all quarters in a year for flow variables (e.g., new policies written, transferred policies, cancelled policies).

The data are publicly available for all companies selling property insurance in Florida from 2009. In 2013, a court ruling permitted insurers to request confidentiality for their information, citing protections related to trade secrets. Following the decision, we observe an increasing number of insurers missing in the data over subsequent reporting periods. Figure C.2 compares the total premiums filed in the QUASR database with those filed at the state-level obtained from regulatory filings. Starting in 2019 the coverage of the QUASR database deteriorates substantially with over 36% of total premiums missing in QUASR. Our analysis therefore focuses on the period between 2009 and 2018 when the coverage of the county level underwriting data is more reliable.

Financial Statements and Operations. We combine the county-level underwriting data with insurers' financial statements and operations data from regulatory filings, which we access through Standard & Poor's Market Intelligence (S&P MI) database. (i) Balance sheet data include total assets, liabilities, and regulatory capital positions. (ii) Data on reinsurance relationships include fraction of premiums that an insurer cedes to or assumes from other insurers and reinsurers. To assess whether insurers' reinsurance partners are able to meet their contractual liabilities, we also collect data on reinsurers' financial strength ratings. (iii) We collect insurers' state-level underwriting data for homeowners and other lines of business. These data provide information on total premiums sold in each U.S. state and total losses incurred (i.e., total amount spent on claims) by lines of business. We use these data to assess insurers' loss ratios and the extent of operational diversification. (iv) Finally, we collect detailed data on insurers' asset positions, including stocks and bonds held, which allows us to assets the riskiness of their invested assets.

Insolvencies. We also collect data on insurers' insolvencies from the National Association of Insurance Commissioners (NAIC) Global Receivership Information Database (GRID) database for the period 2009 to 2022. The data list the insurers that became insolvent and the date of liquidation.

Financial Strength Ratings. We obtain FSRs for all Florida insurers issued by the three rating agencies accepted by the GSEs (AM Best, S&P and Demotech). Ratings are given at the individual operating company level, not at the insurer group level. Ratings data include the date of rating, a letter rating (e.g., "A+"), whether the rating is first for the company or affirming/upgrading/downgrading the most recent rating, and the date an insurer was no longer rated by the agency. We obtain ratings issued by Demotech from 2012 to 2021, and by AM Best and S&P from 2000 to 2021 from S&P MI database. We further hand-collected Demotech ratings prior to 2012 using online archives.

Complaints and regulatory exams. We supplement the regulatory filings data with novel hand-collected data on consumer complaints and regulatory oversight from FLOIR's annual reports for the period 2009 to 2018, which we detail further in Appendix A.1.

2.2. Mortgage Data

Mortgage applications. We use publicly available administrative data from the Home Mortgage Disclosure Act (HMDA). HMDA includes the near-universe of data on mortgage applications in each calendar year, including information about the loan amount, location (census tract), and some borrower characteristics, including income. HMDA indicates whether the mortgage application was actually approved and originated, or whether it was denied. We limit the sample of mortgage applications to first-lien purchase mortgages for single-family, owner-occupied homes. For mortgages that are approved and originated, HMDA also identifies conventional loans and reports which entity purchased the mortgage (e.g., Fannie Mae or Freddie Mac) and whether the loan is sold within the same calendar year that it was originated. We use these two flags to identify GSE mortgages and loans retained on the originating lender's balance sheet.

Purchases of seasoned mortgages. HMDA also contains information on mortgages that were originated in a previous year but sold in the calendar year of reporting. While a large fraction of mortgages are sold or securitized quickly, a number of mortgages are retained on balance sheet and sold several years later (Adelino et al., 2019). These data on seasoned mortgages also contain an indicator for conventional loans and identify whether Fannie Mae or Freddie Mac purchased the mortgage.

Mortgage performance and pricing. We supplement the HMDA data with a comprehensive loan-level dataset from BlackKnight McDash that provides information on mortgage characteristics (loan amount, LTV ratio, interest rate), borrower characteristics (FICO credit score, debt-to-income (DTI) ratio, and property value), and mortgage performance (delinquency, default, foreclosures). The data are compiled from mortgage servicers and account for approximately two-thirds of the overall U.S. mortgage market.

We classify mortgages into two groups: "conforming loans" (loans which are below the conforming loan limit (CLL) and eligible to be sold to the GSEs) and 'jumbo loans" (loans which are above the loan limit and must be retained on balance sheet by banks). To do so, we obtain the limits directly from the Federal Housing Finance Authority's (FHFA's) website, which are set annually and vary by the type of unit (e.g., single-family or multi-family) and by county (depending on local cost-of-living indices). When classifying loans into conforming or jumbo we use the relevant CLL for a given county-year cell for single-family homes. We drop loans in HMDA and McDash that are directly at the boundary because of potential mis-classification error due to rounding (Ouazad and Kahn, 2021, Lacour-Little et al., 2023).

2.3. Final Data Creation

We combine these data sources to obtain a comprehensive picture of both insurance and mortgage markets. At various points, we consider insurer-level analysis or mortgage loan-level analysis separately. When we look at mortgages and insurance together to study the implications of insurance market dynamics on mortgage markets, we merge insurer underwriting data at the county-level with mortgages data at the loan-level. The loan-level mortgage analysis takes place at two levels: (a) mortgage performance and pricing, for which we use the sample of *originated* mortgages from McDash; (b) mortgage applications and denials, for which we use the sample of mortgage *applications* from HMDA. Throughout the subsequent sections, we describe in detail which of these datasets are being used in the analyses.

3. Insurance Market Dynamics

This section documents the dramatic growth of financially fragile insurers that are at a high risk of insolvency, and shows that the GSEs' property insurance requirements are not sufficiently sensitive to insurance market fragility.

3.1. Growth of Demotech Insurers

(i) Decline of traditional insurers. We start by documenting a significant decline in the market share of traditional insurers, i.e. those rated by AM Best or S&P (Figure 1). This decline can be directly linked to traditional insurers canceling policies in Florida. Figure 2 shows that on average 11% of the in-force policies are canceled each year, and at the same time, there is limited underwriting of new policies by traditional insurers.

(ii) Dramatic rise of Demotech insurers. The gap left by traditional insurers is primarily filled by new insurers who are rated by Demotech (Demotech insurers). From having a negligible presence in the early 1990s, when Demotech ratings were first allowed, the share of Demotech insurers has risen to over 50% by 2018. Figure C.3 provides a county-level distribution of market shares in 2009 relative to 2018, showing that Demotech insurers' footprint has grown in every single county in Florida.

The increase in the market share of Demotech insurers in Florida is not an isolated phenomenon, but is part of a broader country-wide trend. Figure C.4 shows that Demotech insurers have an average market share of over 30% in the riskiest states in the U.S.

There are two broad classes of potential explanations for why we see a dramatic rise in the market share of Demotech insurers relative to traditional insurers. The first explanation is that traditional insurers ration by canceling policies and intentionally shrinking their exposure.[18] Alternatively, the second explanation is that Demotech crowds out traditional insurers by under-pricing risks.[19] In Section 6, we provide evidence that traditional insurers ration insurance by canceling policies, and that lenders' acceptance of Demotech insurance for loans in the GSE segment drives this growth.

[18]A Washington Post article about Farmers Insurance exiting Florida, citing climate change risks, provides supporting anecdotal evidence about this broad trend.

[19]There is some evidence to suggest that Demotech insurers under-price risks. Table C.1 shows that, controlling for risks, Demotech insurers charge slightly lower premiums than traditional insurers, and that their premiums have grown slower over the time period. However, the premium differences alone are not large enough to explain the wide gap in market shares given that policyholders tend to be relatively price inelastic (Sastry et al., 2024).

3.2. Fragility of Demotech Insurers

Ex-ante fragility. We next show that Demotech insurers are of significantly lower quality than traditional insurers across most observable measures of financial and operational risks.

(i) Size and solvency. Table 2 panel (a) shows that Demotech insurers are substantially smaller by total assets with the average Demotech insurer having $300 million and the average traditional insurer having close to $4 billion in assets. Importantly, Demotech insurers have lower regulatory risk based capital (RBC) ratio, which is a key measure of insurers' solvency and captures the level of available capital to the level of capital that would be required by regulators given various asset-side, liability-side, and overall business risk exposures. The average Demotech insurer has 57% lower RBC ratio than the average traditional insurer, and thus appears less well capitalized vis-a-vis underlying risks relative to peers.

(ii) Liabilities risk. Demotech insurers carry higher underwriting risks as seen from multiple measures of liability risk. Table 2 panel (b) shows that loss ratios, i.e. the ratio of total claims paid relative to total premiums collected, are higher both in Florida (83% vs. 76%) as well as nationally. This indicates greater exposure to high risk properties relative to peers. Consistent with this, Table C.2 shows that Demotech insurers underwrite more in high climate risk counties of Florida as measured by FEMA's national risk index classification. Finally, Table 2 panel (b) shows that Demotech insurers sell substantially lower coverage per policy, suggesting that they cater to households with lower wealth as coverage amount is positively correlated with loan amount and home value.

(iii) Operational diversification. Table 2 panel (c) shows that Demotech insurers are also significantly less diversified than the traditional insurers geographically, across business lines, and in their group structure. The average Demotech insurer operates in only 3 states (with 56% selling just in 1 state), obtains 70% of its premiums from its homeowners' line alone, and belongs to smaller insurance groups with few operating companies. In contrast, the average traditional insurer operates in 27 states (with only 10% selling in 1 state), obtains only 25% of its premiums from homeowners' line, and belong to larger groups.

(iv) Asset risk. Table 2 panel (d) shows that Demotech insurers tend to allocate slightly higher proportion of assets to safer securities. For example, their allocation to equities and high yields bonds (NAIC3+) is slightly smaller than traditional insurers. They also invest in low duration bonds. Despite lower asset risk, overall Demotech insurers carry higher risks (relative to capital) as seen from their significantly lower RBC ratios.

(v) Reinsurance. Panel (e) shows that Demotech insurers rely more heavily on reinsurance than traditional insurers, ceding close to 50% of its premiums to reinsurers compared to 15% for traditional insurers. While reinsurance could be an effective risk management tool, it

is not a substitute for own capital as reinsurance prices increase substantially after large natural disasters (Froot and O'Connell, 1999). These risks are particularly relevant because a large fraction of Demotech insurers' reinsurance partners have low ratings and also because Demotech insurers tend to have more concentrated reinsurance relationships.

Insurer insolvency risk. We next show that the higher ex-ante riskiness of Demotech insurers also translates to higher rates of insolvencies ex-post. We track all insurers that were liquidated in Florida between 2009 and 2022. Demotech insurers have a dramatically higher likelihood of insolvency. Table 3 shows that 19% of Demotech insurers entered rehabilitation proceedings in this period, while none of the traditional insurers became insolvent.

Furthermore, the quality gap between Demotech and traditional insurers extend far beyond Florida with Table C.4 providing broader evidence on the relative quality of Demotech insurers in high climate risk states.

Regulatory oversight. Insurers' financial solvency is overseen by state regulators. Despite the rise in insurance market fragility, we find declining scrutiny from state regulators over time with Demotech insurers facing lax oversight conditional on ex-ante quality (see Appendix A.1 and Table C.3).

3.3. The GSEs Rating Requirements are Mis-calibrated

Demotech rating bunching. We next show that despite higher risks there is a large bunching of Demotech ratings at the GSE eligibility threshold of an "A" rating. Figure 3 provides a distribution, showing that the vast majority of Demotech insurers receive an A (Exceptional) rating. There are occasional instances of A'' and A' ratings, however, ratings below the GSE threshold are extremely rare. In contrast, there is no bunching at the GSE threshold for AM Best ratings, with higher instances of ratings below the threshold despite traditional insurers being higher quality on average than Demotech insurers.

Counterfactual AM Best Ratings of Demotech Insurers. We next examine whether insurers rated by Demotech would have met GSE eligibility with a rating from one of the traditional rating agencies. To do so, we develop a framework to estimate counterfactual AM Best ratings for insurers rated by Demotech using standard methodologies followed in the literature (Koijen and Yogo, 2016).[20] We show that a vast majority of Demotech insurers would not meet GSE eligibility if subjected to traditional rating agencies' methodologies.

[20] Another approach to infer whether Demotech ratings are inflated would be to compare the ratings of an insurer that has two ratings, one from Demotech and another from AM Best at the same time. However, instances where we have two ratings for the same insurer at the same time are exceedingly rare, and are also likely to be positively selected relative to the population of Demotech insurers more broadly.

We proceed as follows. We first develop an AM Best rating replication model by mapping observable financial and operational metrics widely used as indicators of solvency risk to AM Best ratings. We focus on AM Best because of its substantially higher market share than S&P. This step identifies the best predictors of AM Best FSRs using the sub-sample of insurers that have an AM Best rating. We then take this model to predict AM Best ratings for insurers that only have a Demotech rating by using the characteristics of those insurers. We do so for the last year for which an "A" or a higher rating was assigned by Demotech, i.e. for the year the insurer met GSE eligibility using their Demotech rating.

Specifically, as a first step we run the following regression:

$$AMBFSR_{it} = \alpha + \boldsymbol{\beta} \boldsymbol{X}_{it} + \epsilon_{it}, \tag{1}$$

where $AMBFSR_{it}$ is the AM Best rating of insurer i in year t translated to a numeric scale.[21]. $\boldsymbol{X}_{it}$ is a vector of characteristics and $\boldsymbol{\beta}$ are the corresponding loadings on these characteristics. We choose the characteristics following the literature (Koijen and Yogo, 2016). We include several measures of insurers' risk and capitalization, e.g., total assets, extent of diversification, leverage, RBC ratio, asset risk, and reinsurance. The characteristics also closely overlap with what would be chosen using regularization techniques, e.g., LASSO. In addition, a large number of the chosen characteristics correspond to factors AM Best itself considers in assigning ratings, as described in publicly available reports. We use past three-year average values for each characteristic to account for the slowness in rating changes.[22]

Table C.5 shows different model specifications: a full model with all relevant characteristics (column 1), characteristics selected using a LASSO technique (column 2), and only significant characteristics retained from the full model (column 3). Across specifications, our model explains close to 60% of the variation in AM Best ratings, thus providing a good representation of AM Best's underlying ratings methodology.

We next predict a counterfactual AM Best rating for each Demotech insurer for the last year for which an "A" or a higher rating was assigned by Demotech:

$$\widehat{AMBFSR}_{DEM} = \widehat{\alpha} + \widehat{\boldsymbol{\beta}} \boldsymbol{X}_{DEM}. \tag{2}$$

$\boldsymbol{X}_{DEM}$ refers to the corresponding characteristics. For example, if we observed the last "A"

[21] AM Best rates companies in 15 notches from F to A++. We assign each letter grade a number from 1 (F) to 15 (A++).

[22] As robustness, we include different lagged values (2-years and present only). We also estimate a cross-sectional mean specification in which we regress the timeseries average of ratings for each insurer on the time series average of characteristics. Our findings remain qualitatively and quantitatively similar.

rating for an insurer in 2012, $\boldsymbol{X}_{DEM}$ would refer to average values computed using years 2010-2012 and $\widehat{AMBFSR}_{DEM}$ would show the counterfactual AM Best rating for the year 2012. If the insurer continues to be rated after 2018, $\boldsymbol{X}_{DEM}$ would refer to average values computed using years 2016-2018 and $\widehat{AMBFSR}_{DEM}$ would show the counterfactual AM Best rating for the year 2018.

Figure 4 shows the counterfactual AM Best ratings for all Demotech insurers along with a confidence interval constructed using bootstrapping.[23] Our results show that a large fraction of Demotech insurers would not meet GSE eligibility using our estimates of AM Best rating. In particular, close to 67% of Demotech insurers would not meet Freddie Mac's requirement, 21% would not meet Fannie Mae's requirement, and only 10% (those depicted in the right hand side of the graph) appear to be comfortably meeting AM Best's GSE eligibility requirements.

Evidence from SEC filings. Our results are also validated by the substantially higher insolvency rates of GSE eligible Demotech insurers (i.e. those rated A or better by Demotech) relative to the insolvency rates of GSE eligible AM Best insurers (i.e. those rated B or better by AM Best) as reported in disclosures made to the U.S. Securities and Exchange Commission (SEC), which we detail in Appendix A.2. In fact, eligible Demotech insurers have nearly a 25 times higher insolvency rate than eligible AM Best insurers (Table C.6). Quite starkly, the insolvency rate among insurers that *do not meet* GSE eligibility through AM Best are also over 5 times lower than the insolvency rate among insurers that *meet* eligibility through Demotech (1.7% vs. 9%).

Overall, these results strongly suggest that the GSEs' insurance eligibility requirements are mis-calibrated across rating agencies. In particular, the threshold for Demotech is lax. This allows several high risk Demotech insurers to be GSE eligible who would otherwise not meet eligibility using the criteria applied to the other rating agencies. As the GSEs do not directly price for this risk in their guarantee fees, the miscalibration in their insurer screening criteria implies mispricing of insurer fragility risk. The rest of the paper studies the consequences of this mispricing for mortgage and insurance markets.

4. Who bears insurance counterparty risk?

In Section 3, we show that Demotech insurers are financially fragile despite being GSE eligible. In this section, we explore what this fragility means for mortgage markets, focusing in particular on which segments of the mortgage market bear exposure to fragile insurers.

[23] To compute confidence intervals, for each model in Table C.5, we numerically simulate 1,000 predicted values by bootstrapping the sample, while preserving the within-insurer correlation.

We start with descriptive evidence about mortgage market segmentation (Section 4.1), and then consider a natural experiment to identify strategic behavior by lenders (Section 4.2).

4.1. The GSEs Exposure to Fragile Insurers

We provide two broad approaches to evaluate whether the GSEs are exposed to fragile insurers. First, we examine the county-level correlation between Demotech insurers' annual market shares and the annual share of mortgages that are sold to the GSEs. Table C.7 shows that counties that have a high Demotech footprint are also counties where lenders tend to offload a large fraction of mortgages with the GSEs. This result also holds within a county, i.e. as Demotech insurers' market share grows for a given county, lenders tend to offload a higher fraction of mortgages with the GSEs.

Second, we quantify the market share of Demotech insurers for mortgages that are eligible to be sold to the GSEs (conforming loans) and those that cannot be sold (jumbo loans). Doing this split is less straightforward for insurance markets because we do not have individual-level data that identify an insurer for each borrower. We use coverage-per-policy measures from the QUASR data as a proxy for loan amounts and county-level conforming loan limits to identify the conforming segment.[24] We find that Demotech insurers dominate the conforming segment with an estimated market share close to 90% (Figure 5). In contrast, jumbo loans are significantly less likely to have Demotech insurance. Taken together this evidence shows that borrowers in the GSE segment, as well as loans actually on the GSEs' balance sheet, are predominantly exposed to Demotech insurers.

While these findings show that the GSEs bear large exposures to Demotech insurers, they do not explain what drives this correlation. There are two broad classes of explanations that we examine in depth. The first is that lenders offload insurance fragility risks to GSEs, i.e., lenders strategically reduce their exposure to Demotech insurers by selling the mortgages to the GSEs. The second is that the correlations are driven by negative borrower selection, i.e., lenders simply reduce their exposure to high risk borrowers by selling to the GSEs, with high risk borrowers being more likely to obtain insurance from Demotech insurers.

4.2. Incentives to Offload Risks - Citizens Depopulation Natural Experiment

To isolate the effect coming from lenders' response to insurer fragility, we consider a natural experiment which delivers quasi-exogenous changes to insurer quality while keeping borrower risk fixed. Our natural experiment exploits a time-varying policy instituted by Florida's

[24] We verify that this approach correctly classifies 94% of the loans using data from Sastry et al. (2024).

insurer-of-last-resort (Citizens), which allows us to conduct a sharper test of lenders strategically offloading insurer risk based on insurance contract transfers.

4.2.1. The Depopulation Program

As described in Section 1, Citizens periodically runs programs to "depopulate" its balance sheet by encouraging private insurers to "take out" its policies. When policies are transferred from Citizens to a private insurer, the private insurer assumes the policy, receives the premiums paid, and is responsible for paying out any claims. Upon depopulation, there is a complete shift in the insurer backing the mortgage from Citizens to one of the private insurers assuming the policy. Our analysis focuses on the major depopulation efforts of the early 2010s, and Figure C.5 shows these depopulation policy flows at an aggregate level. The program has been large. At its peak in 2013, Citizens transferred on net more than 200,000 policies to the private sector, with over 800,000 insurance policies transferred over the whole sample.

Two features of the depopulation program are important to note. First, Citizens is removing policies that have been underwritten in the past. This means that we obtain variation in the insurer identity for *existing* and not new mortgages, allowing us to hold fixed borrower risks by examining the GSEs' purchase patterns for the same mortgage over time in response to becoming depopulated. Second, the depopulation program primarily resulted in a transfer of policies from Citizens to one of the Demotech insurers. This is clearly illustrated by two key factors. (i) Demotech insurers dominate the depopulation program. Of the 40 insurers that participate in the depopulation scheme, 39 are Demotech-rated. (ii) Figure C.5 shows that net policies transferred away from Citizens correspond almost one-for-one to policies transferred to Demotech-rated insurers.

Since the insurers which bid on Citizens existing policies were most likely to be rated by Demotech, we obtain quasi-exogenous variation in insurer quality (from a high quality state-backed insurer to a low quality insurer rated by Demotech) for the *same* mortgage. While we do not have detailed micro data on the individual policies that are transferred from Citizens to private insurers, we do have data on depopulation policy flows at the county-year level. By using these policy flows, we can focus on households who experience a change in their insurance provider.

On the mortgages side, the HMDA data allow us to distinguish between newly originated mortgages that were sold to the GSEs in the same calendar year of origination, and mortgages that were originated in prior years but then sold to the GSEs in a subsequent year. We can therefore look at *existing* mortgages that lenders had retained, and see whether lenders are more likely to sell those mortgages following a large depopulation effort.

Depopulation timing. A crucial component of our identification strategy is the fact that the timing of the depopulation is random. That is, the depopulation schedule is chosen by Citizens, not by the borrower or the insurer. This makes the timing of the switch unlikely to be driven by the risk characteristics of the household.

Selection into the depopulation program. While the timing is exogenous, one concern could be that of adverse selection in which types of policies are subject to the depopulation. There are three potential sources of negative selection in our setting as the observed depopulation flows are determined by the choices made by Citizens, insurers, and the policyholders. Negative selection could arise if Citizens puts up riskier policies for depopulation, if insurers select risky policies rather than safe ones, or if only risky borrowers accept the depopulation offer.

We argue that the structure of the program limits this selection concern. Citizens does not proactively select which policies are depopulated. Instead, it allows insurers to access its full policy database so they can choose which policies to assume (Nicholson et al., 2020). Importantly, insurers are unlikely to choose worse quality homeowners that cannot make insurance payments; if anything, they cherry-pick the highest quality borrowers (Citizens, 2024). Given that insurers cherry-pick, that means the pool of depopulated policies becomes positively selected. Therefore, the concern that risky borrowers are the only ones opting in to the depopulation is less of a concern. In addition, the structure of the program limits the extent to which consumer can freely opt out of the depopulation program.

Our test of the depopulation spans 2009-2014, because the structure of Citizens changes thereafter. Section A.3 provides further details on the selection into the depopulation program and our sample selection.

4.2.2. Estimation and Results

We now explain the empirical test and show the results. We subsequently provide evidence that supports the key identifying assumptions outlined above. We consider the following specification using depopulation flows at the county level:

$$LoansSoldtoGSE_{c,t} = \alpha + \eta DepopulatedPolicies_{c,t} + \delta_c + \delta_t + X_{ct}\Gamma + \varepsilon_{c,t}. \tag{3}$$

The dependent variable $LoansSoldtoGSE_{c,t}$ refers to the total number of mortgages in county c originated prior to year t that are sold to the GSEs in year t. The independent variable $DepopulatedPolicies_{c,t}$ is the net number of insurance policies transferred to Demotech insurers in a given county.[25] We adjust the depopulated policies to account for previous sales

[25]Net policies refers to policies received by other insurers minus any transferred to other insurers.

to the GSEs. We do so because a vast majority of the policies with Citizens are associated with mortgages that have already been sold to the GSEs and are not on lenders' balance sheets. In other words, the unadjusted $DepopulatedPolicies$ would include policies associated with loans already sold to the GSEs as well as policies associated with loans retained by the lenders. However, $LoansSoldtoGSE$ only measures sales of loans previously retained by lenders, as a result, leading to a significant under-estimation of β. To address this, we estimate the fraction of previously originated mortgages retained on lenders' balance sheet for each county and year by computing a trailing 3-year moving average of fraction of loans sold to the GSEs. We then scale $DepopulatedPolicies$ by the fraction retained, which gives us an estimate of the number of depopulated policies in a given county which are associated with mortgages that lenders had retained on balance sheet.[26]

The specification includes county fixed effects (δ_c) to exploit the randomization of the timing. This allows for the possibility that Citizens depopulation mechanically will be larger in the counties where its balance sheet is large to begin with. We therefore run this specification within county, and exploit the exogenous timing of when policies are depopulated. In addition, county fixed effects also accounts for other time-invariant county characteristics, e.g., borrower quality that affects lenders' securitization decisions. We include year fixed effects (δ_t) to address any aggregate time trends. The controls X_{ct} include county-year level average values of income and loan amount from HMDA for seasoned mortgages, and DTI ratio, FICO, LTV ratio, property value from McDash for all originated mortgages to account for concurrent shifts in borrower quality. We also control for Citizens' footprint in the county using its lagged market share, to further account for the fact that depopulation is more likely to happen in counties where Citizens has a larger presence. Finally, we account for a county's climate risk exposures by controlling for log property damages from SHELDUS.

The coefficient of interest η quantifies, for every depopulated mortgage that was previously retained by lenders on their balance sheet, the fraction that is sold to the GSEs due to a deterioration in insurer risk.

Identifying Assumptions. Our empirical specification seeks to isolate variation coming from a switch in the insurer for *the same* borrower. Doing so limits the possibility that the results on GSE purchases are driven by unobserved differences in the selection of borrowers. To validate this interpretation, we make the following identifying assumptions.

First, we assume that the timing of the depopulation is quasi-exogenous, i.e. uncorrelated

[26]It is important to note that the adjustment does not matter for our results qualitatively. Table C.8 shows the results of running the regression with the unadjusted $DepopulatedPolicies$. The results confirm that lenders are sensitive to a deterioration in insurer quality. The magnitudes are lower, as expected, because the independent variable includes the policies that were associated with loans already sold to the GSEs.

with a decline in borrower quality. This could be an issue if, for example, the same household becomes more risky over time, and the risky households are the ones who are most likely to be subject to the depopulation. As discussed above, the structure of the depopulation program makes this concern less likely. If anything, we expect to have advantageous selection driven by insurers choosing better quality borrowers rather than negative selection.[27] To validate this assumption, we examine the key financial metrics for Citizens before and after the big wave of depopulation in the early 2010s. If insurers were systematically selecting high risk Citizens policies we would expect to see that over time Citizens balance sheet would reflect less risk taking. Table C.9 shows the opposite. After major depopulation, Citizens loss ratio and combined ratio, a measure of underwriting profitability, both worsen substantially. Citizens share in high risk counties also rises slightly. This evidence strongly suggests that negative selection is less likely. In fact, given that insurers select the better quality borrowers, our depopulation estimate arguably provides a lower bound on lenders' true sensitivity to a deterioration in insurer quality.

Second, we assume that there is no adverse selection in the timing of securitization. In fact, Adelino et al. (2019) show that timing of securitization matters, but they find that in fact worse quality mortgages are sold earlier. This suggests that mortgages which were kept on lender balance sheets are, if anything, positively selected.

Third, we assume that other features of the insurance contract do not change (e.g., premiums, coverage) at the time of depopulation. The structure of the depopulation program prevents insurers from changing the terms of the policy following depopulation. This suggests that only the insurer identity changes without simultaneous changes in other contract characteristics.

Lastly, the specification in some sense assumes that the mortgages which are sold to the GSEs are the ones where there is a switch in the insurance provider from Citizens to Demotech. This assumption cannot be directly validated because the data do not permit us to obtain information on insurance at the loan-level. However, a significant and positive estimate of η even after the inclusion of county fixed effects would suggest that an increase in the number of policies transferred does bring an increase in the number of mortgages sold.

Results. Table 4 shows the results of estimating Equation 3. Given that lenders tend to retain few mortgages, and the loans retained are typically best quality, one may expect that a worsening of insurer quality need not bring any change to lenders' tendency to sell these mortgages. In other words, we might expect $\eta \approx 0$. Instead, we find that η is greater than

[27] We note that risks from the perspective of a lender (e.g., default risk, prepayment risk) are similar to risks from the perspective of an insurer (e.g., claim probabilities). As evidence for this, both Sastry et al. (2024) and Blonz et al. (2024) find that insurers charge higher premiums for low FICO credit scores.

zero, statistically significant, and economically large. In Column (1), with borrower controls, we estimate that lenders sell roughly 27 out of every 100 previously retained depopulated mortgages to the GSEs due to a deterioration in insurer counterparty risk. The estimate does not change much in columns (2) and (3) after controlling for Citizen's market share, borrower characteristics, and a county's climate risk exposures. Overall, our results suggest that mortgage lenders are aware of insurer counterparty risk, and they actively manage these risks by offloading mortgages with high insurer counterparty risk to the GSEs.

5. The Effect of Insurance Fragility on Mortgage Default

The declining quality of insurance provision in Florida (Section 3) coupled with lenders' strategic offloading of counterparty risk (Section 4) raises the natural question about what insurance insolvencies mean for mortgage defaults. In this section, we show that households with exposure to fragile insurers are more likely to default on their mortgage after natural disasters, creating an implicit transfer because such default risk is not priced in the guarantee fees charged by the GSEs.

5.1. Empirical Strategy

We would like to quantify whether exposure to fragile insurers causes mortgage defaults after climate events. The ideal experiment to assess this causal effect would be to randomly assign borrowers to fragile insurers, randomly assign climate disasters to borrowers, and see whether borrowers that are more exposed to fragile insurers are also more likely to default after a disaster. The reason random variation is important is because there may be a concern about negative selection, whereby higher risk borrowers are more likely to match with higher risk insurers. Such selection would make it difficult to attribute any subsequent default to the causal effect of insurance, rather than borrower characteristics. We obtain plausibly exogenous variation in insurance fragility using a natural experiment based on the landfall of Hurricane Irma.

The Timing and Path of the Hurricane. Hurricane Irma made landfall in Florida in September 2017 as a Category 3 storm. This generates two sources of variation in insurance fragility. First, Hurricane Irma delivers variation in insurance fragility <u>over time</u> as it led to a weakening of the insurance sector, with a number of insurers experiencing stress and even insolvencies after the storm. We thus consider what happens to mortgage defaults before and after the storm.

Second, Hurricane Irma provides plausibly exogenous variation in insurance fragility across counties. A number of fragile Demotech insurers operate across a range of high risk locations in Florida. Hurricane Irma hits some counties but not others, leading to stress for those insurers which happen to be exposed to the counties that are hit. Figure 6 shows the counties that were hit by the storm tend to overlap with the counties that were also more exposed to insurers that went insolvent after the storm. Because many areas of Florida which are significantly exposed to hurricane risk were not hit by the storm, there are other high risk Demotech insurers, who also tend to operate in high risk areas and cater to risky borrowers, which do not go insolvent after Irma, because the counties they operate in were not hit by the storm.

Difference-in-differences Design. We can therefore look at how mortgage defaults vary after Hurricane Irma by exposure to insolvent insurers using a standard continuous-treatment difference-in-differences framework.[28]

$$Y_{l,c,o,t} = \beta^{DFLT}(\text{Post Irma}_t \times \text{Insurance Fragility}_c) + \delta_c + \delta_t + \delta_o + \gamma' X_{l,c,o,t} + \varepsilon_{l,c,o,t}. \tag{4}$$

The outcome variable Y is an indicator that equals 1 if loan l in origination cohort o in county c is in default at time t and never recovers. We include default, foreclosure, or REO, plus three missed payments which never become current again. Post Irma is a dummy that equals 1 after the landfall of Irma. $InsuranceFragility$ is measured as the ex-ante 2016 market share (by premiums) of insurers that went insolvent after Irma in county c.[29] The vector X includes borrower-level controls, including granular FICO $\times$ LTV $\times$ Year fixed effects and DTI $\times$ Year fixed effects. For the FICO and LTV categories, we use the break points from the GSEs' loan-level pricing adjustment matrix. We also control for the direct effect of the storm on defaults using Post Irma $\times$ log (damages), to isolate the effect of insurance fragility. Property damages are damages per capita incurred within 3 months after the hurricane taken from SHELDUS. We also include county, year-month, and origination cohort fixed effects.

The coefficient of interest is β^{DFLT}, which measures the increase in mortgage default after Irma in places with more insurance fragility relative to places with less insurance fragility. The idea is that households hit by Irma that are exposed to fragile insurers are less likely

[28]Full liquidation of insurance companies is a complex process that can take several years to complete. An insurance company can stop operating or be in stress for many years before the official liquidation during which they may be slower to pay claims or not pay at all.

[29]This measure uses county-level variation because more granular data for whether a particular borrower is covered by a specific insurer is not available. Our specification makes the assumption that the mortgages which defaulted in high fragility areas were the ones that were matched to the fragile insurers. Our specification, in effect, relates the probability of borrowers defaulting on their mortgage on the probability of the mortgage being covered by a fragile insurer. We run it at the loan-level to include loan-level controls.

to have their insurance claims paid; for some of these borrowers, the size of the property damage is high enough to induce mortgage default.

This empirical strategy relies on the following identifying assumptions for the timing and the path of hurricane to be interpreted as a quasi-exogenous shock. We refer to "high fragility" areas as counties with higher exposure to insolvent insurers, and "low fragility" areas as counties with less exposure to insolvent insurers.

Identification Assumption 1: Storm Path is Random. The first key assumption is that the path of the storm is random. In this context, this requires that the counties hit by Hurricane Irma do not have systematically higher hurricane risk exposures than the ones not hit by Hurricane Irma. We provide evidence in support of this assumption by showing that high and low fragility counties are similar in terms of ex-ante climate risk exposures.

Identification Assumption 2: No Negative Borrower Selection. A related assumption is that borrowers in high fragility areas are not systematically different from borrowers in low fragility areas in terms of their ability to smooth the hurricane shocks. We provide evidence in support of this assumption by showing that on the basis of observable characteristics, borrowers in high and low fragility areas are similar.

Identification Assumption 3: Parallel Trends. The identification strategy assumes intuitively that high fragility areas would have evolved similarly to borrowers in low fragility areas in the absence of insurance insolvency. That is, the change in default for borrowers in counties with low exposure to insolvent insurers is a valid counterfactual for those borrowers in counties with high exposure to insolvent insurers. This assumption would be violated if high fragility areas could be expected to trend differently, such as if these areas were negatively selected prior to Irma. We therefore evaluate whether defaults in high fragility and low fragility areas evolve similarly prior to the landfall of Hurricane Irma.

In Section 5.3.3, we provide further evidence that supports the key identifying assumptions outlined above.

5.2. Separating the Direct Effect of the Storm from Insolvency

Without further assumptions, the coefficient β^{DFLT} from the difference-in-differences design represents a treatment effect that bundles both the effect of insurance fragility as well as the independent effect coming from the intensity of the storm. For our result, it is important that we can separate any independent effect of the storm on mortgage default from the effect that arises due to exposure to fragile insurers. We use the following three approaches to help with the interpretation of the effects as the effect of fragility rather than the storm intensity.

Approach 1: Property Damage. First, we observe the total amount of property damage caused by the storm in every county. This allows us to directly control for property damage in our specifications using the interaction of Post $\text{Irma}_t \times \log(\text{damages})_c$.

Approach 2: Jumbo Loans. Second, we compare default outcomes for conforming and jumbo loans by running Equation 4 separately for the two segments, looking within various narrow bands of the CLL. Jumbos provide a good placebo test because they are far less likely to have fragile Demotech insurance but are no less likely to experience property damage in the storm.[30] If the storm has a direct effect on mortgage default through other channels than insurance fragility (e.g., loss of local employment opportunities) then jumbo borrowers in high fragility areas will also experience more defaults. To use jumbo loans as a placebo test, we need to make an additional identifying assumption.

Identification Assumption 4: Homogeneous Treatment Effect of the Storm. The placebo specification assumes that the treatment effect of the storm on defaults is the same for conforming and jumbo loans, within a narrow band of the CLL, after conditioning on granular LTV × FICO × year fixed effects, and DTI × year fixed effects. While one may be concerned that there is selection on unobservables based on the results in the literature about bunching below the CLL (e.g., DeFusco and Paciorek (2018)), in fact other evidence from Hurst et al. (2016) show that the selection disappears within a narrow band of the CLL after controlling for observable borrower characteristics (namely, FICO credit scores and LTV).

We have three predictions for the sign of the difference-in-differences estimator β^{DFLT}. (i) We expect that $\beta^{DFLT}_{Conforming} > 0$ for conforming loans. If Demotech insurers which go insolvent are less likely to pay out claims after storms, then it should be the case that conforming borrowers in places exposed to insolvent insurers will be more likely to default. (ii) We expect that $\beta^{DFLT}_{Jumbo} >= 0$ for jumbo loans. The positive effect on jumbo default mainly stems from the independent effect of the storm as high fragility counties could be the ones also more exposed to the storm. This is because even though jumbo loans are in counties exposed to insolvent insurers, Figure 5 shows jumbo borrowers are far less likely to obtain insurance from Demotech companies. (iii) Crucially, if there is a causal effect of fragile insurers on default, we expect that $\beta^{DFLT}_{Conforming} > \beta^{DFLT}_{Jumbo}$. This is because conforming borrowers in high fragility area may be defaulting both because of exposure to insolvent insurers and the independent effect of the storm, while jumbo default mainly arises from the direct effect of the storm.

Approach 3: DDD Design. We also estimate a triple difference-in-differences (DDD) design which runs the fully interacted specification multiplying Post Irma_t, Insurance Fragility_c,

[30] In the data, there is limited geographic clustering of borrowers by mortgage market segment. One may wonder whether jumbo borrowers may be less likely to live in the high risk areas of a county. While a reasonable assumption, in fact the opposite is true in the data (Sastry, 2022).

and Log Damages_c for conforming loans, along with the main effects. This directly addresses whether insurance insolvency matters even after holding fixed the intensity of the storm. We focus on conforming loans because Figure 5 shows that this segment of the mortgage market is most exposed to fragile insurers. We therefore want to separate the treatment effect for conforming loans into the effect of insurance fragility and the direct effect of the storm.

5.3. Results

Table 6 shows our results from estimating the difference-in-differences design in Equation 4. Consistent with our hypotheses, we find that conforming loans default significantly more after Irma in areas with fragile insurers. The results hold for both mortgages within 10% and within 5% of the CLL. The magnitude of the effects are sizable. Looking at loans within 5% of the CLL, we estimate $\beta^{DFLT} = 0.155$. This implies that going from a county that has no exposure to insolvent insurers to a county where all the borrowers are exposed to insolvent insurers would increase mortgage defaults by 15.5%. The average county has an insolvency share of 4.6%, implying a 71bps increase in default rates relative to the pre-period on average. As the baseline pre-period default rate is 45bps, this means that insurance fragility causes a 150% increase relative to the baseline. For the most part, this effect can be thought of as an implicit transfer, because the GSEs bear a risk which they do not price.[31] We quantify the exact size of the implicit transfer in Section 5.4.

5.3.1. Independent Effect of the Storm

As discussed in Section 5.2, a natural challenge in interpreting the coefficient for conforming loans comes from the independent effect of the storm: places with exposure to more insolvent exposures may also have had worse realizations of the storm, with the storm driving defaults rather than insurance fragility. This is somewhat addressed by the fact that we control for the direct effect of the storm (Approach 1). That said, if all of our results were driven by the direct effect of the storm with the insurer playing no role, we would also expect jumbo loans in such areas to experience heightened default (Approach 2). In contrast, Table 6 shows that there is no statistically significant change in defaults for jumbo borrowers. The coefficient is statistically insignificant and economically small, representing a 1-2bps effect, which we interpret as a zero. This suggests that the independent effect of the storm on defaults is limited.

We also present our results from the DDD design that examines whether insurance fragility matters separately from the storm itself for conforming loans (Approach 3). The

[31] There may also be dead-weight-losses associated with default, so this result also suggests that there are likely welfare effects.

results are presented in Panel (a) of Table C.11. Only the triple interaction term (Post Irma $\times$ log Damages $\times$ Insurance Fragility) is statistically significant. This implies that even holding fixed the direct effect of the storm, mortgage defaults are increasing in insurance fragility. The estimates also show that the direct effect of the storm is small and that the storm causes higher mortgage defaults *only* if the quality of insurance provision is poor.

We therefore conclude that the increase in default for conforming loans in high fragility areas is not driven by the direct effect of the storm, but rather represents the treatment effect of insurer insolvency on mortgage defaults.

5.3.2. Additional Robustness

Another concern could be that some insurer insolvencies are not randomly driven by the storm. While Figure 6 shows the two are strongly correlated, we directly address this concern by considering the following robustness check. We alter our specification in Equation 4 by adding an additional interaction for whether the county was seriously affected by Irma. Doing so allows us to isolate variation in insurer insolvency coming from where the storm hits, rather than assuming all exposure to insolvent insurers is random. In this way, we consider the effect of insurance fragility *only* in places that were randomly affected by removing the borrowers not affected by the storm but exposed to insolvent insurers from the treated group. Panel (b) of Table C.11 confirms that our results on default are robust to this selection concern.

5.3.3. Validating the Identifying Assumptions

We now present a number of results that help to support each of the identifying assumptions outlined in Section 5.1. Under these assumptions, the results in Table 6 can be interpreted as a treatment effect.

Identification Assumption 1: Storm Path is Random. Table C.10 shows that high and low fragility countries have similar ex-ante climate risk exposure, measured as long-run property damage, and as the share of the county mapped into a high risk area by FEMA.[32]

Identification Assumption 2: No Negative Borrower Selection. Table 5 shows borrower characteristics for mortgage applications and originations in 2015, two years before Irma, within narrow bands of the CLL. We find that mortgage applications and originations are similar in both high and low fragility counties across a range of borrower characteristics, including FICO score, LTV ratios, DTI ratios, and interest rates.

Identification Assumption 3: Parallel Trends. The dynamic treatment effects in Figure 7 suggest that there are limited pre-trends in defaults prior to Hurricane Irma for both conforming and jumbo loans. That is, mortgage defaults in high fragility and low fragility areas

[32] Subsequent large hurricanes that hit Florida after Irma had very different footprints.

trended similarly prior to the storm.

Taken together, these results show that our estimates are driven by insurance market fragility rather than any unobserved differences in borrower characteristics or the independent effect of the storm.

5.4. Quantifying the Implicit Transfer

We now provide a back-of-the-envelope estimation of the overall size of the implicit transfer by quantifying the losses to the GSEs from insurance fragility.

GSEs' Expected Losses in Florida. Our first calculation quantifies the fraction of the GSEs' annual expected losses coming from insurance fragility. The GSEs expected losses can be split into two components: (i) the baseline expected losses, and (ii) the losses due to post-hurricane insurance fragility.

$$\mathbb{E}(\text{Losses}) \quad = \quad \underbrace{\delta_B LGD_B}_{\text{Baseline}} \quad + \quad \underbrace{P_H P_{INS}(\delta_{INS}) \times LGD_H}_{\text{Insurance Fragility}}. \tag{5}$$

The baseline expected losses are given by the baseline default rate (δ_B) times the losses given default (LGD_B). The GSEs also face additional expected losses if there is an increase in mortgage defaults after hurricanes due to insurance fragility, as shown above. Equation 5 says that the expected losses from insurance fragility are given by the probability of a hurricane (P_H) times the probability that borrowers are exposed to insolvent insurers conditional on a hurricane (P_{INS}) times the likelihood of default conditional on being exposed to an insolvent insurer (δ_{INS}) times the LGD after a hurricane (LGD_H).

To estimate the GSEs' exposures, we extrapolate from the default and insurance market dynamics observed during Hurricane Irma. We choose the following parameter values; details are discussed in Appendix B.1. δ_B (the pre-hurricane default rate for conforming loans) = 45bps. P_H (the probability of a major hurricane impact in Florida) = 29%. P_{INS} (the ex-ante market share of insolvent insurers in the average county) = 4.6%. The implicit assumption is that the insurer insolvency dynamics is the same for each hurricane of similar severity as observed after Irma. δ_{INS} (the default rate conditional on a loan being exposed to an insolvent insurer) = 15.5% from Table 6. LGD_B = 40% from An and Cordell (2019). LGD_H is also 40% in the absence of reliable estimates of LGDs after a storm.

Overall, we find that about 31% of the GSEs' expected losses are due to insurance fragility. The expected loss estimates derived from serious delinquency rates reported in GSEs' financial statements following Hurricane Irma closely align with our estimates, as detailed in Appendix B.2. We think of this as a lower bound on the GSEs' insurance exposures because we assume $LGD_H = LGD_B$. It is likely that the LGDs are higher after a hurricane because of damage to the property and potential decline in home values. Indeed, just a one standard deviation higher LGD would increase the GSEs expected losses from insurance fragility to 44%. We also expect these losses to worsen as climate and insurance risks rise.

Guarantee Fees. Our estimates suggest that the GSEs' guarantee fees should be 31% higher than they are currently in Florida to match their expected losses from insurance fragility. Currently, the guarantee fee, which is paid by lenders, does not adjust based on insurance fragility risk (see Section 1).[33] An actuarially fair risk compensation would match the GSEs fees with their expected potential losses and other costs.[34] Unpriced risk means that there is an implicit transfer borne by taxpayers more broadly. This also creates an implicit subsidy for origination in high risk areas, which can distort credit supply (which we discuss in Section 6).

GSEs' Overall Capital. In our next calculation, we ask how large are the GSEs' losses relative to their overall capital after a major hurricane. We estimate that an Irma-like hurricane would result in about $1.7 billion of losses to the GSEs, which is 16% of the GSEs total pre-Irma capital. We obtain the loss estimate by multiplying the outstanding loans in Florida by the default rate after Irma, and by the LGD. We then scale by the GSEs total capital.[35] If LGDs are only one standard deviation higher after a hurricane, losses would be $3 billion or 27% of the GSEs' total capital.[36] It is also important to note that in 2017 when Hurricane Irma hit, the U.S. was in a period of growth. While the default estimates we find are already sizable, we caution that the impact on GSE equity could be even larger if a large climate disaster happens to coincide with a negative macroeconomic environment.

[33]While the FHFA had a proposal in 2012 to charge enhanced guarantee fees for certain high risk states like Florida, this proposal was never implemented.

[34]This calculation assumes the GSEs do not price insurance fragility risk on average– if the baseline guarantee fee incorporates fragility risk, then the adjustment need not be the full 31%. We do not think the GSEs do so because the upfront guarantee fee has only risen by 6bps between 2009 and 2018, which is far less than what would be required to reflect the increase in Florida insurer fragility risk over this same period (2.17% = 7% Florida portfolio × 31% Expected Losses). Based on this evidence, we therefore assume that the baseline GSE guarantee fee does not incorporate insurance fragility risk.

[35]The GSEs had $5.3 trillion in loans outstanding and $11 billion in total capital as of Q4-2016. An estimated 7% of its portfolio comes from Florida. This yields $371 billion of loans outstanding in Florida. The total default rate after Irma = 116bps, which includes the baseline default rate (45bps) and the default rate due to insurance fragility (71bps). LGD=40%.

[36]Consistent with this, we find extensive discussion of hurricane related default losses in the GSEs' financial statements in 2017.

6. Insurance Fragility and New Mortgage Underwriting

Having shown that the GSEs face large unpriced insurance fragility risk (Section 5), which the private lenders are aware of (Section 4.2), we next ask whether the mispriced risk affects lenders' screening behavior at origination? If the GSEs misprice risks, then lenders may not internalize the risks associated with originating a conforming mortgage that they intend to sell, which could distort credit supply in the GSE segment relative to the jumbo segment where lenders are forced to retain insurance fragility risk.

6.1. Empirical Strategy

Causally identifying the extent to which lenders' screening behavior at origination is sensitive to insurance fragility risk requires two key elements. First, we require random variation in the availability of high quality insurance that is exogenous to other borrower characteristics that may impact lender screening at origination. In other words, the ideal experiment would evaluate whether a lender would be more likely to deny a loan for the same borrower if she were randomly assigned to a fragile insurer instead of a traditional insurer. Second, we require variation in lenders' ability to securitize that is also exogenous to borrower characteristics. This would mean examining how lender screening of insurance fragility for the same borrower changes when the mortgage exogenously becomes GSE-eligible.

Obtaining plausibly exogenous variation in the availability of high quality insurance is particularly challenging as it is largely unobserved. We do not observe the full set of insurers who would have been willing to sell insurance at any given point in time. Instead we observe an equilibrium outcome of the matching process of households to insurers.

We overcome this challenge by once again exploiting the landfall of Hurricane Irma as a source of exogenous variation in the availability of high quality insurance for *new* mortgage origination. Key to our argument is that policy *cancellations* by traditional insurers can be interpreted as a pull back by traditional (high quality) insurers from new underwriting. In particular, we require traditional insurer policy cancellations that are exogenous to borrower and climate risk. There are three components of our empirical test:

(1) **Quality of new insurance underwriting.** First, the realization of Hurricane Irma and subsequent insurance market stress brings an exogenous change in the willingness of different insurers to underwrite new policies before and after the storm. In high fragility counties with insurer insolvencies driven by Hurricane Irma, traditional insurers have incentives to cancel policies and limit new underwriting due to the ex-post funding structure of FIGA, the state guaranty fund. FIGA is capitalized by the remaining solvent insurers in

Florida. As a result, high quality insurers cover the unpaid claims of insolvent insurers, which directly increases their exposure to high fragility areas. Insurers can offset this increased exposure by cancelling policies or reducing new underwriting in those areas (Abramson et al., 2024). This creates an exogenous change in the availability of traditional insurance that is driven by the storm, rather than endogenous borrower or climate risk characteristics. To test this interpretation, we examine policy cancellations of traditional insurers over time and across high and low fragility counties in Section 6.2.

(2) **Conforming Loan Limit.** The second component of the test also exploits the CLL. We want to understand in particular what happens *in the conforming segment*, separately from what happens in the jumbo segment. Lenders' behavior in the jumbo segment reflects optimal screening, since they are forced to internalize the full risk of making a loan. We can therefore infer whether screening is lax in the conforming segment by comparing lending decisions in that segment to how lenders behave in the jumbo segment. Because we are looking within a narrow band of the CLL, differences between the two can highlight how the exogenous ability to securitize the mortgage changes lender screening behavior rather than differences in borrower characteristics. This test is inspired by the literature (e.g., Hurst et al. (2016), Ouazad and Kahn (2021), Adelino et al. (2023). Specifically, we examine whether lenders' denial rates and pricing are sensitive to insurance fragility in the jumbo segment, and whether this differs in the conforming segment (Sections 6.3.1 and 6.3.2).

(3) New Demotech Underwriting. We also look at new underwriting of traditional insurers and Demotech insurers in each mortgage market segment. Insurance companies should not be influenced by the CLL, and so any specific changes in new insurance underwriting around the CLL are likely to be outcomes driven by lenders' screening behavior rather than by insurers (Section 6.4). We use this evidence to show the connections between lender behavior in mortgage markets to outcomes in insurance markets.

Identifying Assumptions. The identifying assumptions here are similar to those in Section 5. We again require that: (1) the path of the storm is plausibly random, and (2) there is no negative borrower selection in high fragility areas, both of which we validate in Section 5. (3) In addition, we require a parallel trends assumption that lenders' denial behavior in high fragility areas would have evolved similarly to low fragility areas in the absence of Hurricane Irma. There are two components to this assumption, which we validate in Section 5.3.3. First, that borrower default risks in high and low fragility areas evolve similarly (Figure 7). Secondly, that lender screening of default risks are similar in high and low fragility areas (Table 5). (4) Our fourth assumption, which is new relative to Section 5, is that new jumbo *applicants* are not negatively selected relative to conforming applicants after the storm. We show this assumption holds in Section 6.3.1 by evaluating applicant characteristics.

The rest of the section is organized as follows. First, we will show that Hurricane Irma is indeed an exogenous shock to the availability of high quality insurance (Section 6.2). Second, we examine mortgage lenders' reactions through denials and pricing (Section 6.3). Lastly, we examine how lender screening impacts insurance market outcomes by looking at Demotech market shares (Section 6.4).

6.2. Insurance Market Policy Cancellations

We first show that Hurricane Irma brought about an increase in policy cancellations, particularly in the counties exposed to the insolvent insurers. We do so by estimating the following triple difference-in-differences specification:

$$C_{i,c,t} = \beta^{CNCL}(\text{PostIrma}_t \times \text{InsuranceFragility}_c \times \text{Trad}_i) + \delta_{c,t} + \delta_{t,trad} + \delta_{c,trad} + \varepsilon_{i,c,t}. \tag{6}$$

The dependent variable $C_{i,c,t}$ is the cancellation rate of insurer i, defined as the number of policy cancellations in county c and year t divided by the total number of policies for that county in the prior year $t-1$. This tells us the share of in-force policies that the insurer chooses to cancel. $PostIrma$ and $InsuranceFragility$ are defined as in Equation 4. $Trad$ equals one if insurer i is a traditional insurer. We saturate the specification with county-year fixed effects ($\delta_{c,t}$), year-traditional insurer fixed effects ($\delta_{t,trad}$), and county-traditional insurer fixed effects ($\delta_{c,trad}$). We limit the sample to 2015-2018.[37]

The coefficient β^{CNCL} can be interpreted as the additional increase in policy cancellation rates of traditional insurers relative to other insurers in the places where insurers went insolvent after Irma. An increase in policy cancellations by traditional insurers indicates a pull back of high quality insurers from new underwriting.

Table 7 shows the results. In columns (1) and (2) we limit the panel to traditional insurers only. Column (1) shows the estimates from a simple event study design, finding that traditional insurers cancel 2pp more policies after Irma in the average county. Column (2) shows the estimates from a difference-in-differences design. We find that traditional insurers are more likely to cancel policies in high rather than low fragility counties. Lastly, in column (3), we look at the cancellation behavior of all insurers, and show the results from estimating Equation 6. We find that traditional insurers are more likely to cancel policies than Demotech insurers in high fragility areas. These results suggest that Hurricane Irma brings about a deterioration in the quality of insurance provision: higher quality traditional insurers reduce supply by canceling policies, especially in high fragility areas. As a result, it

[37] We cannot look further post-Irma because the reliability of our QUASR data ends in 2018.

may be harder to find a good insurer to back a new mortgage origination.

6.3. New Mortgage Underwriting

6.3.1. Mortgage Denials

We next ask if lenders react to the limited availability of high quality insurance when screening mortgages, and whether this behavior varies by lenders' ability to securitize a mortgage. We look at loan application-level data and mortgage denials, which is a measure of credit supply and consider the following specification:

$$Denied_{a,c,t} = \beta^{DENY}(\text{Post Irma}_t \times \text{Insurance Fragility}_c) + \delta_c + \delta_t + \gamma' X_{a,c,t} + \varepsilon_{a,c,t}. \tag{7}$$

We limit our sample to mortgage applications made between 2015 and 2018, two-years before and after Hurricane Irma, which we source from HMDA. We limit to mortgage applications within 10% and 5% of the CLL. $Denied_{a,c,t}$ is a dummy variable that equals one if the mortgage application a in county c in year t was denied by the lender and zero if not. The independent variables are as defined before. We include county fixed effects to capture the effects of time-invariant county characteristics, and time fixed effects to capture aggregate trends. The controls in X include all loan application-level borrower characteristics that are available in HMDA (log income, DTI ratio, log loan amount), as well as a control for the direct effect of the storm (Post Irma $\times$ log damages). The coefficient of interest is β^{DENY}, which measures how much mortgage denials change after Irma in high fragility counties relative to low fragility counties.

We have two predictions. For conforming loans, we expect $\beta^{DENY}_{Conf} \approx 0$, because lenders have limited incentives to change their screening behavior for mortgages which can be securitized. For jumbo loans, however, we expect $\beta^{DENY}_{Jumbo} > 0$, because lenders either have more incentives to screen for insurance fragility risk after the hurricane or, given the increase in insurance market fragility associated with the landfall of Hurricane Irma, lenders' tendency to screen would result in higher denials than before.

Table 8 shows the results. Consistent with the predictions, we see a limited change in lender screening behavior for *conforming* loans. If anything, mortgage denials exhibit less sensitivity to insurance market fragility after Irma. The result holds for different bands around the CLL, and is robust to controlling for borrower income, DTI ratios, and the direct effect of the storm. Crucially though, for *jumbo* loans, we see that denials go up significantly, i.e. lenders significantly tighten credit after Hurricane Irma, particularly in places more exposed to insurance market fragility. The economic magnitude for the denial rate in the jumbo segment are substantial. Our estimates imply that the average county experiences about 2.6pp ($= 4.6\% \times \beta^{DENY}_{Jumbo}$) greater jumbo denials relative to a county that has a zero insolvency share. Relative to the baseline denial rate, this represents a 16% increase. A triple differences specification reported in Figure C.7 (a) shows that the differences between conforming and jumbo are also statistically significant.

Lastly, we verify that these results are not driven by negative selection of jumbo applicants after Irma (see Identification Assumption 4). We do so by running Equation 7 using log income, log loan amount, and log DTI as outcome variables (see Table C.12). We find that, if anything, on average the credit risk of new jumbo applicants likely improves after Irma in fragile areas, as seen from an increase in income, and decrease in loan size and debt-to-income ratio of new applicants, although the results are not statistically significant.

6.3.2. Mortgage Pricing

We next evaluate new mortgage pricing, i.e. the interest rates charged. We do so because pricing is another margin on which lenders can adjust their exposure to risk. A concern with interpreting the denial results is that lenders could be screening in the jumbo segment by denying credit, as witnessed in the higher denial rates, and in the conforming segment by increasing interest rates. If so, it would still be the case that lenders price insurance fragility risk in both segments of the mortgage market except that they do so on different margins prices vs. quantities.

To address this issue, we modify Equation 7 to look at interest rates for approved loan applications. We consider the following specification:

$$\text{Interest Rates}_{l,c,t} = \beta^r(\text{Post Irma}_t \times \text{Insurance Fragility}_c) + \delta_c + \delta_t + \gamma' X_{l,c,t} + \varepsilon_{l,c,t}. \tag{8}$$

Following Equation 7, we limit our sample to fixed-rate mortgages originated between 2015 and 2018.[38] We limit to mortgages within 10% and 5% of the CLL. Interest Rates$_{l,c,t}$ is the interest rate of loan l originated in county c in year t. We include county and origination year-month fixed effects. The controls include loan's maturity, DTI ratio interacted with year of origination, and a granular LTV $\times$ FICO $\times$ origination year fixed effect. For the FICO and LTV categories, we use the break points from the GSEs' loan-level pricing adjustment matrix.[39] We do so in order to obtain an estimate that reflects the spread lenders charge

[38] Fixed rate mortgages account for over 90% of the loans in our sample, and our results are robust to including the first rates of non-fixed-rate mortgages as well.

[39] Note that while we try to keep the specifications of Equation 7 and Equation 8 as close as possible, the data on applications come from HMDA, and the data on interest rates come from BlackKnight McDash. As a result, the control variables available are slightly different.

above what the GSEs' require for a loan, following Bartlett et al. (2022). The coefficient of interest β^r provides a measure of the change in interest rates for newly-originated loans after Irma across counties as they vary in their exposure to insurance fragility. As before, we run this test separately for conforming and jumbo loans.

Given our results on loan applications, we have two predictions. For conforming loans, we expect $\beta^r \approx 0$, because lenders have limited incentives to ration credit through prices for mortgages which can be securitized. For jumbo loans, however, we expect $\beta^r > 0$, because lenders have more incentives to price insurance fragility risk after the Irma-related increase in insurance market fragility.

Table 9 shows the results. Consistent with the predictions, we see no statistically significant change in interest rates for mortgages which can be sold to the GSEs. The result holds for mortgages for both bandwidths around the CLL, and is robust to controlling for borrower characteristics. However, in the jumbo segment we see a modest, but significant increase in the interest rates lenders charge after Hurricane Irma in areas exposed to fragile insurance markets. For the average county, among jumbo loans within 5% of CLL, the interest rates increased by 11bps, which is roughly 3% of the baseline interest rates. These results imply that lenders ration credit by denying loans backed by low quality insurers and by charging higher prices for loans they must retain. Meanwhile, for GSE-eligible loans, lenders' screening behavior remains insensitive to insurance fragility risk, neither through prices nor through screening out loans. A triple differences specification reported in Figure C.7 (b) shows that the differences between conforming and jumbo are also statistically significant.

While we find statistically significant evidence that interest rates adjust, it is interesting that price adjustments alone may not be sufficient. Denying a mortgage outright may seem like a blunt way to manage risks at a first glance. However, it may not be straightforward to determine how to adjust prices if lenders are concerned about the future availability of high quality insurance. Even if a household is able to obtain quality insurance at origination, insurance is an annual policy while mortgages are long-term. Insurance contracts may be canceled, leaving lenders less secure over the longer life of the loan. Our results suggest that lenders may rely more on screening out loans when insurance fragility increases.

6.4. Evolution of Insurance Market Shares

We now examine how lender screening impacts insurance market outcomes by looking at Demotech market shares separately for jumbo and conforming segments. We run a similar continuous treatment difference-in-differences specification to examine what happens to new insurance underwriting in high fragility areas. This estimation takes place at the county-year level using our panel dataset from QUASR. The specification is:

$$(9) \qquad DemotechShare_{c,t} = \beta^{DT}(\text{Post Irma}_t \times \text{Insurance Fragility}_c) + \delta_c + \delta_t + \varepsilon_{c,t}.$$

We consider two outcome measures of Demotech market shares. (i) The share of *new* insurance policies that are underwritten by Demotech insurers. Since we are interested in the dynamics of *new credit* origination, it therefore also makes sense to consider which companies underwrite insurance policies for these new borrowers. (ii) Our second outcome variable is the share of overall policies underwritten by Demotech insurers; this is closer to understanding the quality of the overall stock of insurance. The independent variables are same as before. We limit to policies underwritten between 2015-2018.

We run the regression separately for conforming and jumbo loans. Separating insurance markets into conforming and jumbo borrowers is more complex than it is for mortgages, as we lack individual-level data. This prevents us from directly filtering insurance data to only include households that qualify as conforming borrowers based on their loan amounts. As in Section 4.1, we proxy using coverage-per-policy, looking within a 10% band of the CLL. We do not go below that threshold because the scope for mis-classification is higher as one gets closer to the CLL band.

Table 10 shows the results from running this specification. In columns (1) and (2) we find that the share of new policies underwritten by Demotech insurers significantly expands for the conforming segment, and significantly declines for the jumbo segment. In columns (3) and (4) we see that the overall market share of Demotech insurers also expands in the conforming segment and declines in the jumbo segment.

6.5. Interpreting the Results on Mortgages and Insurance

It may be surprising that the Demotech share decreases in the jumbo segment when we report earlier that traditional insurers are canceling policies. We argue that lenders are the key to explaining these seemingly disparate patterns. The results on denials and insurance market shares together suggest that lenders either limit the insurance choices of borrowers to traditional insurers, or they deny jumbo loans that have a high probability of being insured by Demotech insurers. Either of these would manifest as Demotech share of new policies going down in the jumbo segment in equilibrium. In other words, lenders respond to the growing fragility by denying jumbo mortgages backed by Demotech insurers, and as a result, the loans which end up being approved have a higher probability of being backed by traditional insurers. These patterns imply that lender actions have a direct effect on the insurance market outcomes.

In the conforming segment, we see that Demotech shares increase significantly. We argue that this is because there is limited lender screening–neither mortgage denials nor interest rates are sensitive to insurer fragility risks. The outcomes in jumbos show what would have happened in the conforming segment if lenders proactively screened for risks, which would have been the case if the GSEs priced these risks. We take this evidence to suggest that there is excess credit in the conforming segment (relative to jumbos), and that the limited incentives of lenders to screen in this segment has enabled the growth of Demotech insurers in Florida. In a counterfactual, where lenders were forced to internalize risks in the conforming segment, it is likely that credit supply in high risk areas would be much lower and that Demotech shares would also be lower. We quantify this excess origination in the next section (Section 6.6).

There are two alternative explanations that are worth discussing. (1) One interpretation could be that high quality insurance companies choose better quality borrowers. We argue that this explanation is not likely to be the driving force in our context, since borrower quality is unlikely to change around the CLL, looking within narrow bands. The fact that lenders deny more mortgages and charge higher interest rates for originated mortgages also provides evidence against the idea that average jumbo borrower quality has increased. (2) Another interpretation is that households value high quality insurance more, but again it is not clear why household valuations of insurance quality would change around the conforming loan limit threshold. We therefore argue that the results are most likely driven by lenders distorted screening incentives when originating new mortgages that can be sold to the GSEs, leading to excess conforming mortgage originations.

6.6. Quantifying Excess Credit

We now provide a back-of-the-envelope estimation of the excess mortgage origination in the GSE segment due to mispricing of insurance fragility risk. The idea behind this exercise is to obtain a counterfactual estimate of how many fewer conforming loans would have been originated if lenders' screening behavior in the conforming segment were the same as in the jumbo segment where lenders internalize Demotech insurer risks.

Our back-of-the-envelope relies on the following formulation:[40]

$$\begin{aligned}\text{Excess Conforming Loans} = &\ Pr(\text{Denial}_{Jumbo} - \text{Denial}_{Conforming}|Demotech) \\ &\times Pr(Demotech) \\ &\times \text{Total Conforming Applications.}\end{aligned}$$

The first term denotes the excess denial rate in the jumbo segment (i.e. denial rate in the jumbo segment relative to the conforming segment) if the borrower can only obtain a policy with a Demotech insurer. The second term is the probability the borrower has a Demotech insurer. Multiplying the first two terms obtains the additional denial rate in the conforming segment had lenders screening of insurer risk been the same as in the jumbo segment. We then scale this by the total number of conforming applications to obtain the number of conforming mortgages which would have been denied by jumbo lenders.

We obtain the first term by taking the ratio of our two estimated treatment effects: $\frac{\beta^{DENY}_{Jumbo} - \beta^{DENY}_{Conforming}}{\beta^{DT}_{Conforming}}$ from Equations 7 and 9. β^{Deny}_{Jumbo} in the numerator is the change in denial rates for jumbo mortgages as insurer insolvency shares change. The difference in the coefficient estimates ($\beta^{DENY}_{Jumbo} - \beta^{DENY}_{Conforming}$) reflects the excess denial rate, defined as the difference in lender denial behavior for jumbos relative to conforming. We use the excess denial rate estimated in the triple difference-in-differences specification reported in Figure C.7.

The denominator is $\beta^{DT}_{Conforming}$, the change in Demotech share as insurer insolvency shares change. We look at the conforming segment because it reflects how Demotech market shares would have evolved in the absence of lender intervention. This parameter estimate comes from Table 10. The ratio $\frac{\beta^{DENY}_{Jumbo} - \beta^{DENY}_{Conforming}}{\beta^{DT}_{Conforming}}$ then reflects the effect of changes in Demotech market shares on excess jumbo denial rates. This can be interpreted as the excess jumbo denial rate when the borrower can *only* obtain a policy from a Demotech insurer.

We proxy for the second term, which is the probability of a new borrower facing a Demotech insurer, using the average market share of Demotech insurers from the QUASR data over the full sample. We obtain the third term, which is the total number of conforming mortgage applications, directly from HMDA.

With this approach, we find about 450,000 excess conforming loans, translating to ∼\$95 billion in excess origination, during our sample-period 2009-2018. This represents 21% of the originated mortgages in Florida during this period. This means that lenders would have denied nearly one out of every five conforming mortgages had they internalized insurer

[40] Our quantification requires two assumptions. First, that our local treatment effects apply over the full distribution of Demotech shares. Second, that lender screening for Demotech risk in jumbos is the same both before and after Hurricane Irma.

fragility risks in the conforming segment.

7. Policy Implications and Conclusion

7.1. Policy Implications

A natural question is whether our findings are part of a broader dynamic concerning the GSEs. It is well-known that the GSEs historically shied away from risk-based pricing, choosing rather to adopt a uniform pricing rule. Prior to the 2008 crisis, the GSEs did not even price for FICO credit scores and LTVs, two factors which even at that time were known to be strongly related to default behavior (FHFA, 2009). Similarly, Hurst et al. (2016) show that the GSEs do not price for spatial risks, leading to inter-regional redistribution. Part of this comes from a belief about the benefits of risk sharing and diversification that can be achieved through the GSEs across loans nationally (Elenev et al., 2016). To the extent that risks are idiosyncratic, the GSEs as an arm of the government, can choose to promote risk sharing, providing insurance against region-specific shocks (Asdrubali et al., 1996). As long as they price correctly *on average*, uniform pricing can also compensate them for the risks they bear overall.

This belief in the benefits of risk sharing can help contextualize why the GSEs chose to accept Demotech ratings in the 1990s. While it is difficult to pinpoint the exact rationale for this choice in the historical record, anecdotal evidence suggests that the GSEs were heavily influenced by the wave of insurer insolvencies and exodus of traditional insurers following Hurricane Andrew in 1992.[41] This decision may have helped to support Florida's housing market at a time when high quality insurance may have been unavailable, and have knock-on effects for real-estate values and mortgage defaults. This fits in line with the risk-sharing rationale to the extent that such a shock was thought to be idiosyncratic and temporary, thereby effectively diversifiable though the GSEs.[42]

However, the benefits of risk-sharing become muted when risks are not idiosyncratic and persistently high in some areas. In this context, uniform pricing then becomes a subsidy from low-risk to high-risk areas. As we show, this subsidy can have real effects in distorting credit supply–leading to too many mortgages in high risk areas. This, in turn, *increases* the total amount of climate risk in the economy, to the extent that subsidized mortgage pricing encourages spatial reallocation towards high risk areas.

[41] We have struggled to find any documentation showing the exact methodology that was followed to accept Demotech ratings or determine the precise rating threshold to accept.

[42] At this time, the insurer-of-last-resort (residual) market was not state-run and state-backed, as Citizens currently is.

Insurer risk in loan-level price adjustments. A natural policy to address this distortion would be for the GSEs to charge an extra fee to securitize mortgages backed by insurers at high risk of going insolvent. Practically speaking, this could be done by making insurance counterparty an additional factor in the GSEs loan level price adjustment (LLPA) matrix.[43] Having an LLPA for insurer risk will compensate the GSEs for the higher expected default risk and losses given default because of exposure to low quality insurers. It will also provide households and lenders the right signals of insurance market risks, which would help address the distortions in lending markets. This could happen in two dimensions. First, households would be better able to distinguish between high and low quality insurers. Second, lenders may internalize the additional costs of having a low quality insurer when selling loans to the GSEs. Our calculations suggest that the guarantee fees would need to rise by 31% in Florida to match the increase in expected losses due to insurance fragility.

State Insurance Regulation: Another approach would be to strengthen insurer safety and soundness regulation to improve insurer resiliency, such as by promoting higher capital requirements. However, in practice, this may be challenging because of the state-based nature of insurance regulation. First, the state regulator may have different incentives than the GSEs. It is likely that the state regulator is trading off the costs of insolvency borne by local citizens against the benefits of lower cost insurance for Floridians and a growing housing market. They may be willing to accept some amount of insurer insolvency, depending on how they balance these trade-offs. We show a number of facts that are consistent with these political economy incentives. First, insurance regulation has grown lax over time (Section A.1). Second, insurers at high risk of insolvency face similar scrutiny as those that are more financially stable (Section A.1). Third, the insurers approved by the regulator to take out policies from Citizens through the Depopulation are lower quality than the average Demotech insurer. Fourth, even though a large number of Demotech insurers became insolvent, they continued to satisfy the regulatory risk-based capital (RBC) requirements. This suggests that the regulatory capital charges associated with insurers' climate risk exposures may be too low, particularly for small and single-state insurers that tend to be less diversified. Taken together, these facts suggest that state insurance regulators' incentives may be different from the GSEs, the GSEs cannot solely rely on insurance regulation being an effective tool for preventing insurance insolvency.

[43] Following the 2008 crisis, the GSEs added LLPAs for borrowers' FICO credit score and LTV ratio to account for the higher expected default risks and create the right incentives in the lending market.

7.2. Conclusion

This paper explores the consequences of mispricing in two key financial contracts, mortgages and property insurance, that influence location choices of households. We show that the GSE's property insurer requirements are mispriced and trace the implications of this mispricing for credit supply and taxpayer exposures. Specifically, the GSEs accept many high risk insurers who meet eligibility through their Demotech ratings but would not with counterfactual ratings from the traditional rating agencies (e.g., AM Best). This policy choice is a key factor behind the growth of financially fragile insurers that are at a high risk of insolvency. Fragile insurers predominantly serve the GSE segment of the market and cause higher mortgage defaults after natural disasters, creating large taxpayer losses through the GSEs. Lenders strategically respond to GSE mispricing by offloading insurance counterparty risk and by limiting screening for conforming mortgages that can be sold to the GSEs. However, in jumbo mortgages that are retained, private lenders deny mortgages and adjust pricing to account for the insurer fragility risk. If lenders were forced to internalize insurance fragility risk at origination, 1 in 5 GSE-eligible conforming mortgages would not have been originated by private lenders.

While our paper studies one form of fragility coming from the growth of Demotech insurers, the unraveling in the quality of insurance provision has only grown worse since the end of our sample period, and is increasingly taking new forms. More recently, traditional multistate insurers are using new corporate subsidiaries that are less capitalized than the parent company to ring-fence losses in Florida (locally called "pups"). We have also seen the growth of non-admitted surplus insurance lines, which are lightly regulated, under-capitalized, and not protected by state guaranty funds. In addition, while a decade ago the financial stability concerns related to insurers-of-last resort were limited, the growth in climate-related damages has led to new scrutiny of the fiscal exposures from state-run insurers-of-last-resort (like Citizens). It is likely that these trends will pose similar but additional risks to mortgage markets, which future work will help bring to light.

References

Abramson, B., P. Sastry, I. Sen, and A.-M. Tenekedjieva (2024). Climate risk and the economics of insurance state guaranty funds.

Adelino, M., K. Gerardi, and B. Hartman-Glaser (2019, April). Are lemons sold first? dynamic signaling in the mortgage market. *Journal of Financial Economics 132*, 1–25.

Adelino, M., K. Gerardi, and P. S. Willen (2013). Why Don't Lenders Renegotiate More Home Mortgages? Redefaults, Self-Cures and Securitization. *Journal of Monetary Economics 60*(7), 835–853.

Adelino, M., A. Schoar, and F. Severino (2016, July). Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class. *Review of Financial Studies 29*(7), 1635–1670.

Adelino, M., A. Schoar, and F. Severino (2023). Credit supply and house prices: Evidence from mortgage market segmentation. *Journal of Financial Economics*.

An, X. and L. Cordell (2019). Mortgage loss severities: What keeps them so high? *Federal Reserve Bank of Philadelphia Working Paper*.

An, X., S. Gabriel, and N. Tzur-Ilan (2023). The effects of extreme wildfire and smoke events on household financial outcomes.

Asdrubali, P., B. E. Sørensen, and O. Yosha (1996, November). Channels of interstate risk sharing: United states 1963–1990*. *The Quarterly Journal of Economics 111*(4), 1081–1110.

Barbu, A. (2021). Ex-post loss sharing in consumer financial markets.

Bartlett, R., A. Morse, R. Stanton, and N. Wallace (2022, January). Consumer-lending discrimination in the fintech era. *Journal of Financial Economics 143*(1), 30–56.

Bhutta, N. and B. Keys (2022). Moral hazard during the housing boom: Evidence from private mortgage insurance. *Review of Financial Studies*.

Billings, S. B., E. Gallagher, and L. Ricketts (2019, June). Let the Rich Be Flooded: The Unequal Impact of Hurricane Harvey on Household Debt. *SSRN Working Paper No. 3396611*.

Biswas, S., M. Hossain, and D. Zink (2023). California wildfires, property damage, and mortgage repayments. *Federal Reserve Bank of Philadelphia Working Paper No. 23-05*.

Blonz, J. A., M. Hossain, and J. Weill (2024). Pricing protection: Credit scores, disaster risk, and home insurance affordability. *SSRN Working Paper No. 5026600*.

Boomhower, J., M. Fowlie, and A. J. Plantinga (2023, May). Wildfire insurance, information, and self-protection. *AEA Papers and Proceedings 113*, 310–15.

Citizens (2024). Citizens property insurance corporation, exposure reduction committee.

DeFusco, A. A. and A. Paciorek (2018). The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit. *American Economic Journal: Economic Policy 9*(1).

Demyanyk, Y. and O. Van Hemert (2011). Understanding the Subprime Mortgage Crisis. *The Review of Financial Studies 24*(6), 1848–1880.

Downing, C., D. Jaffee, and N. Wallace (2009). Is the Market for Mortgage-Backed Securities a Market for Lemons? *The Review of Financial Studies 22*(7), 2457–2494.

Egan, M., S. Ge, and J. Tang (2021). Conflicting interests and the effect of fiduciary duty: Evidence from variable annuities.

Ehrlich, I. and G. S. Becker (1972). Market insurance, self-insurance, and self-protection. *Journal of Political Economy 80*(4), 623–648.

Elenev, V., T. Landvoigt, and S. Van Nieuwerburgh (2016). Phasing out the gses. *Journal of Monetary Economics 81*, 111–132.

Ellul, A., C. Jotikasthira, L. Christian, and W. Yuhui (2015). Is historical cost a panacea? market stress, incentive distortions and gains trading. *The Journal of Finance 70*, 2489–2537.

Ellul, A., C. Jotikasthira, C. Lundbald, and W. Wagner (2022). Insurers as asset managers and systemic risk. *Review of Financial Studies [Forthcoming]*.

FHFA (2009). Fannie mae and freddie mac single-family guarantee fees in 2007 and 2008. *FHFA report to Congress*.

FHFA (2019). Fannie mae and freddie mac single-family guarantee fees in 2019. *FHFA*.

Fonseca, J. and L. Liu (2024). Mortgage lock-in, mobility, and labor reallocation. *The Journal of Finance 79*(6), 3729–3772.

Foster, C. and R. Van Order (1984). An Option-Based Model of Mortgage Default. *Housing Finance Review 3*(4), 351–372.

Froot, K. A. and P. G. O'Connell (1999). The pricing of U.S. catastrophe reinsurance. In K. A. Froot (Ed.), *The Financing of Catastrophe Risk*, Chapter 5, pp. 195–232. University of Chicago Press.

Gallagher, J. and D. Hartley (2017, August). Household Finance after a Natural Disaster: The Case of Hurricane Katrina. *American Economic Journal: Economic Policy 9*(3), 199–228.

Ganong, P. and P. Noel (2020, October). Liquidity versus Wealth in Household Debt Obligations: Evidence from Housing Policy in the Great Recession. *American Economic Review 110*(10), 3100–3138.

Ganong, P. and P. Noel (2023). Why do borrowers default on mortgages? *The Quarterly Journal of Economics 138*(2), 1001–1065.

Ge, S. (2022). How do financial constraints affect product pricing? Evidence from weather and life insurance premiums. *The Journal of Finance 77*(1), 449–503.

Ge, S., A. Lam, and R. Lewis (2023). The costs of hedging disaster risk and home prices in the face of climate change.

Gennaioli, N., R. L. Porta, F. Lopez-De-Silanes, and A. Shleifer (2022). Trust and insurance contracts. *The Review of Financial Studies*.

Goodman, L., E. Seidman, J. Parrott, and J. Zhu (2014). Gurantee fees – an art, not a science. *Urban Institute Housing Finance Policy Center Commentary*.

Hartwig, R. P. and C. Wilkinson (2016). Residual market property plans – from markets of last resort to markets of first choice. Technical report, III.

Hurst, E., B. J. Keys, A. Seru, and J. Vavra (2016). Regional redistribution through the US mortgage market. *American Economic Review 106*(10), 2982–3028.

IPCC (2023). *Climate Change 2023: Synthesis Report. Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC))*. IPCC, Geneva, Switzerland.

Issler, P., R. H. Stanton, C. Vergara-Alert, and N. E. Wallace (2019). Mortgage Markets with Climate-Change Risk: Evidence from Wildfires in California. *SSRN Working Paper No. 3511843*.

Jaffee, D. M. and T. Russell (1997). Catastrophe insurance, capital markets, and uninsurable risks. *The Journal of Risk and Insurance 64*(2), 205–230.

Jeziorski, W., S. Ramnath, et al. (2021). Homeowners insurance and climate change. *Chicago Fed Letter* (460), 1–6.

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig (2010). Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. *The Quarterly Journal of Economics 125*(1), 307–362.

Keys, B. J., A. Seru, and V. Vig (2012, July). Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets. *The Review of Financial Studies 25*(7), 2071–2108.

Koijen, R. and M. Yogo (2022). The fragility of market risk insurance. *The Journal of Finance 77(2)*, 815–862.

Koijen, R. S. and M. Yogo (2015). The cost of financial frictions for life insurers. *American Economic Review 105*(1), 445–475.

Koijen, R. S. and M. Yogo (2016). Shadow Insurance. *Econometrica 84*(3), 1265–1287.

Kousky, C., M. Palim, and Y. Pan (2020). Flood Damage and Mortgage Credit Risk: A Case Study of Hurricane Harvey. *Journal of Housing Research 29*(sup1), S86–S120.

Lacour-Little, M., A. Pavlov, and S. Wachter (2023). Adverse selection and climate risk: A response to ouazad and khan (2021). *Review of Financial Studies.*

Nicholson, J., P. Born, C. Cole, and C. Nyce (2020). Exposure reduction and depopulation opportunities analysis. *Report ordered by Citizens Property Florida Corporation.*

Oh, S. S. (2020). Social inflation.

Oh, S. S., I. Sen, and A.-M. Tenekedjieva (2023). Pricing of climate risk insurance: Regulation and cross-subsidies.

Ouazad, A. and M. Kahn (2021). Mortgage Finance and Climate Change: Securitization Dynamics in the Aftermath of Natural Disasters. *Review of Financial Studies, forthcoming.*

Quigley, J. M. (1987). Interest rate variations, mortgage prepayments and household mobility. *The Review of Economics and Statistics 69*(4), 636–643.

Rothschild, M. and J. E. Stiglitz (1976). Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. *Quarterly Journal of Economics 90 (4): 630–49.*

Santos, J. and K. Blickle (2022, April). Unintended consequences of “mandatory” flood insurance. *FRBNY Staff Report No. 1012*.

Sastry, P. (2022, December). Who bears flood risk? evidence from mortgage markets in florida. *SSRN Working Paper No. 4306291*.

Sastry, P., I. Sen, A.-M. Tenekedjieva, and T. C. Scharlemann (2024). Climate risk and the us insurance gap: Measurement, drivers, and implications. *SSRN Working Paper No. 4909444*.

Scheutz, J. (2024). How will us households adjust their housing behaviors in response to climate change? *Real Estate Economics*.

Sen, I. (2021). Regulatory limits to risk management. *The Review of Financial Studies [Forthcoming]*.

Sen, I. and D. Humphry (2018). Capital regulation and product market outcomes. *Bank of England WP 715*.

Sen, I. and V. Sharma (2020). Internal Models, Make Believe Prices, and Bond Market Cornering. *Harvard Business School Working Paper*.

Tang, J. (2023). Regulatory competition in the us life insurance industry.

Tenekedjieva, A.-M. (2021). The revolving door and insurance solvency regulation.

Wagner, K. (2022). Adaptation and Adverse Selection in Markets for Natural Disaster Insurance. *American Economic Journal: Economic Policy 14*(3), 380–421.

Yaari, M. E. (1965). Uncertain lifetime, life insurance, and the theory of the consumer. *Review of Economic Studies 32 (2): 137–50.*

Tables and Figures

Figures

Figure 1: Evolution of Property Insurance Market in Florida

The figure shows the evolution of property insurance premiums over time for the different private insurer types (Demotech and Traditional), and for Citizens. Demotech insurers are defined as insurers that have been rated by Demotech at least once during the sample period. Traditional insurers are defined as those rated by traditional rating agencies (AM Best and S&P). Total premiums data are from insurers' state-level statutory filings.

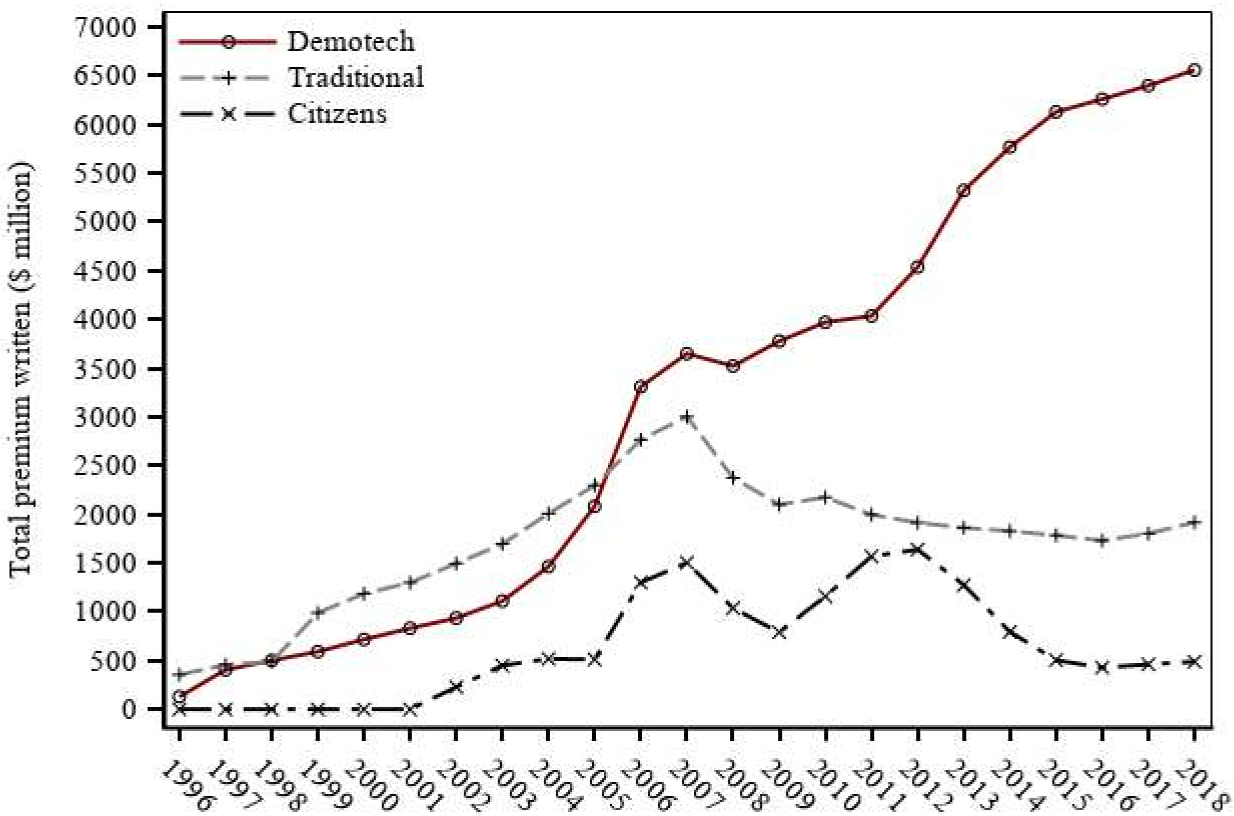
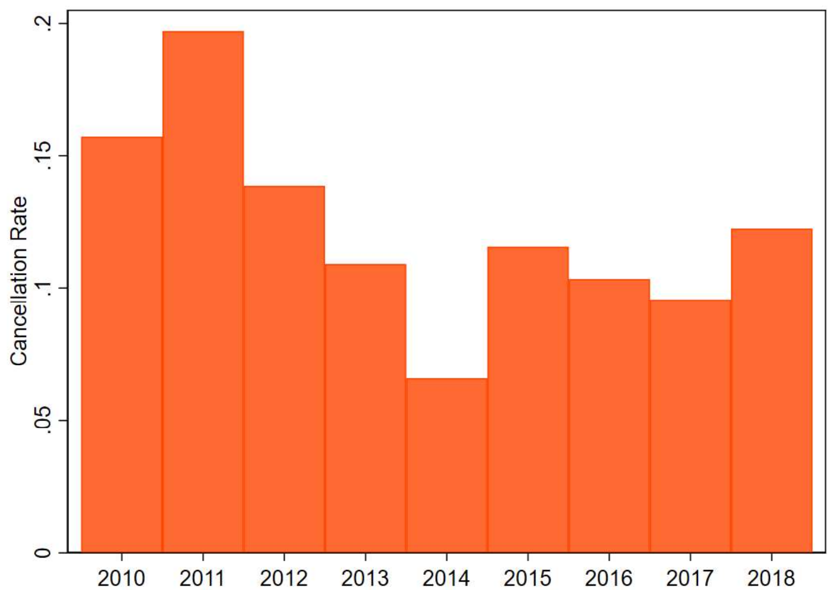


Figure 2: Cancellations and Non-renewals of Insurance Policies by Traditional Insurers

Panel (a) shows the percent of in-force policies that are canceled or not renewed each year for policies underwritten by traditional insurers, defined as those rated by traditional rating agencies (AM Best or S&P). Panel (b) decomposes the flows of policies into new policies, canceled or non-renewed policies, policies transferred from traditional to other insurers, and policies transferred from other insurers to traditional insurers.

(a) Cancellation Rate



(b) Overall Policy Flows

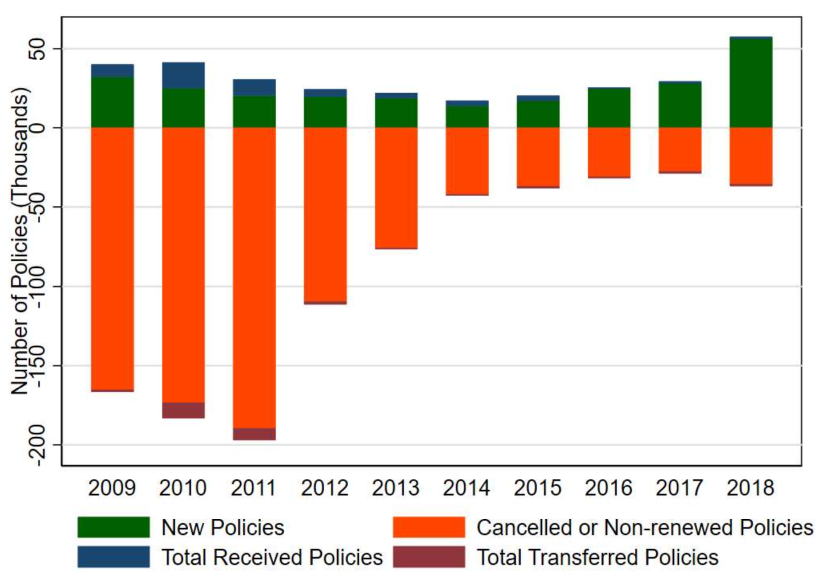
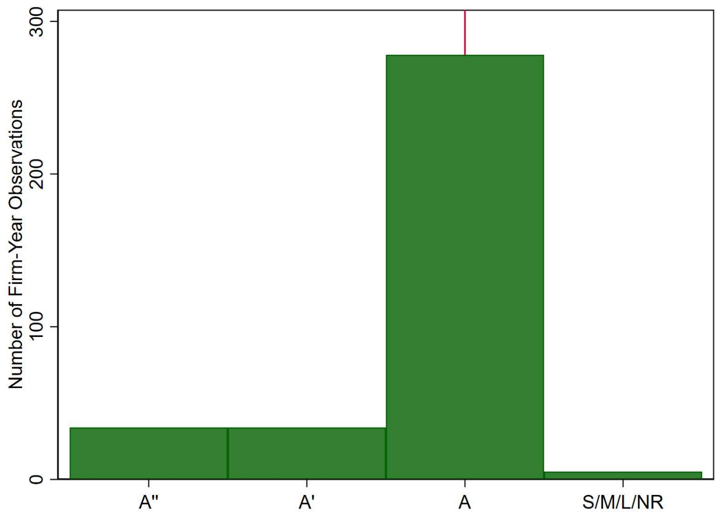


Figure 3: Distribution of Demotech and AM Best Financial Strength Ratings

This figure shows histograms of financial strength ratings assigned by Demotech in panel (a) and AM Best in panel (b). The vertical red line in both charts represents the minimum rating required to be eligible for purchase or securitization by Freddie Mac.

(a) Demotech



(b) AM Best

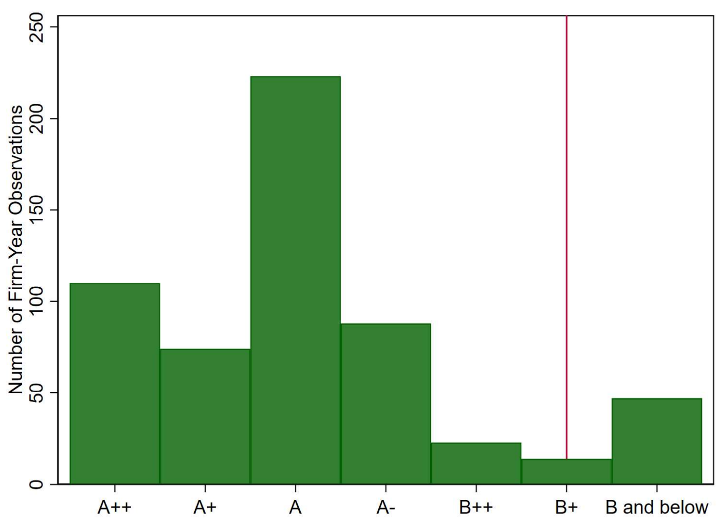


Figure 4: Counterfactual AM Best Ratings of Demotech Insurers

The figure shows the counterfactual AM Best financial strength ratings of Demotech insurers. Each dot shows the average predicted value across all model simulations and the bar shows the 90% confidence interval constructed using bootstrapping. The AM Best replicating models are shown in Appendix Table C.5. The red line shows the GSE eligibility thresholds for Freddie Mac and the blue line shows the GSE eligibility thresholds for Fannie Mae.

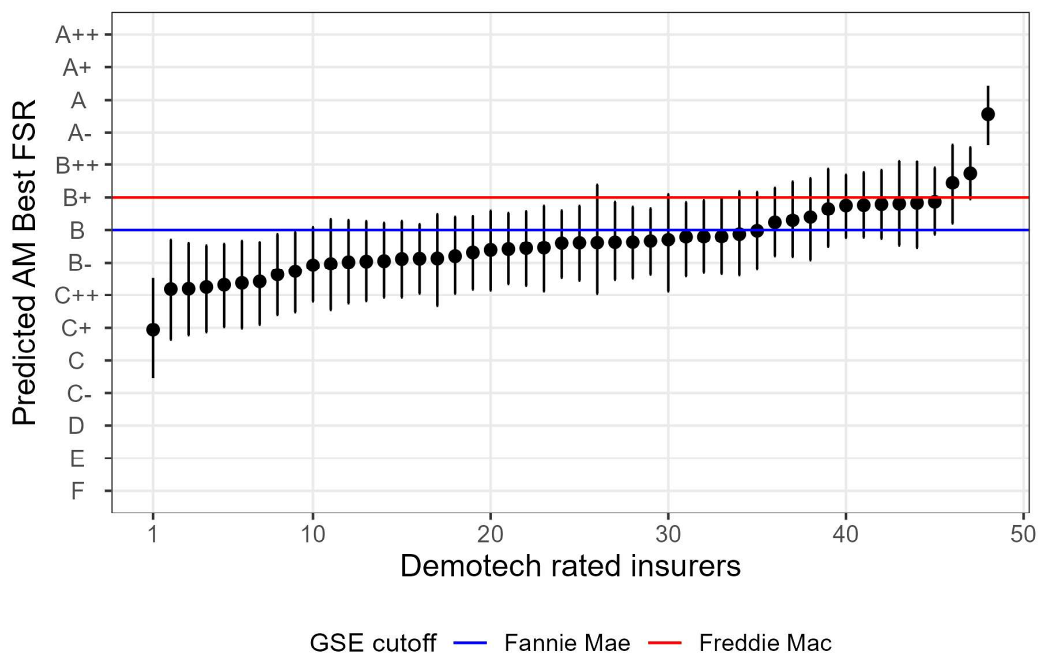


Figure 5: Demotech Market Shares By Loan Type

The figure shows the market share of Demotech insurers by total coverage amounts for each mortgage market segment (conforming and jumbo) for the year 2009, i.e. beginning of our sample. To compute market shares, we exploit a proxy based on coverage-per-policy measures from the QUASR data. We first compute an insurers' average coverage-per-policy in a county. If this value lies below (above) the CLL, we attribute all its policies to the conforming (jumbo) segment. We can then estimate the market share of Demotech insurers for each segment by looking at how many policies or coverage was sold by Demotech insurers in that segment.

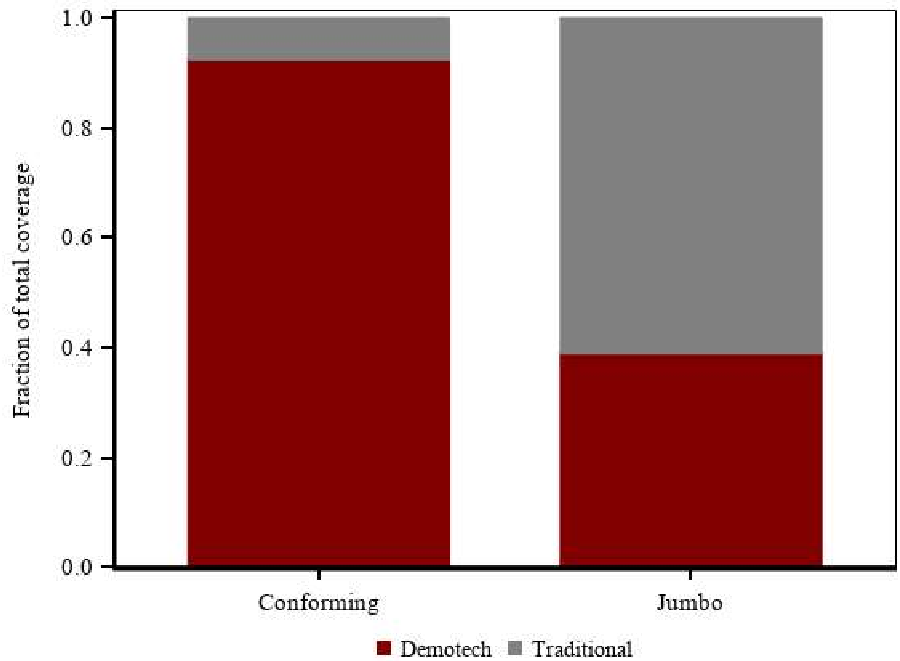
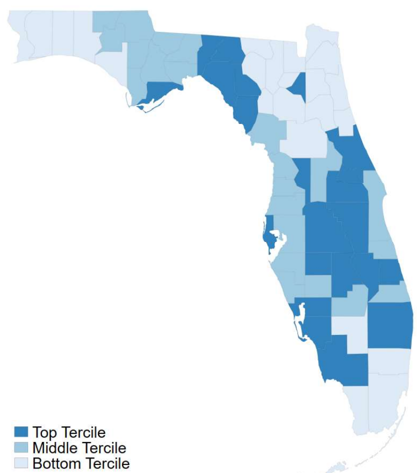


Figure 6: Geographic Distribution of Property Damage and Fragile Insurer Footprint

The figure shows two maps of Florida that depict the geographic distribution of property damage per capita caused by Hurricane Irma (Panel (a)), and the pre-Irma market share of fragile insurers (Panel (b)). To construct the figure, we split Florida counties into three groups based on these two variables. Property damage per capita in Panel (a) is obtained from SHELDUS for the first three months after the landfall of Hurricane IRMA. Market shares in Panel (b) are obtained by looking at the 2016 (pre-Irma) county-level market shares by insurers which went insolvent following Hurricane Irma.

(a) Hurricane Irma Property Damage Per Capita



(b) Pre-Irma Market Share of Fragile Insurers

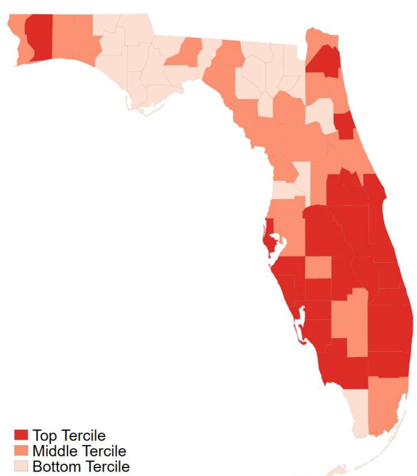
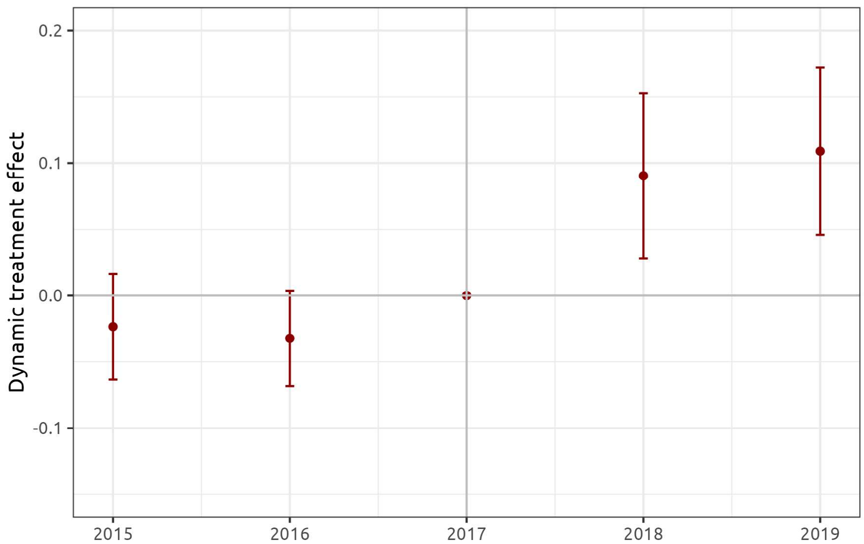


Figure 7: Evidence from Dynamic Continuous Treatment Difference-in-Differences Design

This figure shows the results from estimating a dynamic version of the continuous treatment difference-in-differences design in Equation 4. All the fixed effects and controls are as described in the text. The sample considers mortgages originated five-years prior to the storm, between August 2012 - August 2017. We then track their performances annually from September 2015 - September 2019. Default is defined as a nonpayment event consisting of default, foreclosure, or REO. We limit mortgages to those within 10% bands of the CLL.

(a) Conforming loans



(b) Jumbo loans

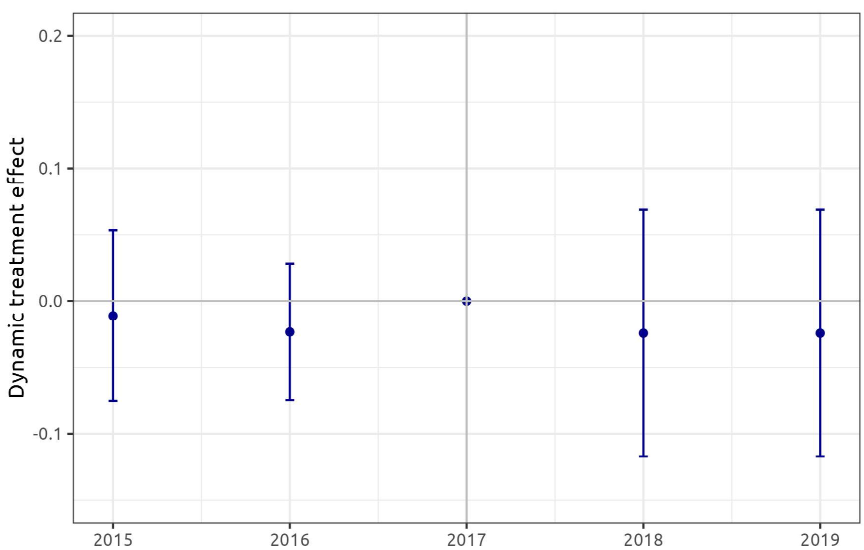


Table 1: Minimum Insurance Financial Strength Rating Requirements for Mortgages

The table reports the minimum financial strength rating required of property insurance companies for the mortgage to be eligible for purchase or securitization by Fannie Mae or Freddie Mac, as well as the year in which the rating agency was recognized as a nationally recognized statistical rating organization (NRSRO) by the Securities and Exchange Commission.

Type	Rating Agency	Began	NRSRO	Fannie Mae	Freddie Mac
Traditional	AM Best	1899	2007	“B” or better	“B+” or better
Traditional	S&P Global	1971	2007	“BBB” or better	“BBB” or better
Emerging	Demotech	1990s	2022	“A” or better	“A” or better

Table 2: Financial and Operational Risks by Insurer Types

The table reports the key characteristics for the different insurer types: Demotech (1) and Traditional (2). Demotech are insurers that have been rated by Demotech at least once during the sample period. Traditional are insurers rated by traditional rating agencies (AM Best and S&P). Definitions of financial and operation risk variables are in Appendix D. We report averages for each insurer type after computing average values for each insurer during our sample period from 2009 to 2018. The last column tests for statistical difference between columns (1) and (2). Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Demotech (1)	Traditional (2)	Difference (1) - (2)
Number of insurers	80	50	
(a) Size and solvency			
Assets ($ million)	312.384	3914.64	-3602.256***
	(150.426)	(1019.99)	
Leverage ratio	0.547	0.516	0.031
	(0.021)	(0.026)	
RBC ratio	2172.77	3789.78	-1617.01*
	(517.105)	(876.289)	
(b) Liabilities			
Loss ratio (Florida)	0.828	0.761	0.067
	(0.1)	(0.121)	
Loss ratio (US)	0.748	0.671	0.077
	(0.086)	(0.057)	
Coverage per policy (in '000)	463.79	1072	-608.21***
	(42.144)	(197.597)	
(c) Operational diversification			
No. states selling HO	3.453	27.68	-24.227***
	(0.731)	(2.874)	
% of insurers selling in only 1 state	0.563	0.1	0.463***
	(0.056)	(0.043)	
% premium from HO	0.697	0.245	0.452***
	(0.034)	(0.032)	
% of assets in the group	0.573	0.246	0.327***
	(0.042)	(0.045)	
No. insurers in the group	5.897	18.494	-12.597***
	(1.002)	(2.176)	
% belonging to a 2 or less insurer group	0.463	0.04	0.423***
	(0.056)	(0.028)	
Stock company	0.938	0.84	0.098*
	(0.027)	(0.052)	

Table 2: Financial and Operational Risks by Insurer Types *(continued)*

	Demotech (1)	Traditional (2)	Difference (1) - (2)
(d) Asset risk			
% assets in equities	0.09	0.146	-0.056*
	(0.017)	(0.026)	
% bonds in corporates	0.353	0.329	0.024
	(0.024)	(0.029)	
% bonds in NAIC 1	0.846	0.853	-0.007
	(0.026)	(0.014)	
% bonds in NAIC 2	0.094	0.119	-0.025
	(0.012)	(0.011)	
% bonds in NAIC3+	0.01	0.028	-0.018**
	(0.003)	(0.006)	
Wtd avg maturity bonds (years)	9.047	16.023	-6.976**
	(0.557)	(2.634)	
(e) Reinsurance			
% premiums reinsured	0.472	0.149	0.323***
	(0.029)	(0.039)	
% reinsurance partners rated above A	0.328	0.395	-0.067*
	(0.01)	(0.036)	
Fraction of premiums ceded to largest partner	0.134	0.039	0.095***
	(0.017)	(0.014)	
Share of FHCF	0.172	0.136	0.036
	(0.024)	(0.052)	

Table 3: Insolvency Rates by Insurer Type

The table shows key statistics on insurer insolvencies by insurer type (Demotech and Traditional). Data on insolvencies are from National Association of Insurance Commissioners (NAIC) Global Receivership Information Database (GRID). We track insolvencies between 2009 and 2022.

	Demotech	Traditional
	(1)	(2)
% of insurers that became insolvent	19%	0%
% insolvent insurers by type	100%	0%

Table 4: Insurer Quality and GSE Mortgage Purchases: Depopulation Experiment

This table shows the results of estimating Equation 3 in the text. The dependent variable is the total number of mortgages originated in prior years that are sold to the GSEs in a given year. The independent variable is the net number of insurance policies transferred to Demotech insurers in a given county adjusted to account for previous sales to the GSEs. The controls X_{ct} include county-year level average values of income and loan amount from HMDA for seasoned mortgages, and DTI, FICO, LTV, property value from McDash for all mortgages to account for shifts in borrower quality (borrower controls). We also control for Citizens footprint in the county using its lagged market share and a county's climate risk exposures by log property damage in SHELDUS (climate risk controls). County and year fixed effects are included where indicated. Standard errors are clustered at the county level and reported in parentheses. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	LoansSoldToGSE		
	(1)	(2)	(3)
DepopulatedPolicies	0.271***	0.267***	0.265***
	(0.0430)	(0.0428)	(0.0423)
Borrower controls	Yes	Yes	Yes
Lagged Citizens market share	No	Yes	Yes
Climate risk controls	No	No	Yes
County Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	335	335	335
Adjusted R^2	0.945	0.945	0.944

Table 5: Borrower Characteristics by Insurance Fragility Prior to Irma

This table presents average borrower characteristics at origination from 2015 for borrowers in counties with low exposure to insolvent insurers and for borrowers in counties with high exposure to insolvent insurers, which is defined as above versus below the mean insolvency share. Florida counties are grouped into two groups based on the county's pre-Irma exposure to insurers that went insolvent after Irma. Borrower application data comes from HMDA, and data on originated mortgages come from both HMDA and McDash. The p-values in (4) and (8) are obtained by an OLS regression on a dummy for high fragility with standard errors clustered at the county level. We limit the sample to loans within 10% of the CLL (Columns 1-4), and to loans within 5% of the CLL (Columns 5-8). Loans directly at the CLL are dropped because of measurement error due to rounding.

	± 10% CLL				± 5% CLL			
	High Fragility	Low Fragility	Difference	P-Value	High Fragility	Low Fragility	Difference	P-Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Mortgage Applications								
Conforming (Y/N)	0.81	0.79	0.02	0.23	0.81	0.79	0.01	0.55
Debt-to-Income Ratio	2.94	3.24	-0.31	0.16	2.93	3.19	-0.26	0.30
Income (000s)	172.53	166.01	6.52	0.18	178.01	172.25	5.76	0.30
Loan Amount (000s)	405.53	407.90	-2.37	0.56	411.65	413.90	-2.25	0.57
Denied (Y/N)	0.13	0.16	-0.03	0.26	0.13	0.17	-0.04	0.25
Panel B: Originated Mortgages								
Conforming (Y/N)	0.82	0.80	0.01	0.36	0.81	0.81	0.01	0.81
Debt-to-Income Ratio	2.75	2.87	-0.11	0.02	2.73	2.86	-0.13	0.07
Income (000s)	174.94	166.66	8.28	0.10	180.35	170.46	9.89	0.13
Loan Amount (000s)	405.30	407.39	-2.09	0.58	411.41	413.35	-1.95	0.59
Interest Rate (Percent)	3.93	3.96	-0.03	0.70	3.91	3.95	-0.03	0.65
Credit Score	748.32	744.32	4.00	0.46	749.10	744.47	4.63	0.43
Loan-to-Value Ratio (Percent)	83.10	84.64	-1.54	0.25	81.92	83.89	-1.97	0.21

Table 6: Mortgage Defaults After Hurricane Irma

This table shows the results of estimating the continuous treatment difference-in-differences design shown in Equation 4. The dependent variable is an indicator for whether a mortgage defaults. The sample considers mortgages originated five-years prior to the storm, between August 2012 - August 2017. We then track their performances annually from September 2015 - September 2019. Default is defined as a nonpayment event consisting of default, foreclosure, or REO. Post-Irma is an indicator for all month-years after September 2017. Insurance fragility is the ex-ante market share (by premiums) as of year-end 2016 for each county of insurers that went insolvent after Irma. All regressions control for the Post-Irma dummy interacted with log of the property damages per capita, as reported in SHELDUS, incurred within 3 months after Hurricane Irma. Loan-level controls refer to the loan's maturity, DTI ratios interacted with year fixed effects, and FICO and LTV categories interacted together and then also interacted with year fixed effects. For our FICO and LTV categories, we use the break points from the GSE's loan-level pricing adjustment matrix. County, year and loan cohort (month of origination) fixed effects are included where indicated. Standard errors are clustered at the county level and reported in parentheses. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Mortgage Defaulted (Y/N)			
	± 10% CLL		± 5% CLL	
	Conforming	Jumbo	Conforming	Jumbo
	(1)	(2)	(3)	(4)
Post Irma × Insurance Fragility	0.118***	−0.013	0.155***	−0.003
	(0.033)	(0.050)	(0.049)	(0.085)
Loan-level controls	Yes	Yes	Yes	Yes
County Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Origination Fixed Effect	Yes	Yes	Yes	Yes
Observations	73,235	14,640	35,485	8,035
Adjusted R^2	0.021	0.045	0.025	0.093

Table 7: Impact of Hurricane Irma on Traditional Insurer Cancellation Rates

This table shows the effect of Hurricane Irma on insurance policy cancellation rates for insurance companies classified as "traditional insurers", following Equation 6. Cancellation rates are defined as total cancelled policies in a given year divided by total policies in force for the prior year. The sample period is limited to 2015-2018. Insurance fragility refers to the premiums share in 2016, the year prior to the storm, of insurers which subsequently become insolvent after the landfall of Hurricane Irma. Columns (1) and (2) limit the sample to traditional insurers. Column (3) considers the full sample of all insurers. In Column (3), "trad" is a dummy variable which equals one if the insurer is categorized as a "traditional insurer." All regressions are weighted by an insurers' policies in force in the prior period. County fixed effects, year fixed effects, county-year fixed effects, year-trad fixed effects, and county-trad fixed effects are included where indicated. Standard errors are clustered at the county level. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Cancellations		
	Traditional Insurers		All Insurers
	(1)	(2)	(3)
Post Irma	0.0197***		
	(0.00243)		
Post Irma × Insurance Fragility		0.158**	
		(0.0652)	
Post Irma × Insurance Fragility × Trad			0.117***
			(0.0384)
County Fixed Effect	Yes	Yes	No
Year Fixed Effect	No	Yes	No
County-Trad Fixed Effect	No	No	Yes
Year-Trad Fixed Effect	No	No	Yes
County-Year Fixed Effect	No	No	Yes
Observations	5,504	5,504	18,415
Adjusted R^2	0.0498	0.0497	0.0236

Table 8: Impact of Hurricane Irma on Denials by Mortgage Market Segment

This table shows the difference-in-differences regression studying the effect of Hurricane Irma on mortgage denial rates separately for jumbo loans and conforming loans, as in Equation 7. We limit mortgages to those with amounts within a ±10% or a ± 5 % window of the CLL. We limit the sample period to 2015-2018. We drop any loan amounts exactly at the CLL boundary (due to the issues with rounding in HMDA). Insurance fragility refers to the premiums share in 2016, the year prior to the storm, of insurers which subsequently become insolvent after the landfall of Hurricane Irma. All regressions include a control for the Post Irma dummy interacted with log of the property damages per capita, as reported in SHELDUS, incurred within 3 months after Hurricane Irma. Loan-level controls refer to DTI ratios interacted with year fixed effects, log income interacted with year fixed effects, and log loan amount interacted with year fixed effects. County fixed effects and year fixed effects are included in all specifications. Standard errors are clustered at the county level. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Mortgage Denied (Y/N)			
	± 10% CLL		± 5% CLL	
	Conforming	Jumbo	Conforming	Jumbo
	(1)	(2)	(3)	(4)
Post Irma × Insurance Fragility	-0.0941	0.481**	-0.406	0.566**
	(0.134)	(0.220)	(0.243)	(0.241)
Loan-level controls	Yes	Yes	Yes	Yes
County Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	36,962	14,487	18,133	9,848
Adjusted R^2	0.0225	0.0339	0.0266	0.0370

Table 9: Impact of Hurricane Irma on Interest Rates by Mortgage Market Segment

This table shows the difference-in-differences regression studying the effect of Hurricane Irma on interest rates separately for jumbo and conforming loans, as in Equation 8. We limit mortgages to those with amounts within a ±10% or a ± 5 % window of the CLL. We limit mortgages to fixed-rate loans originated between 2015 and 2018, and drop any loan amounts exactly at the CLL boundary (due to the issues with rounding). Insurance fragility refers to the premiums share in 2016, the year prior to the storm, of insurers which subsequently become insolvent after the landfall of Hurricane Irma. All regressions include a control for the Post Irma dummy interacted with log of the property damages per capita, as reported in SHELDUS, incurred within 3 months after Hurricane Irma. Loan-level controls refer to the loan's maturity, DTI ratios interacted with year fixed effects, and FICO and LTV categories interacted together and then also interacted with year fixed effects. For our FICO and LTV categories, we use the break points from the GSE's loan-level pricing adjustment matrix. County fixed effects and origination month-year fixed effects are included in all specifications. Standard errors are clustered at the county level. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Interest Rates			
	± 10% CLL		± 5% CLL	
	Conforming	Jumbo	Conforming	Jumbo
	(1)	(2)	(3)	(4)
Post Irma × Insurance Fragility	0.197	1.195*	0.630	2.416**
	(0.299)	(0.674)	(0.398)	(0.925)
Loan-level controls	Yes	Yes	Yes	Yes
County Fixed Effect	Yes	Yes	Yes	Yes
Origination Fixed Effect	Yes	Yes	Yes	Yes
Observations	14,665	2,391	7,766	1,250
Adjusted R^2	0.594	0.543	0.591	0.563

Table 10: Impact of Hurricane Irma on Insurance Underwriting

This table shows the difference-in-differences regression studying the effect of insurance fragility following Hurricane Irma on insurance underwriting, as in Equation 9. Insurance fragility refers to the premiums share in 2016, the year prior to the storm, of insurers which subsequently become insolvent after the landfall of Hurricane Irma. We limit the sample to 2015-2018. In Columns (1)-(4), we consider the effect of Demotech Market Share separately for jumbo loans and conforming loans. We limit insurance companies to those whose average coverage-per-policy in a county lies within a ±10% window of the CLL. All specifications include county fixed effects and year fixed effects. Standard errors are clustered at the county level. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	± 10% CLL			
	Demotech Share (New Policies)		Demotech Share (All Policies)	
	Conforming	Jumbo	Conforming	Jumbo
	(1)	(2)	(3)	(4)
Post Irma × Insurance Fragility	2.109***	-1.907**	1.325**	-1.362*
	(0.622)	(0.951)	(0.613)	(0.772)
County Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	265	254	268	263
Adjusted R^2	0.768	0.730	0.820	0.762

A. Additional Institutional Details

A.1. *Insurance Financial Oversight Regulation*

Supervision and regulation of insurance companies is conducted at the state level. Regulators have two key responsibilities: (1) financial supervision to monitor the solvency of insurance companies that have regulatory headquarters (domicile) in the state, and (2) market conduct, i.e. ensuring that all insurers operating in the state follow the relevant state guidance, such as paying out their contractually obligated claims in a timely manner. Since a large number of Demotech insurers are domiciled in Florida, their solvency oversight falls to the Florida Office of Insurance Regulation (FLOIR).

Regulators monitor insurers' solvency using the risk-based capital (RBC) ratio, which examines whether an insurer has sufficient capital relative to its risk exposures. Insurers also undergo regular financial examinations (audits) to assess their financial stability, claims handling, underwriting practices, consumer complaints, and accuracy of their filings. Exams take place either on a pre-determined schedule (e.g., every three to five years) or on an ad-hoc basis if regulators deem it necessary, e.g., due to a high likelihood of financial hardships or consumer complaints. Regulatory exams may lead to several types of actions ranging from warnings, restatements, and in extreme cases license suspension or revocation.

We assess the degree of regulatory oversight by studying the number of financial exams and restatements, following Tenekedjieva (2021). See Section 2 for data sources. First, we find suggestive evidence of higher regulatory forbearance over time. Panel (a) of Table C.3 shows that both the likelihood of regulatory exams, and negative outcomes after the regulatory exams, such as financial report restatements, have decreased over time. This is despite insolvency risks trending upwards over time.

Second, we find that despite Demotech insurers carrying more risks (as seen from their lower RBC ratio in Table 2), they are not subject to significantly more oversight than traditional insurers. Panel (b) shows that even though they are more likely to face an exam in a given year and more likely to have restatements than traditional insurers, the differences are not economically or statistically significant. This suggests that Demotech insurers face more lax financial regulation than traditional insurers conditional on quality. Third, Panel (c) shows that Demotech insurers are far more likely to have a consumer complaint, and account for a disproportionately large share of all consumer complaints. This suggests that they also face more lenient market conduct supervision.

A.2. Financial Strength Ratings Performance from SEC Filings

This Section provides external validity on the main rating agencies' performance. Rating agencies are required to report their overall performance statistics to the Office of Credit Ratings of the Security and Exchange Commission (SEC) as part of their nationally recognized statistical rating organization (NRSRO) filings. The main performance metric available is the default (insolvency) rates of the companies rated across the U.S. for each letter rating. We collect these data for the two main rating agencies of insurers, AM Best and Demotech. The data for Demotech are for the year 2022, the year Demotech became a NRSRO. The closest year for which AM Best filings are available is 2021.

Panels (a) and (b) of Table C.6 show the 10-year insolvency rates for each letter rating for insurers across the United States.[44] To facilitate comparison, we compute the insolvency rates for insurers in the GSE-eligible segment for both the rating agencies, i.e. insurers that meet the GSE FSR threshold. Specifically, we compute the insolvency rates for Demotech ratings from A'' to A and for AM Best ratings from A++ to B by weighting the insolvency rates of individual ratings by the number of FSRs outstanding in that category. Similarly, we also compute the insolvency rates for insurers in the *ineligible* segment for both the rating agencies.

The NRSRO filings show that GSE-eligible insurers rated by Demotech have a 9% insolvency rate over 10 years. In contrast, the number for AM Best is 0.4%. In other words, there is a wide gap in the insolvency rates of GSE eligible Demotech insurers (i.e. those rated A or better by Demotech) relative to the insolvency rates of GSE eligible AM Best insurers (i.e. those rated B or better by AM Best). In fact, eligible Demotech insurers have almost a 25 times higher insolvency rate than eligible AM Best insurers. Quite starkly, the insolvency rate among insurers that *do not meet* GSE eligibility through AM Best are also over 5 times lower than the insolvency rate among insurers that *meet* eligibility through Demotech (1.7% vs. 9%). These results strongly strongly show inconsistencies in the GSEs' eligibility requirements across rating agencies.

[44]See AM Best's and Demotech's full NRSRO filings. AM Best (here) and Demotech (here). Data accessed on 03/13/2024.

A.3. Depopulation Program: Institutional Details

Florida insurance markets have been under stress since at least 1992, when Hurricane Andrew caused record-breaking losses and led to eleven insurer insolvencies and large-scale insurer exits. To address this issue, after Hurricane Andrew, the state of Florida created a residual insurance market, i.e. an insurer-of-last-resort to provide insurance to homeowners who could not otherwise obtain a policy through the private market. Since 2002, the residual market in Florida has been operated by the state-run Florida Citizens Property Insurance Corporation (Citizens), with liabilities fully backed by the state.

The market share of Citizens ebbs and flows (Figure 1). The growth in Citizens market share often follows large hurricane events, with households losing access to private insurance and transferring to Citizens. Declines in market share are driven by Florida's periodic "depopulation" campaign. "Depopulation" is a program that encourages private insurers to "takeout" policies from Citizens' balance sheet, meaning that the policy is transferred from Citizens to the private insurer. The purpose of the program is to reduce the number of properties that Citizens insures to decrease its financial exposure. The depopulation program has been large. Between 2009 and 2018, over 850,000 policies were transferred to private insurers. Furthermore, as residual markets grow, several other states (e.g., California, Louisiana) are also undertaking this depopulation policy.

To participate in takeouts, insurers must be approved by the Florida Office of Insurance Regulation (FLOIR). Insurers interested in participating apply with the FLOIR. The FLOIR reviews these insurers' (takeout companies) financial conditions and assigns a number of policies which the insurer is supposed to assume. Some of these insurers have existing operations in Florida and some of them are formed by taking out policies from Citizens (e.g., Magnolia, see below). Citizens then allows the approved insurers to select any policy off its balance sheet. Once private insurers select the policies that they wish to take out, a letter is sent to the policyholders notifying them of the change. A letter is also sent from Citizens to the mortgage lender notifying them that the policy is being depopulated.

Depopulated policies are positively selected by design: One concern is that Citizens may have incentives to proactively select high risk policies to be depopulated, which would lead to negative selection. In reality, the program details suggest that the opposite is true. Citizens books are entirely opened up to the insurance companies, and the insurer can cherry pick which of the Citizens' policies they would like to take on. Nicholson et al. (2020), a study commissioned by Citizens on the depopulation, writes: *"The current Citizens depopulation methodology is based on a 'pull' approach where TOCs [takeout companies] that meet OIR [regulatory] approval are eligible to access a database of Citizens policies and* *can independently select policies for assumption. [...] From a risk transfer perspective, the current methodology has a high likelihood of Citizens retaining the properties which are least desirable to the private market, and in particular can lead to concentrations of policies that external parties may view as having inadequate premium to catastrophe risk ratios."* In other words, the Depopulated policies are *positively selected*, with Citizens retaining the highest risks.

The fact that the depopulation lets insurers choose the best policies is well-known and frequently discussed. For example Brian Donovan, the vice president and chief actuary of Citizens, says: *"Citizens lets companies cherry-pick."* See Citizens Summary Minutes of the Exposure Reduction Committee Meeting Tuesday, April 9, 2024 here. Bruce Lucas, CEO of Slide Insurance, an insurer participating in the depopulation, said to Washington Post *"You are underwriting and cherry-picking the best policies, leaving kind of the worst ones there."* Michael Peltier, a Citizens spokesman said *"It was designed to cherry-pick. We wanted them to pick what would be attractive to them so they would keep the policies."* The rationale behind letting private companies choose the best risks is to help Citizens shrink as much as possible even if it retains the highest risk policies.

The changes in Citizens' balance sheet following the depopulation are consistent with the depopulated policies being positively selected. Column (1) of Table C.9 shows Citizens' average financial condition prior to the major 2011-2013 depopulation wave (Figure C.5), and Column (2) shows the financial conditions after the wave. The 2013 depopulation clearly achieved its intended goal to shrink Citizens exposures, with total coverage declining by nearly 60% and the number of policies declining by over half. However, despite this shrinking in size, Citizens' loss ratio and combined ratios increased, implying that the policies that were left behind are more risky.

Takeout companies are higher risk than Citizens: As government provided insurance, Citizens has lower insolvency risk than private insurers. Any losses in excess of premiums collected are funded through a combination of surcharges on Florida insurance consumers and general funds. For example, to cover Citizens' deficit in the 2004-2005 hurricane season, Florida's state legislature approved a one-time $715 million revenue appropriation. In addition, there were surcharges passed on to consumers through their insurance premiums, spread over a 10-year period (Hartwig and Wilkinson, 2016). In other words, Citizens is able to fund its balance sheet deficits through premium surcharges ex-post.

In contrast to Citizens, private insurers have higher insolvency risk. This concern is particularly salient in this case because, of the 40 insurers that participated in the depopulation program, 39 are Demotech-rated. Furthermore, Figure C.6 shows that almost 50% of all

Demotech insurers participate in the depopulation scheme. By contrast, less than 5% of traditional insurers participate. For some participants, almost all of their policies came from depopulation.

The fragility of the depopulation takeout companies is well-known. Florida congressman Jose Javier Rodriguez (D-District 112) expressed concern about fragile depopulation insurers in a 2015 interview *"The governor and the state are so hard-charging to try to shrink Citizens that we are not watching closely on where we are sending people, potentially creating a repeat of what we have seen in prior years with under-capitalized and small companies."* Moreover, from minutes of a meeting of Citizens suggests that Florida regulators review takeout companies' financial health at a time when the balance sheet looks most robust. *"[E]specially these new companies...[must] have reinsurance and everything in place for the office to approve them to do a [sic] depop within the hurricane season. If they do it at the end of the year, the requirements for reinsurance are so much lower that [it is] affordable for them to do that because then they have most of the risk off-season and it just allows them to take that unearned premium and earn it out so by the time June comes around, they can afford the reinsurance for the bigger program [...] the next year"*, says Jennifer Montero, (Citizens). See Citizens Summary Minutes of the Exposure Reduction Committee Meeting Tuesday, April 9, 2024 here.

To make the fragility concern concrete, consider the following example of the property insurer Magnolia Inc. Magnolia began its Florida operations in April 2008 with a financial strength rating of "A" (Exceptional) from Demotech. In the same month, it received regulatory approval to participate in Citizens depopulation program and took over more than 100,000 policies from the state-run insurer by the end of the year.[45] Despite Magnolia's thin capitalization, its high financial strength rating ensured that the GSEs could purchase any mortgages whose underlying properties were insured by Magnolia. However, our estimates show that its predicted AM Best rating would have been a B- and with such a rating Magnolia would have not meet the GSEs' eligibility threshold. Almost immediately after entering Florida, it experienced losses and reinsurance costs that were dramatically higher than its projections.[46] By the end of 2009, it stopped filing quarterly financial reports, it was placed under state supervision, and had its "A" rating suspended. It was liquidated in April 2010.

Timeline and the Citizens Clearinghouse: We end our study of the depopulation program in 2014, because of the creation of the Citizens Clearinghouse in 2014, which serves

[45] Magnolia's Insolvency Report and Citizens Depopulation Report, 2008.

[46] Its projected loss ratio was 25%, but ended up being 47%; projected reinsurance costs were 38%, but ended up being 55%; projected investment income was 5%, but ended up being 1%. Florida Office of Insurance Regulation. Magnolia Insolvency Report, p.7

as an alternate tool to help shrink Citizens' balance sheet. The Clearinghouse is a centralized portal whereby private companies offer alternate insurance contracts to people with Citizens policies. In 2015, the Clearinghouse opened all Citizens policies to private insurers, subject to the following constraints: *"if the clearinghouse identifies a comparable private-market offer with a premium equal to or less than your Citizens premium, your Citizens policy will be nonrenewed."* That is, Citizens will automatically non-renew their policy if they see that an alternative private insurer offer exists. This policy changes the economics of how we can interpret the depopulation, because now the policies that are depopulated may be the ones that private insurers had chosen not to bid on through the Clearinghouse. This induces the possibility of negative selection, thereby changing the interpretation of the depopulation shock.

B. The GSEs Expected Losses

B.1. Parameter Values

This Section provides the details on the parameters values chosen for computing the GSEs' expected losses in Section 5.4.

- δ_B, which is the default rate prior to the hurricane for conforming loans, is 45bps based on the observed default rates in the data.
- P_H, which is the average probability of a major hurricane impact in Florida, is 29%. This estimate is taken from Colorado State University Tropical Cyclone Impact Probabilities report. We only consider major hurricanes (Category 3 to 5) as our default estimates pertain to Hurricane Irma, a Category 3 storm. One way to validate this estimate is by calculating the number of major hurricanes in Florida. Between 1980 and 2023 (i.e. in 44 years), 12 major hurricanes made landfall in Florida. This translates to an annual hurricane probability of 27%.
- P_{INS} is the ex-ante market share of insolvent insurers in the average county prior to Irma, which stands at 4.6%. This is saying that after Hurricane Irma, the average county had 4.6% of its loans exposed to an insolvent insurer. In using this number, the implicit assumption we are making is that the insurer insolvency dynamics would remain the same for each hurricane of similar severity as observed after Hurricane Irma.
- δ_{INS}, which is the default rate conditional on a loan being exposed to an insolvent insurer, is 15.5%. This estimate is obtained from Table 6 column (3).
- LGD_B is assumed to be 40% based on the average value of LGD reported in An and Cordell (2019) (see their Table 1 and Figure 1). In some instances, we also consider a one standard-deviation shock to LGD, which is 29% from their Table 1.
- LGD_H is assumed to be 40% also in the absence of reliable estimates of LGDs after a hurricane. Part of the property damage may be offset by payouts from FIGA, which makes claim payments to both the homeowner and the lender. This would result in higher recoveries. However, the FIGA payouts are likely substantially smaller than the actual damages, as discussed in Section 1. Our LGD estimates are still an under-estimate because we only consider "normal" times LGD of 40%.

B.2. Expected Losses Implied by the GSEs Financial Statements

In this Section, we seek to validate our expected loss estimates by comparing them to what would be implied by the GSEs self-reported serious delinquency rates after Hurricane Irma.

To do so, we collect the serious delinquency rates reported by the GSEs in their financial statements. Figure B.1 provides an excerpt from Fannie Mae's 2017 10K as an example. We proceed in two steps.

Step 1. First, we seek to estimate the increase in delinquency rates in Florida after Hurricane Irma due to insurance fragility risk, δ^{FL}_{INS}. To do so, we compute the change in the serious delinquency rates between Q4:2016 and Q4:2017 for Florida. Figure B.1 shows that serious delinquency rates increased from 189bps to 371bps. To partial out any macro-trends that may be confounding this increase, we subtract the change in the delinquency rates in all the other states over the same period. Note that the delinquency rates in all the other states are computed as the weighted average of the delinquency rates, where the weights are the GSEs outstanding book size in the state. More specifically, we have

$$\delta^{FL}_{INS} = (Delq^{FL}_{2017} - Delq^{FL}_{2016}) - (Delq^{US(exFL)}_{2017} - Delq^{US(exFL)}_{2016}). \tag{10}$$

Given that the direct effect of the storm is minimal, as shown in Section 5.3, we attribute this change in the delinquency rates δ^{FL}_{INS} to insurance fragility risk.

Using the reported numbers in Figure B.1, for Fannie Mae we get $\delta^{FL}_{INS} = 192$bps. Using similar estimates obtained from Freddie Mac's 10K, for Freddie Mac we get $\delta^{FL}_{INS} = 201$bps.

Step 2. Second, using the estimate of δ^{FL}_{INS} we recompute the portion of the GSEs expected losses that can be attributed to insurance fragility risk in Florida, following the steps outlined in Section 5.4. Using the same parameter values outlined above, and a baseline serious delinquency rate in Florida of 189bps (Fannie) and 142bps (Freddie), we get that 23% of Fannie Mae's expected losses and 29% of Freddie Mac's expected losses are coming from insurance fragility risk.

These estimates are close to the estimate of 31% that we obtain in Section 5.4 using our causal estimates of insurance fragility on mortgage default. While close, there are two important differences that are worth keeping in mind. (i) The 10Ks only provide serious delinquencies. In some instances, some seriously delinquent mortgages might recover and become current again either by themselves or upon receiving forbearance. In contrast, we only consider defaults and delinquencies that do not become current again. (ii) Our estimates in Section 5.4 are based on the causal effect of insurance fragility risk on defaults, where we extensively control for borrower characteristics. We are unable to account for the differences in borrower characteristics when using data from the GSEs' financial statements.

Figure B.1: Serious Delinquency Rates Reported in the GSEs 10K

The figure shows the serious delinquency rates reported in Fannie Mae's 10K as of year-end 2017 for single-family conventional loans.

	2017			2016		
	Percentage of Book Outstanding	Percentage of Seriously Delinquent Loans[(1)]	Serious Delinquency Rate	Percentage of Book Outstanding	Percentage of Seriously Delinquent Loans[(1)]	Serious Delinquency Rate
States:						
California	19%	5%	0.42%	19%	6%	0.50%
Florida	6	19	3.71	6	10	1.89
New Jersey	4	5	2.15	4	8	3.07
New York	5	7	2.02	5	10	2.65
All other states	66	64	1.09	66	66	1.11

C. Additional Tables and Figures

Figure C.1: Main Economic Agents in Mortgage and Property Insurance Markets

The figure shows a stylistic representation of how households, lenders, insurers, GSEs, and rating agencies come together in the mortgage market.

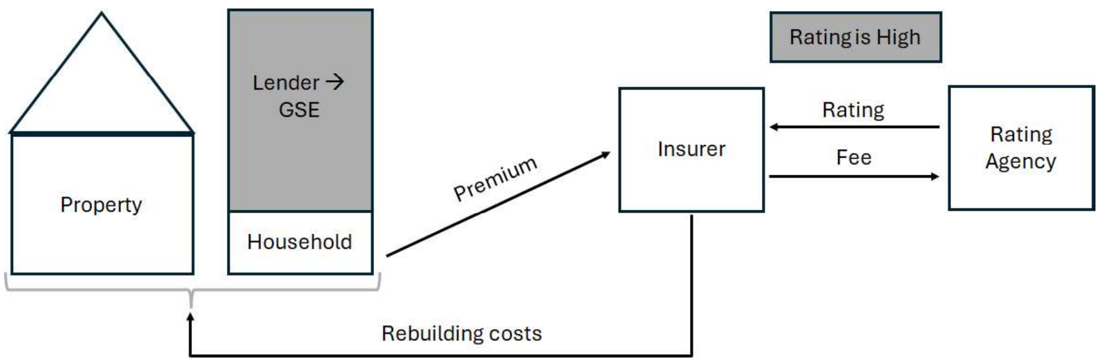


Figure C.2: Percent of premiums written by insurers not reported in QUASR

The figure shows the fraction of property insurance premiums written in Florida by insurers missing in the QUASR database. QUASR premiums are benchmarked against premiums reported in regulatory filings obtained from S&P MI.

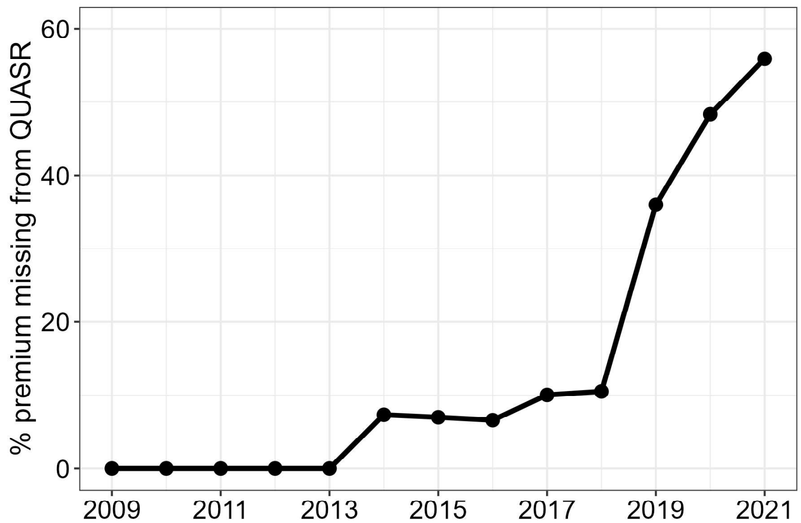


Figure C.3: Histogram of Demotech Insurers' Market Shares in 2009 vs. 2018

The figure shows the distribution of Demotech insurers' market shares (by total premiums) across counties. The white bars show the distribution of market shares in 2009, and the green bars show the distribution in 2018. Demotech insurers are defined as insurers that have been rated by Demotech at least once during the sample period.

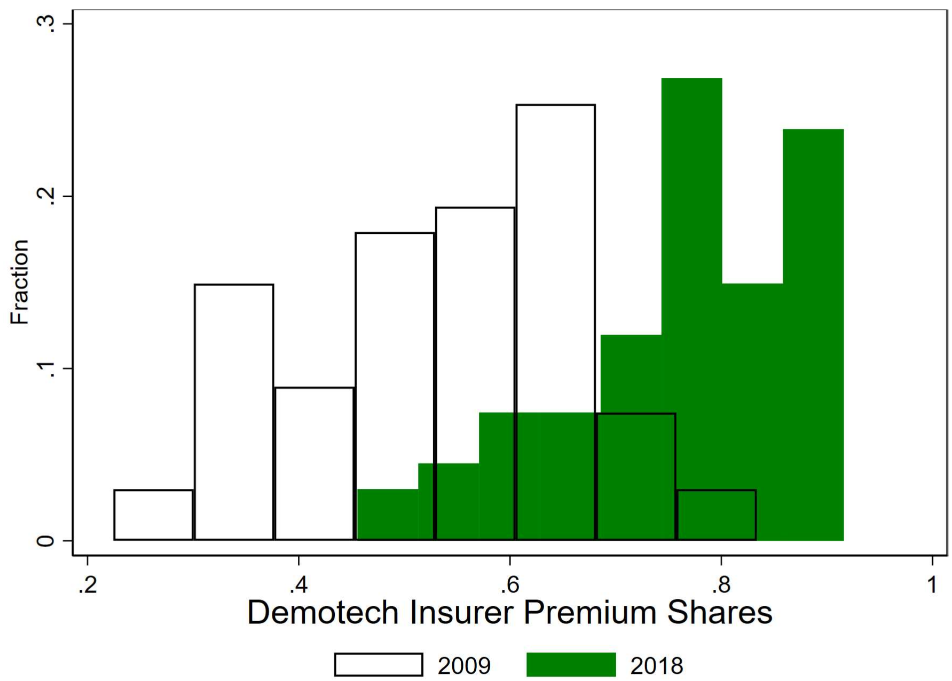


Figure C.4: Top 10 High Climate Risk States vs. Others

This figure shows the market share of Demotech insurers in the top 10 high climate risk states relative to all the remaining states. Top 10 high risk states are states having the highest property damage per capita, as reported in SHELDUS.

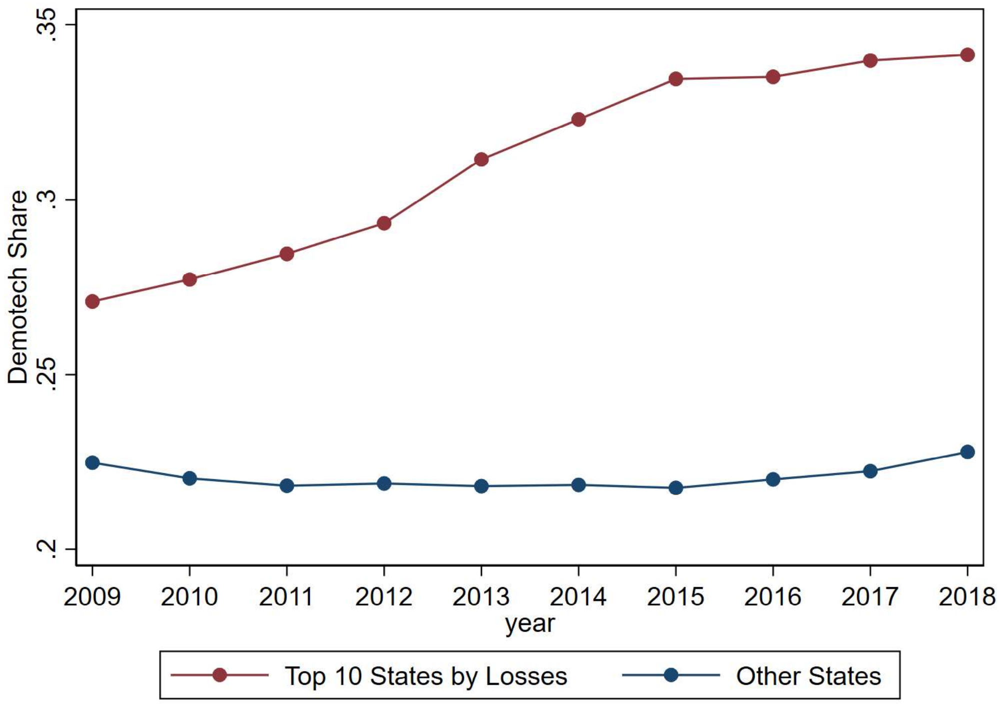


Figure C.5: Citizens' Depopulation and Policy Flows

The figure shows the total number of policies transferred from Citizens, and the total number of policies received by private insurers at an aggregate level. We categorize insurers into two groups Demotech and Traditional by who provides their financial strength ratings. Policies data come from FLOIR's QUASR database.

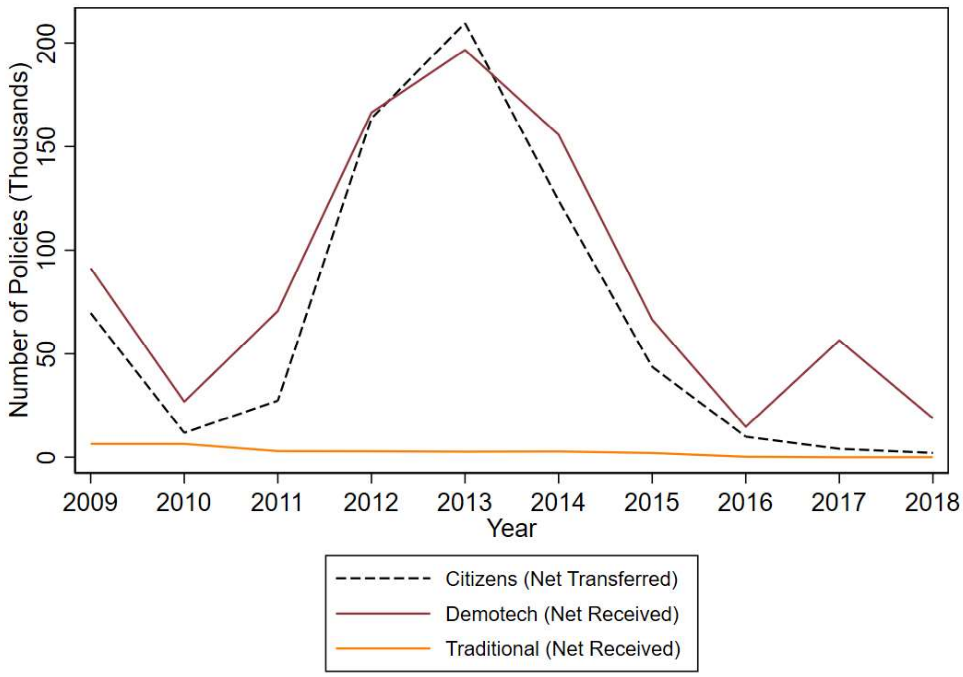


Figure C.6: Participation in Citizens' Depopulation Program

This figure shows which insurers participated in "takeouts", which refers to whether an insurer took over policies from Citizens during its Depopulation program. Data are from Citizens Property Insurance Corporation.

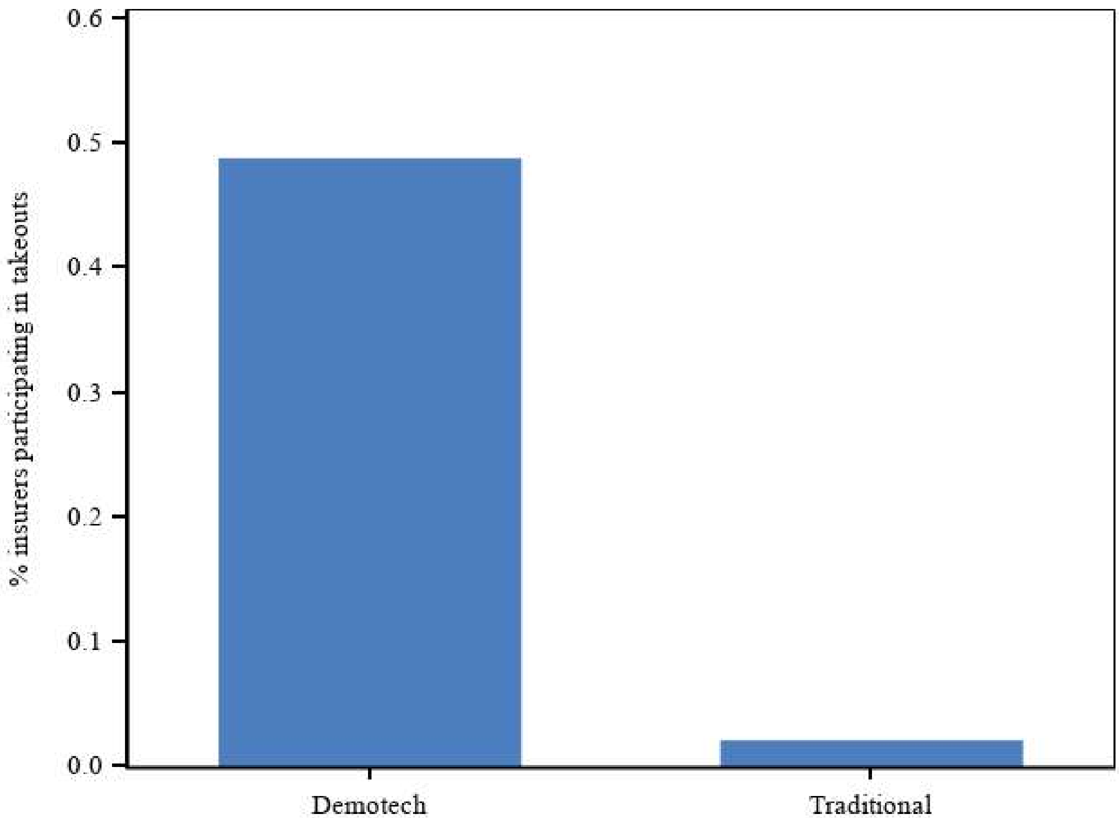
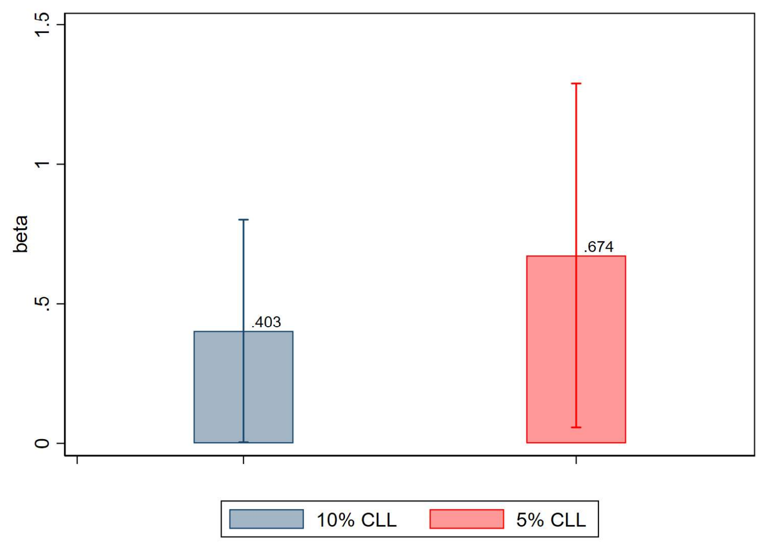


Figure C.7: The Impact of Hurricane Irma on Denials and Interest Rates by Jumbos relative to Conforming

This figure plots the coefficient from a continuous treatment triple difference-in-differences regression that shows how the effect of Hurricane Irma and insurer insolvency varies by mortgage market segment (jumbo and conforming): a modified version of Equation 7 and Equation 8. The design runs the fully saturated model with all interactions between Post Irma, Insurance Fragility, and Jumbo indicator. The figure plots the coefficient on the triple interaction Post Irma × Insurance Fragility × Jumbo. We run the triple difference-in-differences regression for two different samples. The first limits to mortgages within a ±10% window of the CLL. The second restricts the window to 5%. We use two dependent variables: a dummy for mortgage denial (Panel (a)) and interest rates (Panel (b)). We also include county and year fixed effects, as well as controls. Controls for denials are the same as those reported in Table 8, and controls for interest rates are the same as those reported in Table 9. Standard errors are clustered at the county level.

(a) Mortgage Denial



(b) Interest rates

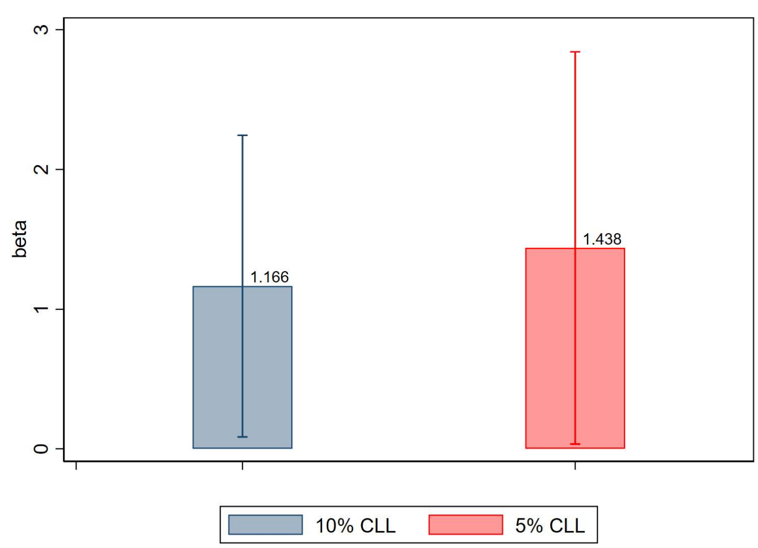


Table C.1: Pricing by Insurer Types

We estimate the differential pricing behavior of Demotech insurers relative to Traditional insurers. The dependent variable in columns (1) and (2) is premium per $100k of coverage and in columns (3) and (4) is annual premium growth. We control for risk using coverage amount as a proxy. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Premium		Premium growth	
	(1)	(2)	(3)	(4)
Demotech	69.66***	-38.08**	0.0002	-0.013***
	(11.3)	(18.2)	(0.002)	-0.002
Risk controls	No	Yes	No	Yes
County Fixed Effect	No	Yes	No	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	46,313	46,311	39,555	39,554

Table C.2: Risk Exposures by Insurer Types

This table uses data at the insurer-year level to assess how exposures in high climate risk counties varies by insurer types. High risk counties are those classified by FEMA as being in risk categories 3, 4, and 5. We consider three different measures of exposures to high risk counties: premium share in high risk counties (1), policy share (2), and coverage share (3). We regress each dependent variable on a dummy variable for which rating agency provides that insurer's financial strength rating. The omitted dummy is the category for traditional insurers, so all effects can be interpreted relative to the omitted category. All specifications include year fixed effects. We report heteroskedasticity robust standard errors in parentheses. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Share Underwritten in High Risk Counties		
	Premiums	Number of Policies	Coverage
	(1)	(2)	(3)
Demotech	0.0242***	0.0243***	0.0215***
	(0.00505)	(0.00488)	(0.00504)
Year Fixed Effect	Yes	Yes	Yes
Observations	924	924	924
Adjusted R^2	0.022	0.025	0.017

Table C.3: Regulatory Supervision by Insurer Types

We compare regulatory oversight and consumer complaints for different sub-groups. Panel (a) shows differences in regulatory oversight between the period 2009 to 2013 and 2014 to 2018. Panel (b) shows differences in regulatory oversight across insurer types (Demotech and Traditional). Panel (c) shows differences in consumer complaints across insurer types. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a) Regulatory supervision over time	2009-2013 (1)	2014-2018 (2)	Difference (1) - (2)
Likelihood of exam in a year (%)	36.2	28.1	8.1
% insurers ever restated	34.4	24.6	9.8
% exams with restatements	37.6	21.3	16.3**
(b) Regulatory supervision across insurers	**Demotech (1)**	**Traditional (2)**	**Difference (1) - (2)**
Likelihood of exam in a year (%)	32.6	25.7	6.9
% insurers ever restated	35.5	28.6	6.9
% exams with restatements	30.8	21.4	9.4
(c) Consumer complaints	**Demotech (1)**	**Traditional (2)**	**Difference (1) - (2)**
Share of complaints	87.9	12.1	75.9***
Likelihood of any complaints in a year (%)	79.7	48.5	31.2***

Table C.4: Financial Risks, Operational Risks, and Insolvency Rates by Insurer Type (Top 10 States by Climate Risk)

The table reports the key characteristics for the different insurer types: Demotech (1) and Traditional (2). The sample includes insurers that have sold property insurance in any of the top 10 states by climate losses between 2009 and 2018. The top 10 states include Arkansas, California, Florida, Georgia, Kansas, Louisiana, Mississippi, Nebraska, Oklahoma and Texas. Definitions of financial and operational risk variables are in Appendix D. We report averages for each insurer type after computing average values for each insurer during our sample period from 2009 to 2018. The last column tests for statistical difference between columns (1) and (2). Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Demotech (1)	Traditional (2)	Difference (1) - (2)
Number of insurers	194	392	
(a) Size and solvency			
Assets ($ million)	641.24	1819.39	-1178***
	(284.65)	(270.8)	
Leverage ratio	0.5	0.49	0.01
	(0.015)	(0.01)	
RBC ratio	3810.7	5002.86	-1192.2**
	(457.766)	(345.233)	
(b) Liabilities			
Loss ratio (US)	0.76	0.71	0.05
	(0.049)	(0.03)	
Exposure to high risk states	0.72	0.56	0.16***
	(0.025)	(0.019)	
Exposure to high hurricane/	0.61	0.38	0.23***
tropical storm risk states	(0.032)	(0.021)	
(c) Operational diversification			
No. states selling HO	6.16	10.67	-4.51***
	(0.71)	(0.73)	
% of insurers selling in only 1 state	0.41	0.32	0.09**
	(0.035)	(0.024)	
% premium from HO	0.511	0.23	0.281***
	(0.0251)	(0.014)	
% of assets in the group	0.45	0.26	0.19***
	(0.028)	(0.017)	

Table C.4: Financial and Operational Risks by Insurer Types *(continued)*

	Demotech (1)	Traditional (2)	Difference (1) - (2)
(c) Operational diversification			
No. insurers in the group	10.77	18.64	-7.87***
	(0.892)	(0.905)	
% belonging to a 2 or less insurer group	0.31	0.09	0.22***
	(0.033)	(0.015)	
Stock company	0.851	0.795	0.056*
	(0.026)	(0.02)	
(d) Asset risk			
% assets in equities	0.13	0.13	0.005
	(0.014)	(0.009)	
% bonds in corporates	0.34	0.28	0.06***
	(0.016)	(0.01)	
% bonds in NAIC 1	0.86	0.89	-0.03**
	(0.014)	(0.006)	
% bonds in NAIC 2	0.1	0.083	0.017**
	(0.008)	(0.004)	
% bonds in NAIC3+	0.017	0.016	0
	(0.003)	(0.002)	
Wtd avg maturity bonds (years)	8.51	10.82	-2.31***
	(0.319)	(0.483)	
(e) Reinsurance			
% premiums reinsured	0.31	0.15	0.16***
	(0.021)	(0.014)	
(f) Insolvency rates			
% of insurers that became insolvent	11.9%	2.55%	

Table C.5: AM Best Rating Replication Models

We estimate the relationship between AM Best FSRs and various measures of insurers' solvency risk, as shown in Equation 1. Column (1) shows the full model, which includes all relevant characteristics. Column (2) shows characteristics selected using the LASSO technique. Column (3) shows the characteristics selected if only the significant variables are retained from the full model. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	AM Best rating$_{it}$		
	(1)	(2)	(3)
% bonds in NAIC 3+	0.838		
	(1.362)		
% assets in equities	−1.185**		−1.127**
	(0.569)		(0.561)
No. states selling HO	−0.012***	−0.011**	−0.012***
	(0.005)	(0.004)	(0.004)
% of assets in the group	0.012***	0.009***	0.012***
	(0.003)	(0.002)	(0.003)
% premium from HO	0.024***	0.023***	0.024***
	(0.003)	(0.003)	(0.003)
Leverage ratio	−5.474***		−5.591***
	(1.461)		(1.447)
Leverage ratio^2	8.838***	3.644***	8.921***
	(1.578)	(0.572)	(1.571)
Log(Assets)	−1.584***	−0.520***	−1.572***
	(0.482)	(0.050)	(0.481)
Log(Assets)^2	0.042**		0.042**
	(0.018)		(0.018)
Log(RBC ratio)	−0.276***	−0.095	−0.286***
	(0.100)	(0.093)	(0.099)
Loss Ratio (Florida)	0.478***	0.388***	0.491***
	(0.140)	(0.141)	(0.138)
% premiums reinsured	1.505***	2.177***	1.529***
	(0.332)	(0.287)	(0.330)
Constant	17.550***	8.446***	17.579***
	(3.537)	(1.289)	(3.535)
Variable choice	All	Lasso	Selected
Observations	589	589	589
R^2	0.588	0.564	0.588
Adjusted R^2	0.580	0.558	0.580

Table C.6: Financial Strength Ratings Performance Statistics from SEC Filings

This table reproduces the performance statistics for AM Best and Demotech FSRs, as reported to the Securities and Exchange Commission's Office of Credit Ratings. For Demotech, the number of FSRs outstanding are as of 12/31/2012 and the 10-year default (insolvency) rates are from 12/31/2012 to 12/31/2022. For AM Best, the number of FSRs outstanding are as of 12/31/2011 and the 10-year default rates are from 12/31/2011 to 12/31/2021.

Panel (a) Demotech

FSRs	GSE-eligible	No. of FSRs outstanding	10 year insolvency
A"	Yes	42	2.40%
A'	Yes	98	9.20%
A	Yes	214	10.30%
S	No	7	14.30%
M	No	0	
L	No	0	
Insolvencies in the GSE-eligible category			9.06%
Insolvencies in the ineligible category			14.30%

Panel (b) AM Best

FSRs	GSE-eligible	No. of FSRs outstanding	10 year insolvency
A++	Yes	118	
A++	Yes	547	
A	Yes	1292	0.10%
A-	Yes	864	0.60%
B++	Yes	309	
B+	Yes	198	2.50%
B	Yes	75	2.70%
B-	No	32	
C++	No	10	10.00%
C+	No	8	
C	No	3	
C-	No	3	
D	No	2	
Insolvencies in the GSE-eligible category			0.40%
Insolvencies in the ineligible category			1.72%

Table C.7: Insurer Quality and GSE Mortgage Purchases

The dependent variable is the share of all originations and purchased mortgages that are sold to Fannie Mae or Freddie Mac, in dollar volumes. The independent variable is the premium share underwritten by Demotech insurers. Loan-level controls from HMDA include log income and DTI. Additional controls are county-by-year averages from McDash, and include FICO score, LTV, and log property value at origination. County and year fixed effects are included where indicated. Our McDash sample does not always include all counties, explaining the different number of observations in Column (4). Standard errors are clustered at the county level. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	GSE Share			
	(1)	(2)	(3)	(4)
Demotech Share	0.291***	0.224***	0.0820**	0.0768**
	(0.0388)	(0.0599)	(0.0403)	(0.0365)
Controls	No	No	No	Yes
County Fixed Effect	No	No	Yes	Yes
Year Fixed Effect	No	Yes	Yes	Yes
Observations	670	670	670	651
Adjusted R^2	0.255	0.283	0.746	0.787

Table C.8: Depopulation Experiment using Unadjusted Depopulated Policies

This table shows the results of estimating Equation 3 in the text. The dependent variable is the total number of mortgages originated in prior years that are sold to the GSEs in a given year. The independent variable is the net number of insurance policies transferred to Demotech insurers in a given county. The controls X_{ct} include county-year level average values of income and loan amount from HMDA for seasoned mortgages, and DTI, FICO, LTV, property value from McDash for all mortgages to account for shifts in borrower quality (borrower controls). We also control for Citizens footprint in the county using its lagged market share and a county's climate risk exposures (climate risk controls). County and year fixed effects are included where indicated. Standard errors are clustered at the county level and reported in parentheses. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	LoansSoldToGSE		
	(1)	(2)	(3)
DepopulatedPolicies	0.0290***	0.0285***	0.0283***
	(0.00380)	(0.00382)	(0.00384)
Borrower controls	Yes	Yes	Yes
Lagged Citizens Market Share	No	Yes	Yes
Climate risk Controls	No	No	Yes
County Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	335	335	335
Adjusted R^2	0.945	0.945	0.944

Table C.9: Citizens Financials Before and After Major Depopulation

The table shows key financial metrics for Citizens before and after the big wave of depopulation in the early 2010s. Share in high risk counties refers to the fraction of Citizens business written in counties designated by FEMA as high risk (by total premiums). Loss ratio and combined ratio data are from PIPSO. Loss ratio is the total losses (claims) incurred scaled by total premiums earned. Combined ratio, defined as the sum of incurred losses and expenses divided by the earned premium, is a measure of insurers' underwriting profitability with high values indicating low profits. The years prior to major depopulation are 2011-2013 and the years after major depopulation are 2014-2016. We stop in 2016 to ensure the results are not driven by the effects of Hurricane Irma. All reported values are 3-year averages.

	Prior to Major Depopulation	After Major Depopulation
Total coverage sold ($ billion)	390	159
Total policies (million)	1.53	0.71
Share in high risk counties	0.89	0.90
Loss ratio	0.49	0.64
Combined ratio	0.72	0.99

Table C.10: County Characteristics by Insurance Fragility Prior to Hurricane Irma

This table presents average county characteristics prior to Hurricane Irma for counties with low exposure to insolvent insurers and high exposure to insolvent insurers, defined as above versus below mean insolvency share. Florida counties are grouped into two groups based on the county's pre-Irma exposure to insurers that went insolvent after Irma. Data on property damage per capita is calculated from 1980-2015, and come from SHELDUS. Data on FEMA Flood Zone Share come from the National Flood Hazard Layer. The p-value in column (7) is obtained by an OLS regression on a dummy for high fragility with standard errors clustered at the county level.

	Mean	SD	High Fragility	Low Fragility	Difference	P-Value
Property Damage Per Capita	73.63	131.47	53.13	85.55	-32.42	0.28
Flood Zone Share	37.99	19.47	33.53	40.48	-6.95	0.16

Table C.11: Mortgage Defaults After Hurricane Irma (Robustness)

In Panel (a), we show the results of a triple difference-in-differences (DDD) design, where we consider the fully interacted specification of Post Irma, Insurance Fragility, and Log Damages. The dependent variable is an indicator for whether a mortgage defaults. The sample is limited to conforming loans. Column (1) uses our baseline Insurance Fragility measure as in Table 6. In column (2), we use a modified measure of insurance fragility, where the insolvent insurer share variable is interacted with a dummy for whether the county was hit by Hurricane Irma. Panel (b) shows the results of estimating the continuous treatment difference-in-differences design shown in Equation 4 using the modified measure of insurance fragility described above. All regressions are estimated on panels within a ±5% window of the CLL and include fixed effects and controls as in Table 6. Standard errors are clustered at the county level. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel (a): Evidence from the DDD Design for Conforming Loans

	Defaults	
	(1)	(2)
Post Irma × log Damages × Insurance Fragility	0.022**	0.034*
	(0.009)	(0.017)
Post Irma × log Damages	−0.001***	−0.001***
	(0.0004)	(0.0003)
Post Irma × Insurance Fragility	0.055	−0.038
	(0.058)	(0.125)
Loan-level controls	Yes	Yes
County Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
Origination Fixed Effect	Yes	Yes
Observations	35,485	35,485
Adjusted R^2	0.025	0.025

Panel (b): Modified Insurance Fragility

	Defaults	
	Conforming	Jumbo
	(1)	(2)
Post Irma × Modified Insurance Fragility	0.198***	0.056
	(0.048)	(0.055)
Loan-level controls	Yes	Yes
County Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
Origination Fixed Effect	Yes	Yes
Observations	35,485	8,035
Adjusted R^2	0.025	0.093

Table C.12: Impact of Hurricane Irma on Applicant Characteristics by Mortgage Segment

This table shows the results from difference-in-differences regressions studying the effect of Hurricane Irma on mortgage applicant characteristics separately for jumbo and conforming loans, as in Equation 7. We limit mortgages to those within a ±5% window of the CLL. We limit the sample period to 2015-2018. We drop any loan amounts exactly at the CLL boundary (due to the issues with rounding in HMDA). Insurance fragility refers to the premiums share in 2016, the year prior to the storm, of insurers which subsequently become insolvent after the landfall of Hurricane Irma. All regressions include a control for the Post Irma dummy interacted with log of the property damages per capita, as reported in SHELDUS, incurred within 3 months after Hurricane Irma. County fixed effects and year fixed effects are included in all specifications. Standard errors are clustered at the county level. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Log Income		Log Loan Amount		Log DTI	
	Conforming	Jumbo	Conforming	Jumbo	Conforming	Jumbo
	(1)	(2)	(3)	(4)	(5)	(6)
Post Irma=1 × Insurance Fragility	-0.0225	0.0115	-0.0979	-0.157	-0.0742	-0.170
	(0.357)	(0.581)	(0.146)	(0.187)	(0.309)	(0.448)
County Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	18133	9848	18316	10017	18133	9848
Adjusted R^2	0.0105	0.0180	0.855	0.835	0.0170	0.0136

D. Insurance Variable Definitions

1. *Assets* are total net assets of the operating company.
2. *Leverage ratio* is defined as total liabilities divided by total net assets.
3. *RBC ratio* is the ratio of available capital to required capital.
4. *Loss ratio* is the ratio of incurred losses to total written premiums.
5. *Coverage per policy* is the ratio of total coverage sold to total policies written.
6. *No. states selling HO* is the number of states in which an insurer has written positive premia.
7. *% premium from HO* is the fraction of total premiums arising from the homeowners' line of business.
8. *% of assets in the group* is the share of the operating company's assets in the overall group assets.
9. *No. firms in the group* is total number of operating companies belonging to the insurer's group.
10. *Stock company* is an indicator variable =1 for stock companies and =0 for mutual and other types.
11. *% assets in equities* is the total carrying value (book value) of equities divided by total carrying value of bonds and equities.
12. *% bonds in corporates* is the total carrying value in corporate bonds divided by total carrying value of all types of bonds.
13. *% bonds in NAIC 1, 2, 3+* are the total carrying value in NAIC 1 (2) (3+) bonds divided by total carrying value of bonds, where NAIC 1 are bonds rated AAA, AA, A, and treasuries, NAIC 2 are bonds rated BBB, and NAIC 3+ are bonds rated below BBB.
14. *Wtd avg maturity bonds* is the remaining maturity of bonds (weighted by carrying values).
15. *% premiums reinsured* is the fraction of premiums ceded to third-parties.
16. *Share of partners rated above A* is the fraction of reinsurance partners having an AMBEST rating of A or better.

17. *Fraction of premiums ceded to largest partner* is the premium ceded to the largest reinsurance partner divided by total premiums.

18. *Share of FHCF* is the share ceded to Florida Hurricane Catastrophe Fund (FHCF).

19. *Likelihood of exam in a year (%)* For all Florida domiciled insurers that sold HO insurance, we compute the average likelihood for an exam in a given year (number of exams divided by the years the insurer operated over a given period).

20. *% of insurers ever restated* is the percentage of insurers who received at least one exam that forced restatement out of all insurers who sold HO insurance in Florida.

21. *% exams with restatements*: Percent of financial exams which resulted in a restatement among the financial exams of all Florida insurers.

22. *Share of complaints (%)*: We estimate for each year the total share of complaints coming from each insurer type, and then estimate the mean of this share for each insurer type across the years.

23. *Likelihood of any complaints in a year (%)*: We estimate for each insurer the average likelihood for at least one complaint in a given year (i.e. the percentage of years there was at least one complaint against the insurer). Then we compute the average likelihood for each insurer type.