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

Parinitha Sastry
Columbia GSB

Ishita Sen
Harvard Business School

Ana-Maria Tenekedjieva
Federal Reserve Board

June 2024

Abstract

This paper examines the impact of growing climate-related losses on homeowners insurance and mortgages in Florida. We show that as traditional insurers cancel policies in high-risk areas, new undercapitalized and underdiversified insurers enter to fill the gap. Though nearly 20% of these newer insurers become insolvent, they obtain high ratings from emerging rating agencies, allowing them to meet GSE eligibility requirements. These insurers now dominate the conforming segment. We show they would not meet GSE eligibility under traditional rating methodologies. Lenders respond to declining insurance quality by selling exposed loans to GSEs. We quantify the insurance counterparty risk for the GSEs by examining the surge in mortgage default after Hurricane Irma. Lastly, we show that these dynamics have welfare implications, with lax lender screening of insurance risk in the conforming segment leading to distortions in credit supply.

Keywords: Climate Risk, Property Insurers, Banks, GSEs, Mortgage Securitization, Credit Rating Agencies, Insurance Regulation, Financial Stability.

*For helpful comments we thank Alex Barbu, Sid Biswas, Thomas Flanagan, Shan Ge, Robin Greenwood, Ivan Ivanov, Ralph Koijen, Tomek Piskorski, Antoinette Schoar, Adi Sunderam, Stijn Van Nieuwerburgh, and seminar and conference participants at NBER Innovative Data in Household Finance, Adam Smith Workshop, NBER Insurance Working Group, NYU Stern/ NY Fed Summer Climate Finance Conference, ECB-FRBNY Workshop, Midwest Finance Association, ASU Sonoran Winter Conference 2024, Baruch College Conference on Climate Finance and ESG, SFS Cavalcade, NYU Fifth Annual Volatility and Risk Institute, MIT Sloan Finance Juniors Conference, Harvard Business School, Columbia Business School, Boston College, FHFA, Columbia SIPA, Freddie Mac Climate Risk, Federal Reserve Board, Federal Reserve Bank of Philadelphia, University of Wisconsin Madison. Kris Shen provided excellent research assistance. The views in this paper are solely the authors' and do not reflect the views of the Board of Governors or the Federal Reserve System. All errors are our own.

Sastry: prs2107@columbia.edu; Sen: isen@hbs.edu; Tenekedjieva: ana-maria.k.tenekedjieva@frb.gov.

1. Introduction

The last few decades have seen an unprecedented growth in property damage from natural disasters. Forecasters expect losses to accelerate further as climate change brings an increase in the frequency and intensity of natural disasters (Davenport et al., 2021). Households bear large exposures to climate risk through their homes. Insurance provides a first line of defense against losses from most natural disasters for households, covering at least 60% of all property damage by some estimates.[1] However, there are a handful of states where these insurance markets are beginning to unravel – particularly high climate risk states. We study this unraveling and the direct risks it poses for mortgage markets.

Mortgage markets bring a range of different financial institutions together. Banks and non-banks originate loans. The government-sponsored enterprises (GSEs) purchase, guarantee and securitize mortgages. Property insurers help households rebuild after these disasters. By preserving collateral values and reducing the likelihood that a borrower defaults, insurance directly reduces risks for banks and the GSEs. Unsurprisingly, banks require insurance for all mortgages, and the GSEs only purchase loans backed by good quality insurers, which they assess using insurer ratings. Despite being ubiquitous, the role that property insurers play in mortgage markets is understudied in the literature. This paper shows how banks and insurers interact to influence mortgage market outcomes and the distribution of climate risk to the wider economy.

Our paper makes three contributions. First, we show a dramatic decline in the quality of insurance provision in Florida. Well-established traditional insurers are cancelling policies in high risk areas, and the gap is being filled by poor quality under-diversified and under-capitalized insurers that are at high risk of becoming insolvent. Though these insurers secure high enough ratings to meet the minimum rating requirements set by the GSEs, we find that many of them would not have been eligible under the methodologies of the traditional rating agencies. This implies that the GSEs' insurer rating requirements are mis-calibrated.[2] Second, we examine how lenders respond to the changing insurance market dynamics. We find that lenders are keenly aware of insurance counterparty risk. They are more likely to sell conforming loans they had previously retained to the GSEs when the insurance company backing the loan exogenously switches from a high quality to low quality one. We also show that lenders do not screen for insurance counterparty risk at origination

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

[2] Financial stability ratings are central to insurance companies' operations. Ratings convey information about insurers' future solvency and ability to pay claims. As a result, insurance demand tends to be sensitive to ratings (Froot and Stein, 1991). However, in addition to households, GSEs also care about insurers' ratings and they impose minimum rating requirements to screen insurers.

when loans can be offloaded to the GSEs, but they do for jumbo loans that must be retained on balance sheet. Third, we show that that these dynamics create large implicit transfers and have implications for welfare. We show that insurance fragility amplifies the effect of climate shocks on mortgage defaults, leading to loss exposures for the GSEs and thus taxpayers. Furthermore, GSE policy creates a distortion in terms of efficient credit supply, exacerbating ex-ante moral hazard. Taking behavior in jumbo markets as a benchmark for efficient behavior, we find that lenders originate too many conforming loans backed by fragile insurers.

While we document the widespread deterioration in the quality of insurance intermediation across a number of states, our paper mainly focuses on the mortgage market in Florida for the following reasons. First, Florida ranks among the top states in terms of both past and projected future climate losses and therefore serves as an early case study of the risks these losses pose to insurance and mortgage markets.[3] Second, we have granular insurance underwriting data available for Florida, while these data are primarily only available at the state level for other states. Third, we can exploit a unique policy that allows us to examine plausibly exogenous variation in insurance provision. The state of Florida ran programs that shifted insurance policies from the balance sheet of the state-run insurer-of-last-resort to the balance sheet of these lower quality private insurers. These programs deliver an exogenous change in insurer quality that is plausibly unrelated to the fundamentals of the underlying loan and borrower characteristics, as we describe in more detail below.

Our paper uses a number of novel data to obtain a comprehensive picture of insurance and mortgage markets. First, we collect granular county-level underwriting data for each insurer operating in Florida, which are reported directly to the state of Florida. This data has the unique feature that we can observe precise flows of insurance policies, including new policies underwritten and policies transferred between insurers at a granular level. Second, we combine the underwriting data with insurers' financial and operational statements collected from statutory filings. We observe detailed accounts of assets, liabilities, reinsurance relationships, and key operation metrics, providing us a comprehensive picture of insurers' financial strength across their entire underwriting portfolio. Third, we collect the financial stability ratings histories of property insurers made by both traditional and emerging rating agencies. Historically, insurance companies have primarily been rated by traditional rating agencies, such as AM Best and Standard & Poor's (S&P). More recently, several new rating agencies have emerged, in particular Demotech Inc. Fourth, we compile detailed data on insurers' supervisory examinations. Finally, we combine this information with mortgage originations and securitization data from the Home Mortgage Disclosure Act (HMDA), and

[3] CoreLogic Climate Risk Analytics. May 17, 2023. See here.

mortgage performance data from BlackKnight McDash.

We start by documenting three new facts on the dynamics of property insurance markets and rating agencies. First, there is a large decline in the market share of insurers rated by traditional rating agencies (traditional insurers henceforth). This is a direct result of traditional insurers pulling back from underwriting, especially in the more risky and loss-prone areas. However, instead of insurance becoming completely scarce, the gap is filled by two separate types of insurers: the state-run insurer-of-last resort known as Citizens Property Insurance Corporation (Citizens)[4] and, more importantly, new insurers, primarily rated by emerging rating agencies such as Demotech (Demotech insurers henceforth).[5] We document a dramatic increase in the market share of Demotech insurers. From having a negligible presence in the 1990s, when they entered the market, their share rises to over 50% in 2018. We show that this is not unique to Florida and part of a broader country-wide trend, especially in states more prone to weather- and climate-related disasters.

Second, we show that Demotech insurers are of significantly lower quality than traditional insurers across most observable measures of financial and operational risks. (a) Demotech insurers have riskier liabilities and operate in high risk areas. (b) They are under-diversified: they are smaller in size by total assets; they operate in fewer states with a large majority only selling in a single state; they predominantly sell homeowners' insurance while traditional insurers have many other product lines; and they are part of insurance groups with fewer other operating companies, further decreasing ability to diversify. (c) They have riskier and concentrated reinsurance relationships and are more exposed to counterparty risk of reinsurers. (d) They have higher leverage and lower risk based capital ratios, and thus appear under-capitalized relative to underlying risks.

Third, the GSE requirements on insurers are less strict for Demotech than for traditional insurers. We find that ratings assigned by traditional agencies have higher dispersion than those assigned by Demotech. They span the full range of the distribution, including ratings low enough to not meet GSE minimum eligibility requirements. In contrast, Demotech ratings are almost uniformly high and sufficient to meet the GSE threshold. This is despite the fact that traditional insurers are higher quality on average. Therefore, we test if Demotech issues less strict ratings than traditional ratings: we estimate counterfactual AM Best ratings for Demotech insurers by mapping observable insurer characteristics to numeric ratings. We find that a vast majority of Demotech insurers would not meet GSE eligibility under

[4]More broadly, the insurer-of-last resort is referred to as "residual market".

[5]We use the phrase "Demotech Insurers" as a short-hand for insurers that have a FSR at any point from Demotech. They mey also have FSRs from other rating agencies, or may lose their Demotech FSR at some point.

AM Best's methodology. Our results are validated by the fact that Demotech insurers have a much higher likelihood of insolvency. 19% of Demotech insurers entered rehabilitation proceedings in the past decade, while none of the traditional insurers did.

We next explore how banks and mortgage lenders respond to the deterioration in insurers' quality. We first analyze this question by showing that securitization shares in a county strongly covary with the market share of Demotech insurers. We also show that Demotech insurers have a dominant market share in what are likely conforming loans. These results strongly show that the GSE's have large exposures to Demotech insurers.

However, the above results do not identify whether banks strategically securitize mortgages to offload counterparty risk, since it does not account for the fact that borrowers are likely not randomly assigned to Demotech or traditional insurers. It is possible that borrowers with high default risk are also more likely to obtain insurance from Demotech insurers, and so the correlation between securitization share and the market share of Demotech insurers could be explained by underlying shifts in borrower characteristics rather than the causal effect of insurance. The ideal experiment would look at the securitization outcomes for two otherwise identical borrowers who only differ in terms of the insurance policy they obtain.

We address this endogeneity issue by studying the Florida Depopulation Program. Starting in the 1990s, Citizens (the Florida residual market) repeatedly expanded after particularly bad hurricane seasons. This led to the adoption of a "depopulation" policy in the early 2000s, where the state of Florida incentivized private insurers to "take out" Citizens' policies (i.e., borrower policies were transferred from Citizens to a private insurer). The Demotech insurers dominated the depopulation effort, accounting for over 95% of participating insurers. The depopulation effort ultimately led to over 18% of Citizens policies to be sold to the private market and serviced by Demotech insurers; at its peak in 2012, over 200,000 policies were depopulated in a single year. By using these policy flows, we can focus on what happens to existing mortgage borrowers that switch from the arguably safer state-run insurer to more risky private insurers.

On the mortgages side, we can similarly separate flows into new mortgage originations that are sold to the GSEs in the same calendar year that they are originated, and older mortgages that are sold in a subsequent calendar year. We then examine securitization dynamics of older mortgages and test whether there is a change in the likelihood that these mortgages are subsequently sold to a GSE following a switch from Citizens to a private insurer in that same county. At its core, our identification strategy tries to trace the same borrower before and after their insurance policy is sold, allowing us to obtain variation in insurer quality that is plausibly exogenous to other characteristics of the mortgage borrower.

In studying this program, we find that a 1% increase in policies transferred to Demotech insurers in a given county brings a .03% increase in mortgages that are sold to the GSEs. Overall, our results suggest that mortgage lenders actively manage insurer counterparty risk by offloading mortgages with high insurer counterparty risk to the GSEs.

To make our findings concrete, consider the following illustrative example. The property insurer Magnolia Inc. began its Florida operations in April 2008 with a financial stability 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.[6] These policies came disproportionately from Florida's highest risk, coastal counties. Despite Magnolia's thin capitalization, its high financial stability rating ensured that 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 GSE's eligibility threshold. Almost immediately after entering Florida, it experienced losses and reinsurance costs that were dramatically higher than its projections.[7] 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. Our results imply that banks sold many of the 100,000 mortgages transferred to Magnolia in its two years of operation to the GSEs as GSEs were willing to assume the counterparty risk exposure to Magnolia.

In the final part of the paper, we quantify GSEs risks due to unpriced insurance market exposures. We identify two sources of risks. The first is an *implicit risk transfer*, which arises from risks previously insured by property insurers now migrating to the GSEs due to lenders securitizing loans. The second source of risk comes from a *distortion in the credit supply* due to lax lender screening standards for insurance fragility in the conforming segment. Relative to the jumbo segment, which we assume provides an efficient benchmark, the tendency to neglect insurance fragility implies that there are too many conforming mortgages backed by fragile insurers.

To quantify the size of the transfer we show that exposure to fragile insurers increase mortgage defaults in the aftermath of natural disasters. We exploit the landfall of Hurricane Irma in Florida in August 2017, which led to several Demotech insurers becoming stressed and insolvent. We examine loans in narrow bands around the conforming loan limit (CLL) for two reasons. (i) Demotech insurers dominate among conforming but not jumbo loans. (ii)

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

[7] 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

At the same time, conforming loans around narrow bands of the CLL are more likely to be similar in unobservable borrower characteristics. We show that defaults increase by 27 bps for conforming loans, which are more likely insured by Demotech insurers, but not for jumbo loans, which are more likely insured by traditional insurers. The increase is sizeable at 70% of the baseline default rate. Moreover, the increase in defaults for conforming loans is more pronounced for counties with fragile insurers (those with large ex-ante market share of insolvent insurers), suggesting that mortgage defaults increase after hurricanes and the immediate effects are exacerbated by fragile insurers. These results are robust to loan selection issues (i.e. conforming loans in fragile areas are not negatively selected) and controlling for the direct exposure of counties to the hurricane. We provide a back-of-the-envelope estimation of the size of the implicit transfer, extrapolating from the delinquency dynamics observed during hurricane Irma. We estimate that about 16% of the GSEs expected losses are due to insurance market fragility. The large exposure can be explained by meaningfully greater defaults after hurricanes, which is amplified by the high likelihood of major hurricanes and the insolvency risk of insurers.

To quantify the amount of excess credit supply, we examine lenders' loan denial decisions and ask if fewer loans would have been originated had lenders not offloaded their insurance counterparty risk? We focus on narrow bands around the CLL, which gives us variation in lenders ability to securitize, while holding fixed borrowers' unobservable differences. We then show that lenders' denial decisions are sensitive to insurance fragility *for jumbo* (loans banks retain) but *not for conforming* (loans they can offload to the GSEs). We obtain exogenous variation in insurance fragility by exploiting a county's ex-ante exposure to insolvent Demotech insurers induced by Hurricane Irma. When counties are more exposed to insurers at the brink of insolvency, what happens to insurance market fragility in the places that they operated in? We show that these areas experience an increase in insurance fragility in the future. At the same time, the ex-ante shares themselves are exogenous to borrower quality since the timing and the path of the hurricane is likely unrelated to borrower characteristics. Stated another way, though a number of high risk insurers operate in Florida, the places which are actually exposed to insolvent insurers is plausibly random and determined by which places happen to get hit by the storm. We verify this assumption by showing that counties with both high and low insolvent insurers are similar across a range of borrower and insurance market characteristics. Overall, we find that jumbo denials increase by 2pp due to lenders screening fragile insurers. In contrast, there is no screening in the conforming segment where Demotech share of new policies grows. Our estimates suggest that one extra conforming loan is being approved for every two new jumbo applications translating to over 8,000 new loans and close to $2 billion in excess origination per year.

Related Literature: This paper contributes to three strands of the literature. First, we add to the literature documenting supply-side frictions in climate risk insurance markets. Froot and O'Connell (1999) and Jaffee and Russell (1997) study the role of capital market frictions; Oh et al. (2023) study the role of state-level price regulation, Boomhower et al. (2023) study the role of information asymmetry for pricing of homeowners' insurance.[8] Our paper also relates to the broader insurance literature on supply side frictions, including financial, regulatory, and legal frictions, and their effects on product markets and asset selection (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; Gennaioli et al., 2021; Egan et al., 2021). We identify a new source of friction – one coming from GSE requirements – that affects the I/O of homeowners' insurance markets. Our results emphasize how insurers are connected to other intermediaries through the mortgage market and how incentives and constraints of these intermediaries spill over to insurance markets.

Second, this paper contributes to the growing literature on the capitalization of climate risk in real-estate markets.[9] A new set of papers study the connection between real estate and insurance markets in the context of growing climate risk, e.g., how flood insurance market affects mortgage lending (Sastry, 2022) and real estate prices (Ge et al., 2023), and how insurance pricing can guide adaptation (Boomhower et al., 2023). The literature shows that climate events create financial losses for lenders through increases in defaults, and that insurance payments offset much of the rise in delinquencies after disasters (Gallagher and Hartley, 2017; Kousky et al., 2020; Billings et al., 2019; Issler et al., 2019; An et al., 2023; Biswas et al., 2023). We show how property insurers create counter-party risk for mortgage lenders and that lenders react to increasing insurer counterparty risk by offloading risks to the GSEs. To our knowledge, this is the first paper drawing such a link between private property insurance and mortgage markets.

Third, we add to the large literature on adverse selection in mortgage securitization. Several papers show that the ability to offload risks through securitization distorts lender incentives to screen and monitor mortgages and that mortgages that end up securitized are of lower quality and perform worse compared to mortgages with similar observable charac-

[8] A separate literature also studies insurance demand in the context of the federal flood insurance market (e.g., Wagner (2022)).

[9] There are now a large number of papers broadly exploring whether climate risks are capitalized in house prices (Baldauf et al., 2020; Bernstein et al., 2019; Gibson and Mullins, 2020; Giglio et al., 2021; Keenan et al., 2018; Murfin and Spiegel, 2020; Mulder and Keys, 2020). A handful of papers have explored whether lenders screen for climate disaster risk by adjusting where they originate mortgages (Garmaise and Moskowitz, 2009; Cortés and Strahan, 2017; Gropp et al., 2019) and mortgage pricing (Garbarino and Guin, 2021; Mulder and Keys, 2020; Sastry, 2022; Santos and Blickle, 2022).

teristics (Downing et al., 2009; Keys et al., 2010; Demyanyk and Van Hemert, 2011; Adelino et al., 2013, 2016). Ouazad and Kahn (2021) explore whether this pattern holds even in the climate risk context – whether lenders are more likely to originate loans below the conforming loan limit after a large hurricane strikes, and whether these mortgages have worse ex-post delinquency outcomes.[10] A number of papers also show that the pricing of guarantee fees by the GSEs ignores important component of risks, such as local house price risk (Hurst et al., 2016). Bhutta and Keys (2022) explore how the expansion of private mortgage insurance enabled GSE purchase of riskier, more highly leveraged, mortgages in the run-up to 2008, leading to a large-scale collapse of both sectors in the crisis. We contribute to this literature by showing a new type of adverse selection coming from exposure to fragile property insurers and the exit of traditional insurers. We document significant heterogeneity in insurer quality in terms of ex-ante financial risk measures. We also show that fragile insurers amplify the direct effects of climate shocks on serious mortgage delinquency. We document that lenders seek to strategically offload this counterparty risk to the GSEs because of miscalibrated GSEs rating requirements across agencies.

2. Institutional Details

2.1. Homeowners Insurance and Mortgages

A well-operating mortgage market depends on a fully functional homeowners insurance market. Mortgage lenders require borrowers to maintain homeowner (HO) insurance for the duration of their mortgage to make sure the underlying property is protected against physical damage. Doing so helps preserves the collateral value of the property that secures the lien. As a result, the insurance product is ubiquitous, with insurers selling annually over $15 trillion in homeowners multi-peril insurance coverage to almost 85% of all U.S. homeowners (Jeziorski et al., 2021).

The standard contract is annual and covers damages from most climate-related disasters, except those from floods.[11] If the insured property experiences physical damage due to an insured event, the insurer pays out to cover losses up to the coverage limit specified in the contract. Both households and lenders are beneficiaries of the insurance policy, meaning that they both have claims to the insurance proceeds in loss events.[12] If the loan is sold or

[10] This question is also explored in independent work by Lacour-Little et al. (2023).

[11] Flood insurance is carved out and mostly provided from the federal government through the National Flood Insurance Program.

[12] Insurance checks are made out to both the household and the lender; therefore, cashing a check requires the endorsement of both the lender and the household, meaning that lenders play a role in determining how insurance proceeds are used. Insurance payments are often used to repair physical damage, helping to

securitized, the ultimate mortgage owner most often still requires homeowners insurance.[13]

Lenders and mortgage owners are keenly aware of the importance of insurance markets for managing risks. Homeowners often rely on insurance proceeds to repair their homes and make mortgage payments after large loss events (Gallagher and Hartley, 2017). Several studies show that being uninsured or underinsured increases the propensity of household default after large climate events (Kousky et al., 2020; Issler et al., 2019). If insurers become insolvent at the same time that the households experience the financial shock of the disaster, lenders may face both an increase in borrower default rates and increased losses given default, since the disaster event can destroy the collateral value of the property used to secure the mortgage.[14]

Financial Stability Ratings: Given the counter-party risk that insurer insolvency poses to mortgage owners, lenders often set precise guidelines on which type of private insurance policies they are willing to accept. For example, the GSEs Fannie Mae and Freddie Mac require that the mortgaged property is covered by a homeowner insurance policy as a condition for the mortgage to be purchased or securitized by them. In addition, they require that the insurer underwriting the policy meets a minimum financial stability rating (FSR) threshold.[15] FSRs intend to measure an insurers' ability to meet ongoing insurance policy and contract obligations. They are given at the individual insurer level, not the group level, consistent with the level at which financial regulation of insurance takes place.[16]

FSRs are provided by third parties in exchange for payment by the insurers. For homeowners' insurance, the government-sponsored enterprises accept FSRs from three rating agencies: AM Best, S&P Global, and Demotech.[17] Table 1 shows the minimum acceptable FSR for insurers by the GSEs. Notably, the threshold varies by the issuing rating agency.

The three rating agencies have important differences in their business models. The traditional rating agencies, AM Best and S&P, have longer histories, larger market share, and rate companies all over the U.S.[18] In contrast, Demotech, an emerging rating agency, is relatively

preserve the collateral value of the property.

[13]Insurance requirements are then monitored and processed by the institution that services the mortgage on behalf of the ultimate owner.

[14]There could also be a second-order effect on collateral values if local house prices also decline in the aftermath of storms, such that a home without any property damage would also decline in value.

[15]The government agency Ginnie Mae has a similar requirement based on FSRs.

[16]Therefore, if an insurance group consists of two individual insurers – a large, diversified multi-state insurer and a insurer that operates only in the Florida market – the two insurers would have separate financial strength ratings.

[17]Starting 2018, KBRA (formerly, Kroll) was added to this list, but given the time frame of the study, we only focus on the other three.

[18]AM Best has been issuing FSRs for over a hundred years, while Demotech entered the homeowners market in the 1990s.

newer and concentrated mostly in Florida. Figure A.2 shows that Demotech's footprint in Florida, which is currently at more than 60%, dwarfs its market share in the other top five states in which it operates. The agencies also differ by rating methodologies and the type of insurer they rate. Demotech is more likely to provide ratings for single-state insurers that tend to be smaller than the multi-state insurers rated by the traditional rating agencies.[19]

2.2. Insurer-of-last-resort: Citizens Property Insurance Corporation

Homeowners insurance markets have been under increasing stress in recent years. In high-risk states like Florida, losses between 2003 and 2018 increased by 206% compared to the previous 15 years.[20] Large insurers are reportedly choosing to exit Florida by cancelling policies and refusing to originate new ones (Nicholson et al., 2020). Exiting insurers point to growing natural disaster risks. These exits occur despite the fact that Florida makes up 10% of the U.S. HO market and has the highest average price in the country.

Florida was one of the first states to experience a rapid increase in insurance losses. In fact, Florida's insurance markets have been under stress since at least 1992, when Hurricane Andrew caused record-breaking losses and led to 11 outright insurer insolvencies and large-scale insurer exits. The deterioration of the market resulted in close to 1 million coastal properties that could not find insurance. To address this issue, after Andrew Florida created a residual insurance market, i.e. a market 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 the state-run Florida Citizens corporation (Citizens).

While 31 other states and DC also have residual markets, Florida (and Louisiana) are unique in that their residual market is a fully state-run insurance provider, with liabilities borne by the state. 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 contrast, for the other 31 states, any losses in excess of the collected premiums are distributed among insurers licensed to do business in the state, meaning that taxpayers do not directly back the program.[21]

[19]For example, Demotech states in its promotional materials that "financial stability can be independent of size" and that "well-managed, properly reinsured, regional and specialty insurers can be as financially stable as larger insurers".

[20]Estimated using SHELDUS for the states with highest amount of property damages – California, Florida, Texas, Louisiana and Mississippi. The numbers are adjusted for inflation.

[21]Notably, before 2002, Florida's residual market was funded in a similar way, but as losses grew, the

As an insurer of last resort, Citizens has eligibility requirements: A consumer is eligible to purchase a policy from Citizens if she can prove she is unable to find a private insurance coverage or if the private market charges significantly more than the residual market rate (the threshold as of 2020 is 20% more, according to Citizens' website). Several features of Citizens can make it an attractive option to consumers. It has a price growth cap, and it cannot cancel policies following loss events, so it is often more reliable alternative than the private market. However, the disadvantage of Citizens is that its policies provide more minimal coverage than private insurers – they pay out for fewer loss events, and they have a coverage limit which varies over time.

Although intended to function as an insurer of last resort, Citizens has a uniquely large market share, even among residual markets. Over time, Citizens' market share has varied greatly: at its peak in 2011, it was 23%, then it gradually dropped to 4% in 2019, and has been again increasing since. An article by ABC Action News from January 11, 2023 reports that by the end of the year, Citizens is expected to reach a new record – 1.7 million policies.

Depopulation: Since the early 2000s, Florida has sought to decrease Citizens' market share using a "depopulation" campaign, which encourages private insurers to take on Citizens policies–meaning that the policy is transferred from Citizens to the private insurer. Insurers must be approved by the Florida Office of Insurance Regulation to participate in the Depopulation program. Between 2003 and 2019, Citizens' depopulation efforts resulted in 18% of all Citizens' policies being transferred to the private market, with only around 400,000 individuals remaining on Citizens' balance sheets. Private companies are offered financial incentives to take on the policies, receiving bonuses of up to $100 per policy (Nicholson et al., 2020). Initially, consumers could refuse to switch to the private insurer; however, after 2022, consumers were forced to accept the transfer if certain conditions were met.[22] While the Depopulation is an ongoing effort, in this paper we focus on the depopulation efforts of the early 2010s.

2.3. The Government-Sponsored Enterprises and Securitization

The government-sponsored enterprises (GSE) Fannie Mae and Freddie Mac directly own or guarantee a large portion of the $12 trillion US mortgage market. To sell a mortgage to the government-sponsored enterprises, a mortgage must meet criteria that are set out in the GSE's origination guides. Furthermore, the GSE's servicing guides maintain requirements

funding source shifted from insurers to consumers. The funding structure of Florida's residual market may become more popular if losses continue to grow nationwide.

[22] If the premium offered by the depopulating insurer was within 20% of the Citizens premium, consumers are forced to switch.

that must be maintained throughout the life of the loan. The most well-studied criteria are the GSE's conforming loan limits, which limit mortgages based on the size of the loan balance at origination, and the FICO score criteria (Keys et al., 2010, 2012). Less well known are the financial stability ratings requirements that property insurers must meet, as discussed earlier. 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.

When selling or securitizing a mortgage with the GSEs, lenders have to pay an upfront fee called a guarantee fee (or g-fee). Prior to the financial crisis of 2008, this fee was uniform and did not vary by borrower risk characteristics. Following the crisis, there GSEs added additional charges based on the borrower's credit score and loan-to-value ratio at origination.[23] Importantly, these fees do not vary with other key features of risk. This includes measures of collateral risk or counterparty risk, including local house price risk (Hurst et al., 2016), as well as insurance counterparty risk. For example, lenders do not have additional fees to sell mortgages backed by properties that are insured by riskier property insurers.

3. Data

We combine data from a number of sources to obtain a comprehensive view of lending and insurance markets: (i) insurers' underwriting operations at the county level, financial statements and reinsurance relationships, as well as data on regulatory exams at the insurer level, (ii) insurers' financial strength ratings, and (iii) mortgage data.

3.1. Insurance Data

Insurer-County-Level Data: We use a novel data on homeowner underwriting operations in Florida. All homeowner insurers that operate in the state must report their *county-level* underwriting operations to the Florida Office of Insurance Regulation (FLOIR). We access this data through FLOIR's Quarterly and Supplemental Reporting System − Next Generation (QUASRng). The insurers report total premiums written, number of policies written, total coverage of the written policies, as well as policies transferred to and assumed from other insurers. The data are available at a quarterly frequency, so to bring it to the annual level, we use Q4 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, transferred policies, cancelled policies).

[23]See for example Fannie Mae's Pricing Matrix.

The data are publicly available for all companies doing business in Florida between 2009 and 2013, after which a court decision allowed companies to request that their information is not released to the public due to trade secret limits. After the decision, we do not observe the QUASR filings for State Farm Florida starting from 2014 Q1, and of three more companies starting 2017 Q1 (United P&C, Family Security and American Coastal). Starting 2019, we no longer observe the data for 19 more companies, and the number further grows. In Figure A.1 we show the percent of the premiums written by insurers missing from QUASRng, and we see that before 2018, less than 10% of premiums are missing, the number exceeds 36% starting in 2019. Therefore, we consider 2018 the last year for which county-level underwriting data is available.

Insurer Financial Statements and Operations Data: Every year, property and casualty (P&C) insurers file annual reports, which we access through Standard & Poor's Market Intelligence (S&P MI) database. From these filings, we access four types of information for each insurer: (i) data on underwriting operations in a given state and line of business, (ii) balance sheet data, (iii) data on regulatory actions against the insurer and (iv) data on reinsurance relationships.

(i) Underwriting data: Insurers report their underwriting activities for each state and business line that they operate in. This underwriting data contains information on total homeowners' premiums sold (which refers to the total sale of homeowners' policies) and total losses incurred (i.e., total amount spent on claims).

(ii) Balance sheet data: Insurers also report detailed financial statements as part of their regulatory filings, including balance sheets, regulatory capital positions, and the part of insurance liabilities ceded to or assumed from other insurers and reinsurers. These variables are all available at an insurer-year level.

(iii) Examinations and restatements: We collect data on regulatory scrutiny the company faces from the insurers' annual filings. Insurers must report annually the state which is responsible for their financial regulation (state of domicile), year of their last financial exam, and whether that financial exam resulted in restatement. These variables are all available at an insurer-year level. Financial exams are a proxy for regulatory strictness and are discussed at length in Tenekedjieva (2021). The domicile state regulators conducts exams to observe the insurers' financial state and assess if they are financially capable of honoring its liability obligations.

Exams must happen at least once every five years, but they can happen more frequently at the discretion of the regulator. The exams can have various outcomes, varying from no recommendations to the company being deemed insolvent and put into state receivership. In this setting, the only outcome we observe is whether the exam forced the firms to restate their financial statements. This outcome happens if during the exam the regulators found inconsistencies in the reported financial statements, and require that the insurer corrects them. Such restatements can trigger automatic review by rating agencies and are considered a bad outcome for the insurer. Thus, to proxy of regulatory strictness we check how often these exams take place, and how likely they are to result in a restatement.

(iv) Reinsurance relationships: Insurers also report information about the reinsurance contracts they maintain active. S&P MI further matches each reinsurer to their AM Best financial rating. Note that reinsurers' rating is separate from the insurers' financial strengh rating; it captures the ability of reinsurers to honor their contractual liabilities. We collect data on all reinsurance contracts for insurers that sell HO insurance in Florida in 2019.

We supplement the data from insurers' annual filings with a novel hand-collected data set on consumer complaints against each insurer. The information comes from FLOIR's annual reports, and we collect it for the years 2009 to 2018 for all homeowner insurers.

3.2. *Insurers' Financial Strength Ratings*

We obtain FSRs for all Florida insurers issued by the three rating agencies accepted by the GSEs in the period until 2018: AM Best, S&P and Demotech. Each rating for an individual insurer's includes the date, rating level (a letter) and whether the rating is first for the company, or affirming/upgrading/downgrading existing the most recent rating, and the date an insurer chose to longer be rated by the agency if needed. We collect each rating issued by Demotech from 2012 to 2021, and by AM Best and S&P from 2000 to 2021 from S&P MI. We further hand-collected Demotech ratings for Florida insurers from 2006 to 2012 using online archives.

3.3. *Insurance Pricing Data*

We obtain granular ZIP code-level data on insurance rates from Quadrant Information Services (QIS) for the period 2011 to 2020. The data cover 1,029 ZIP codes across Florida. As a representative product, we focus on a contract providing insurance coverage of $350,000 with a deductible of $1,000 on a 30-year old single-family home for an average credit profile household.[24] The QIS database tracks pricing data for the largest insurers selling HO insurance in a state. We observe insurance rates for about 29 insurers in Florida, who collectively hold about 70% of the market share by total premiums. For these insurers, we observe insurance rates for all ZIP codes within the state. The rates reported in the QIS database represent quotes rather than actual transaction prices, which is useful because quotes are closer to depicting insurers' supply schedule rather than equilibrium prices.

3.4. Mortgage Data

We use publicly available administrative data on mortgage applications and originations from the Home Mortgage Disclosure Act (HMDA). HMDA data includes the loan amount, location (census tract), an indicator for which entity purchased the mortgage, and some borrower characteristics including income, gender, and race. We limit the sample to first-lien purchase mortgages for single-family, owner-occupied homes. We look at two types of mortgages. First, we refer to "originated mortgages" as those which were originated in the calendar year of HMDA reporting.[25] For these mortgages, a purchaser is reported if it is sold within the same calendar year that it was originated. Second, we refer to "purchased mortgages" as those which were originated in a previous year but then sold in the calendar year of reporting.[26] While most mortgage are sold or securitized quickly, a number of mortgages are retained on balance sheet and sold later (Adelino et al., 2019).

We then aggregate the data to the county-year-purchaser level for each of these two types. We use the "purchaser type" and "loan type" variables to categorize mortgage purchasers into four groups: GSE, Ginnie Mae, other-private, and on-balance-sheet.[27]

We supplement the HMDA data with county-level information from the BlackKnight McDash dataset, a comprehensive, loan-level dataset on mortgages that includes information on mortgage characteristics, borrower characteristics (including FICO and property values), and mortgage performance (deliquency, default, prepayment). The data is compiled from mortgage servicers and accounts for approximately two-thirds of the overall mortgage market.We aggregate their information on borrower characteristics to the county-year level.

[24] These product features come close to a representative HO insurance contract in the U.S.: the median age of a home is 37 years and the average home costs $348,000.

[25] In the data, these are those loans classified as "action type" = 1.

[26] In the data, these loans are classified as "action type" = 6.

[27] Specifically, we identify GSE loans as those that are purchased by Fannie Mae, Freddie Mac, or Farmer Mac (purchaser types 1, 3, and 4). Other-private loans are those that are purchased by private financial companies (purchaser types 5, 6, 7, or 9). On-balance-sheet loans are those that are either not sold, or sold to an affiliate of the same bank (purchaser type missing, 0, or 8). Lasly, Ginnie Mae loans are those that are purchased by Ginnie Mae (purchaser type 2) or are separately classified as FHA- or VA- insured (loan type 2, 3, or 4). This classification is comprehensive, and every loan fits one of these four groups.

3.5. Final Data Creation

We combine these data to create two final samples. The first is an insurer-level panel on firm characteristics from their regulatory filings and their financial stability ratings. The second data set a county-level panel which combines insurance and mortgage information. We use the insurer-county level data to obtain the relative market shares of the different types of insurers in each county and year. We then merge in the collapsed mortgage data at the county-level. This data covers the 67 counties in Florida and also spans 2009-2018.

4. Insurance Market Dynamics

This section discusses how insurance markets have evolved in Florida, and factors that have contributed to the insurance market changes.

4.1. Broad Insurance Market Trends

We start by documenting how market shares have evolved for the three main types of insurers in Florida.

(i) Exit of traditional insurers. First, there is a large decline in the market share of insurers that only have financial stability ratings from AM Best and/or Standard & Poors (henceforth traditional insurers). Figure 2 shows that, at its peak in 2007, traditional insurers underwrote over $3 billion in premiums, which declines to $2.1 billion in 2018. This is a direct result of traditional insurers pulling back from underwriting. Figure 3 shows that on average 11% of in-force policies are cancelled or not renewed each year by traditional insurers. It also shows that exits are higher in high climate-risk counties, and that insurer exit is complemented by reduced underwriting of new policies.

(ii) Entry of Citizens and Demotech insurers. Second, we show that insurance does not completely disappear. The gap left by traditional insurers is filled by two types of insurers. (i) Citizens, the state-run insurer-of-last resort, overtakes a large burden of insurance intermediation. At its peak in 2011, Citizens market share was close to 20% of the overall market. It fell thereafter as a result of conducting several rounds of "depopulation", as we discuss in the next section. (ii) New insurers, those with financial stability ratings from the emerging rating agency Demotech (henceforth, Demotech insurers), have rapidly gained market share. We document a dramatic increase in their market share: from having a negligible presence in the 1990s, when they entered the market, their share rises to over 50% by 2018. Figure A.3 shows the histogram of Demotech premium shares in 2009 relative to 2018, showing that the entire distribution shifts right. An important source of Demotech insurers'

growth is through policies taken over from Citizens through the depopulation program. In other words, Citizens operates as a temporary stop-gap, a bridge between traditional and new insurers.

The increase in the market share of Demotech insurers is not unique to Florida but is part of a broader country-wide trend. Figure 1 shows the share of Demotech insurers across the US.[28] Demotech insurers have a market share of over one-third in the riskiest states in the US, including states in the south- and mid-atlantic region and the Gulf coast, and over one-fifth in the remaining low risk states.

4.2. Fragility of Demotech Insurers

Quality based on ex-ante metrics: We next compare the Demotech and traditional insurers across a range of financial and operational characteristics. Table 2 shows that Demotech insurers are of significantly lower quality than traditional insurers across most observable measures of financial and operational risks.

(i) Balance sheet and solvency. Panel A shows that Demotech insurers are 10 times smaller by total assets. The average Demotech insurer has $300 million of assets, while the average traditional insurer has over $3 billion. Demotech insurers have greater leverage and, importantly, have lower *regulatory* risk based capital (RBC) ratio. RBC ratio, which is the ratio of available capital to required capital, depicts insurers' solvency, i.e. whether an insurer is well capitalized relative to its risks. These risks encompass asset-side, liability-side, and overall business risks. While being above the regulatory cutoff, the average Demotech insurer has 57% lower RBC ratio than the average traditional insurer, and thus appears under-capitalized vis-a-vis underlying risks relative to peers.

(ii) Liabilities. Demotech insurers have riskier liabilities than traditional insurers. We first compare their loss ratios (the ratio of total claims paid to total premiums collected). Loss ratios are higher for Demotech insurers both in Florida (83% vs. 76%) as well as nationally, suggesting that Demotech insurers carry higher risks. However, the loss ratio can be high not only if an insurer insures riskier properties but also if it has lower pricing power. To tell the two apart, we separately examine risk and pricing behavior. We first rank counties by climate risk using FEMA's national risk index classification. We then consider three different measures of exposure to high risk counties: premiums share in high risk counties, policy share, and coverage share. Panel A of Table A.2 shows that Demotech insurers have higher exposure to riskier counties in Florida by all three measures.[29] Finally, Table 2 Panel

[28] Figure A.2 shows the states with the highest market share of Demotech insurers.

[29] We next examine pricing behavior in Panel B, which shows that Demotech insurers also have higher

B shows that Demotech insurers sell lower coverage per policy. Since insurance typically covers the full replacement cost of a house, this suggests that Demotech insurers cater to households that have lower value homes.

(iii) Operational diversification. Panel C shows that Demotech insurers are significantly less diversified than the traditional insurers across states and products. The average insurer operates in 3 states only (with 56% selling only in 1 state) and obtains 70% of its premiums from a single business line (homeowners' insurance). In contrast, the average traditional insurer operates in 27 states (with 10% selling only in 1 state), and obtains only 25% of its premiums from homeowners' insurance line, i.e. they operate across many other product lines. Panel C also shows that Demotech insurers belong to insurance groups that are themselves less diversified. In particular, Demotech insurers operate in groups with a small number of other operating companies (6 vs. 18) and where they represent the majority of assets (57% vs. 25%). They are also on average more likely to be stock companies rather than mutuals. In sum, Demotech insurers are less diversified in three dimensions: geographically, across business lines, and in their group structure.

(iv) Assets. Perhaps because of their riskier liabilities, Demotech insurers tend to allocate slightly higher proportion of assets to safer securities. For example, their allocation to equities is slightly smaller than traditional insurers (9% vs. 14.6%). Within bonds, they invest less in high yield bonds (NAIC Level 3+) than the traditional insurers, although both groups have only a small allocation towards riskier bonds. Similarly, the weighted average maturity of their bond portfolio is shorter than traditional insurers (9 vs. 16 years). However, even though the asset-side of Demotech insurers' balance sheet is less risky, overall they have higher risks relative to capital as seen from their significantly lower RBC ratios.

(v) Reinsurance. Panel E shows that Demotech insurers more heavily rely on reinsurance than traditional insurers. The average Demotech insurer cedes close to 50% of its premiums to reinsurers, compared to less than 15% for the average traditional insurer. On the one hand, reinsurance could be an effective way to reduce risk exposures. On the other hand, heavy reliance on reinsurance can introduce counterparty risk and pro-cyclicality as reinsurance prices increase substantially after large natural disasters (Froot and O'Connell, 1999). These concerns are particularly relevant here because a smaller proportion of Demotech insurers' reinsurance partners have a good rating themselves.[30] Moreover, Demotech insurers have a larger share of their premiums concentrated in just one reinsurer as seen from significantly larger fraction of premiums ceded to a single reinsurer (13% versus 3.9%).

market power, consistent with their greater market share. This potentially explains why loss ratios do not fully reflect the extent to which Demotech insurers' liabilities are riskier than traditional insurers'.

[30] We obtain the AM Best ratings of reinsurers. A "good" rating is defined as "A" or above.

Insurer insolvencies: 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. None of the traditional insurers were liquidated.

For external validity, Table A.1 provides broader evidence on the relative quality of Demotech insurers compared to traditional insurers. We focus on insurers that operate in the top 10 climate risk states (defined as states with the highest property damage per capita as reported in SHELDUS). We show that the average financial characteristics for both groups differ significantly. We also find large differences in insolvency rates in panel (f), suggesting that the quality gap between Demotech and traditional are widespread, extending beyond Florida.

4.3. Financial Stability Ratings

We next consider whether the large differences in observable characteristics are reflected in the financial stability ratings across rating agencies. Figure 4 shows that there is limited dispersion in the financial stability ratings assigned by Demotech and that these ratings are almost always high enough to meet GSE requirements. Ratings are either A″ (Unsurpassed), A′ (Unsurpassed), or A (Exceptional), which translates into an (ex-ante) 10-year default probability between 2% and 10% according to Demotech's estimates, lower than the actual insolvency rate of close to 20% in Table 3.[31] In contrast to Demotech, ratings assigned by traditional agencies have higher dispersion and span the full range of the distribution, including ratings low enough to not meet GSE minimum eligibility requirements. This is despite the fact that traditional insurers are higher quality on average.

Counterfactual AM Best Ratings of Demotech Insurers: We next develop an AM Best rating replication model by mapping observable insurer characteristics to AM Best financial stability ratings. Using the model, we predict counterfactual AM Best ratings for Demotech insurers. 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. $\boldsymbol{X}_{it}$ is a vector of characteristics and $\boldsymbol{\beta}$ are the corresponding loadings on these characteristics. $\boldsymbol{X}_{it}$ includes past three-year average values for each characteristic to account for the slowness

[31] See Demotech Credit Ratings Performance Measurement Statistics (2023).

in rating changes.[32] The sample only includes insurer-year observations for which we have an AM Best rating available.

We choose the characteristics following the literature (Koijen and Yogo, 2015). 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 corresponds to factors AM Best itself considers in assigning ratings, as described in publicly available reports. Table A.3 shows three different model specifications. Column I shows the full model, which includes all relevant characteristics. Column II shows characteristics selected using the LASSO technique. Column III shows the characteristics selected if only the significant variables are retained from the full model. 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 the counterfactual AM Best ratings for Demotech insurers:

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

We 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. $\boldsymbol{X}_{DEM}$ refer to the corresponding characteristics. For example, if we observed the last "A" rating for an insurer in 2012, $\boldsymbol{X}_{DEM}$ would refer to average values computed using years 2010-2012 and $AM\widehat{BFSR}_{DEM}$ 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 $AM\widehat{BFSR}_{DEM}$ would show the counterfactual AM Best rating for the year 2018.

Figure 5 shows the counterfactual AM Best ratings for all Demotech insurers. For each model in Table A.3, we numerically simulate 1,000 predicted values by bootstrapping the sample, while preserving the within-insurer correlation. Each dot shows the average predicted value across all simulations and the bar shows the 90% confidence interval constructed using bootstrapping.

The results suggest that a large fraction of Demotech insurers would not meet GSE eligibility with our estimated counterfactual AM Best rating. In particular, our estimates imply that close to 67% of Demotech insurers would not meet Freddie Mac's eligibility requirement and 21% would not meet Fannie Mae's requirement (at a 90% confidence level).

[32]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. The conclusions remain similar.

Moreover, only 10% of the Demotech rated insurers (these are depicted in the right hand side of the graph) appear to be comfortably meeting AM Best's GSE eligibility criteria. Overall, these results strongly suggest inconsistencies in the GSE eligibility requirements across rating agencies. These inconsistencies could encourage ratings shopping, in particular among poor quality insurers who would not otherwise meet GSE eligibility.

4.4. Regulatory Supervision

We next compare the extent of regulatory supervision for Demotech and traditional insurers along two dimensions: financial supervision and market conduct. We focus on financial oversight of insurers domiciled in Florida, using financial exams as a proxy of regulatory supervision (as described in section 3). First, we find suggestive evidence of higher regulatory forbearance over time. Panel A of Table 4 shows that both likelihood of exams, and negative outcomes after the exams, such as financial report restatements, have decreased over time. Second, we find that despite Demotech insurers carrying more risk, 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 account for a disproportionately large fraction of consumer complaints, suggesting that they face more lenient market conduct supervision.

4.5. Explaining the growth in Demotech share

There are two broad classes of potential explanations behind why we see the market share of Demotech insurers increase so dramatically while traditional insurers' market share declines. The first explanation is a "supply side" one. Traditional insurers may be unwilling to underwrite risks in Florida, so they cancel policies and intentionally shrink their exposure.[33] In these cases, the households whose policies were cancelled by the traditional insurers are left with two options: obtaining a policy with a Demotech company in order to stay with a GSE-eligible insurer, or if that is not possible, going to the residual market (Citizens).

Alternatively, the second explanation is a "demand side" one. In this explanation, Demotech crowds out traditional insurers by under-pricing risks. Households may be price sensitive because they need to pay to insure the full property, but only have equity in part

[33] There is anecdotal evidence of this occuring in Florida, such as Farmers. See "Citing climate change risks, Farmers is latest insurer to exit Florida." July 12, 2023. Washington Post.

of it, or because they cannot distinguish between high and low quality insurers and then choose to go with the lower-priced product. From the perspective of the servicer of the mortgage, as long as households choose GSE-eligible insurers, their servicing obligation is met. Thus, Demotech insurers' ability to provide insurance at a lower cost while maintaining GSE-eligibility will see their market share grow at the expense of traditional insurers.

We find suggestive evidence of both explanations. Consistent with demand-side explanation we see in Table A.4 that once we account for risk, Demotech insurers sell products for around $38 dollars less than traditional insurers (per $100k of coverage), and their premia has grown 1.3 percent slower over the time period. Consistent with the supply-side explanations, we see in Figure 3 that traditional insurers are limiting their footprint by limiting new underwriting and cancelling policies, with cancellations increasing with the climate risk score of the county. While quantifying the cause of the expansion of Demotech is beyond the scope of the paper, what is key for both stories is that the expansion of Demotech is enabled by GSE eligibility requirements. The rest of the paper will focus on the implications of this policy choice.

5. Mortgage Market Dynamics

In Section 4, we show that Demotech-rated insurers are more fragile than traditional ones despite having high financial stability ratings. In this section, we explore what this fragility means for mortgage markets.

5.1. Who Bears Insurance Counterparty Risk?

Demotech-rated insurers are more likely to become insolvent than traditional ones, creating counterparty risk for mortgage lenders. As discussed in Section 2, lenders are listed as beneficiaries to the property insurance contract. Insurance lets lenders hedge disaster risks by preserving the collateral value of properties securing the mortgages. However, unreliable insurance could result in a situation where large climate shocks may cause property damage at the exact time that the property insurer becomes insolvent, increasing household default incentives and losses given default. Therefore lenders have strong incentives to manage their counterparty risk exposure to lower quality insurers.

Securitization is an important way that lenders can mangage their counterparty risk exposure. The key to this strategy is that both Fannie Mae and Freddie Mac accept financial stability ratings from Demotech insurers (Table 1). If lenders are truly worried about collateral risk and insurance quality, we may expect them to sell mortgages that bear more exposure to such insurers.

We first test whether the likelihood that lenders sell mortgages to the GSEs varies with Demotech insurers' market share. To do this, we run the following regression:

$$GSE\_Share_{c,t} = Demotech\_Share_{c,t} + \delta_c + \gamma_t + X_{ct}\Gamma + \varepsilon_{c,t} \tag{3}$$

The dependent variable $GSE\_Share_{c,t}$ refers to the dollar volume of mortgages sold to Fannie Mae or Freddie Mac divided by the dollar volume of all mortgages from county c in year t. This universe spans mortgages that were originated in calendar year t, as well as mortgages that were originated in prior years that were sold in the calendar year t.[34] The key regressor of interest, $Demotech\_Share_{c,t}$, refers to the total premiums collected by Demotech-rated insurers divided by premiums collected by all insurers in county c and year t. We also include county and year fixed effects (δ_c, γ_t), to absorb aggregate trends over time and time-invariant county characteristics. Standard errors are clustered at the county level.

Table A.5 reports the results of estimating Equation 3. Column (1) of Table A.5 shows that a 100 percentage point increase in the premiums share is associated with a 30 percentage point increase in the share of mortgages sold to Fannie Mae or Freddie Mac. To interpret this coefficient, Demotech's market share grew by 20 percentage points over the period between 2009 and 2019, implying that this brought a 6 percentage point increase in securitization. This coefficient tells us that the GSEs do bear disproportionate exposure to Demotech insurers, but it does not explain what drives this correlation. We consider for observable differences in borrower composition by including time-varying county controls for average log income, FICO credit score, and property value of new mortgage borrowers.[35] As Column (4) of Table A.5 shows, we see little change to the results when including these controls for borrower quality. The fact that the coefficient does not change much between Column (3) and Column (4) suggests that the correlation is not driven by observable decline in borrower quality, though of course it does not speak to the possibility of unobserved characteristics.

To better understand what drives the correlation between Demotech shares and GSE shares, we include additional controls and fixed effects sequentially. The coefficient is similar in Column (2) after adding year fixed effects, which control for any unobservable aggregate trends over time. However, the coefficients shrink in Column (3) when adding county fixed effects, suggesting that much of the relation between property insurers and securitization is between-county, not within-county.

[34] This refers to both "activity type = 1 " and "activity type = 6" mortgages in HMDA.

[35] These variables are county-year average constructed from the loan-level McDash and HMDA data.

To quantify GSEs exposure to Demotech insurers, we provide Demotech market share for different coverage bands. Because our data is at the insurer-county-year level we first compute the average coverage per policy offered by each insurer in every county it operates in. We then create groupings based on the average coverage-per-policy, and the total share of policies provided by Demotech insurers in that coverage bucket. Figure 6 shows that there is a strong negative relationship between Demotech share and coverage per policy. Moreover, Demotech share is over 90% for counties, where household have purchased on average below \$500,000 of coverage, at a time when the average conforming loan was around \$417,0000.[36] This supports the earlier evidence that borrowers in the conforming loan segment are more likely to obtain insurance from Demotech insurers.

There are a number of explanations for the correlation between GSE share and Demotech share. There are two in particular that we would like to unpack further. a) Lenders offload risks to GSEs: that lenders strategically try to reduce their exposure to Demotech insurers by selling the mortgages to the GSEs, and b) Borrower selection: that lenders simply reduce their exposure to higher risk borrowers by selling to the GSEs, and being a high risk borrower is correlated with obtaining insurance from Demotech insurers.

5.2. Incentives to Offload Risks - Citizens Depopulation Natural Experiment

To distinguish between these two channels, we use a natural experiment where we observe lenders' GSE allocation responses to exogenous drop in insurance quality. The natural experiment more directly addresses the possibility that we are capturing incentives to offload risk due to borrower selection rather than the causal effect of insurance. To do so, we exploit a time-varying policy instituted by Florida's insurer-of-last-resort (Citizens), and conduct a sharper test based on insurance contract flows.

The policy we study is Citizens' scheme to "depopulate" its balance sheet. As described in Section 2, Citizens provides financial incentives for private insuers to "take out" policies from its balance sheet, meaning that the policy is transferred from Citizens to the private insurer. That is, private insurers assume the policy, receive the premiums paid and are responsible for paying out any claims. While we do not have detailed micro data on the individual policies that are transferred from Citizens to private insurance, we do have aggregate data on insurer participation, and we observe the policy flows in the FLOIR QUASAR data at a county level. Demotech insurers dominate the depopulation program. Of the 40 insurers that participate in the Depopulation Scheme, 39 are Demotech-rated. Furthermore, Figure 7

[36] The baseline conforming loan limit (that is outside high-cost areas) was 417,000 between 2006 to 2017. It increased in 2017 to 424,1000, and to \$454,100 in 2018.

shows that almost 50% of all Demotech insurers participate in the depopulation scheme. By contrast, less than 5% of traditional firms participate.

The Depopulation program is also very large. Looking at the policy flows in Panel A of Figure 8, we see that at its peak in 2013, Citizens transferred on net more than 200,000 policies. By using these insurer flows, we can focus on households who switch their insurance from Citizens to a Demotech-rated insurer. In other words, since the insurers which bid on Citizens policies were most likely to be rated by Demotech, we obtain variation in Demotech-share that is driven by existing mortgage borrowers moving into the balance sheets of Demotech insurers.

On the mortgages side, the HMDA data allow us to distinguish between newly originated mortgages that were sold in the same calendar year of origination, and mortgages that were originated in prior years but then sold in a different year. We can therefore look at *existing* mortgages, and see whether lenders are more likely to try and sell those mortgages following a large depopulation effort. For mortgage borrowers that are impacted by the Depopulation scheme, since the mortgages have already been originated, lenders have limited options when it comes to managing that counterparty risk exposure.[37] This is why we focus on the securitization margin; lenders can try to sell the mortgage throughout the life of the loan, not just at origination.

We consider the following specification:

$$log(GSE)_{c,t} = \alpha + \beta log(Demotech)_{c,t} + \gamma_c + \delta_t + X_{ct}\Gamma + \varepsilon_{c,t} \tag{4}$$

The dependant variable $log(GSE)_{c,t}$ refers to the log of the total dollar value of mortgages that are sold to the GSEs in county c in year t. The independent variable $log(Demotech)_{c,t}$ is the net number of insurance policies transferred to Demotech insurers.[38] The specification includes county fixed effects (δ_c) and year fixed effects (γ_t) to address any aggregate time trends or time-invariant county characteristics. We include as a control X_{ct} the average income of borrowers with existing mortgages that get sold in calendar year t but were originated prior to t. The coefficient β can be interpreted as an elasticity – a 1% increase in policies transferred to Demotech brings a β% increase in the dollar value of mortgages sold to the GSEs.

We run this regression with county fixed effects to exploit the randomization of the

[37]At origination, lenders can try a number of strategies to manage their counterparty risk exposure. For example, they could limit which insurers borrowers can use as a condition of the mortgage; alter the terms of the mortgage (i.e. rate, downpayment) for borrowers that choose to buy from lower quality insurers; or completely pull-back from mortgage origination in high risk areas, where access to insurance is more valuable.

[38]Here, net policies refers to policies received by other insurers minus any transferred to other insurers.

timing. This allows for the possibility that Citizens does not randomly choose which counties get Depopulated; this is possible if, for example, Citizens depopulates in high climate risk counties– the ones where its balance sheet tends to be large to begin with. We therefore run this specification within county, and exploit the exogenous timing.

Identifying Assumptions: With this specification, we seek to isolate variation coming from a switch in insurance policy for *the same* borrower, in order to limit the possibility that the results on GSE purchases are not driven by unobserved differences in the selection of borrowers. To validate this interpretation, we make the following identifying assumptions.

First, we assume that the policies transferred to Demotech insurers comes from Citizens. We validate this assumption in Panel B of Figure 8, which shows that policies transferred away from Citizens in a given county in a given year correspond almost one-for-one to policies transferred to Demotech-rated insurers.

Second, we assume that there is no adverse selection in which types of policies are subject to the Depopulation. 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. We argue that the structure of the program limits this concern. Insurers can choose which policies to assume from Citizens, and they are unlikely to choose worse quality homeowners that cannot make insurance payments; if anything, they are likely to choose higher quality borrowers. Furthermore, the timing of the switch from Citizens to private insurers is not dictated by the borrower or the insurer–it is governed by the Depopulation schedule set by Citizens. So the timing of the switch is also unlikely to be driven by risk characteristics of the household.

Third, 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.

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 β 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 value of mortgages sold.

Results: Table 5 shows the results of estimating Equation 4. In Column (1), we estimate that a 1% increase in policies transferred to Demotech brings a 0.03 percent increase in mortgages sold to the GSEs. This estimate does not change much in Column (2) after controlling for average borrower income.

To interpret economic magnitude of this elasticity, we consider the following hypothetical scenario. Suppose Citizens conducts a takeout of 100,000 policies in 2020. This number is similar to the depopulation efforts in 2013 or 2014, and far below its peak in 2012 (200,000), and below the number currently being considered by Citizens (300,000).[39] Our elasticity suggests that such a program would lead to a 24% increase in the dollars securitized with the GSEs. This is because 100,000 represents an 800% increase in policies transferred relative to 2019, our last year of data. Multiplying this by 0.03 gives us 24%.

While on its face the estimated magnitude may seem low, the reality is that the sheer size of the Depopulation program is large enough for even a small elasticity to have large effects on the GSE's counterparty risk exposure. Overall, our results suggest that mortgage lenders actively manage insurer counterparty risk by offloading mortgages with high insurer counterparty risk to the GSEs.

6. Quantifying GSE Risks

In section 4 we show that the quality of insurance provision in Florida has deterioriorated, and in section 5 we show that lenders are aware of this counterparty risk and offload seasoned mortgages exposed to worse insurers when they can. In this section, we seek to understand the broad effects of unpriced insurance counterparty risk. The first question we seek to answer is the overall size of the *implicit transfer*. If the GSEs bear default risk which is not priced in the g-fees they charge, this induces an implicit transfer. We therefore want an estimate of how insurance fragility translates into direct losses for the GSEs, and what their overall exposure is to this risk.

The second question we seek to answer is whether there are real effects of the GSE's choices on the efficient allocation of credit. The idea here is that there are risks which households lenders do not have to internalize because they don't face full risk-based pricing when their loans are backed by the GSEs. This may induce households to locate more in high risk areas, because that risk is not being priced. We therefore seek to estimate how many extra mortgages are originated in high risk areas because the GSEs accept unpriced counterparty risk. Both of these questions require a new identification strategy We take each question in turn. Section 6.1 focuses on how we quantify the GSE's losses. Section 6.2 explains how we quantify the size of the distortion in credit supply.

[39] Tampa Bay Times, "Florida Citizens customers: Check mail or face costly insurance switch", September 19, 2023.

6.1. The Implicit Transfer

We begin by describing the empirical tests we use to quantify the size of the implicit transfer. We have shown earlier that insurers at high risk of insolvency now dominate insurance markets in Florida, and particularly serve the conforming segment. To round out this argument, we are interested in now showing the flip side – that insurer insolvency after storms make mortgage default more likely and thus create losses for the GSEs.

6.1.1. The Path of the Hurricane

To quantify the size of the GSE's implicit transfer, we want to know how much mortgage default is triggered by exposure to insolvent insurers. This is the loss the GSEs face, because they must still pay out to MBS investors if the underlying borrower defaults. To do so, we would ideally like to obtain random variation in insurance fragility after climate events, and identify the causal effect of that insolvency on default for GSE borrowers. Importantly, to isolate the effect coming from insurance, we would ideally like to keep underlying borrower characteristics fixed.

Our identification strategy exploits the landfall of Hurricane Irma, which landed in Florida in August 2017. Hurricane Irma led to a weakening of the insurance sector, with a number of insurers experiencing stress and even insolvency after the storm.[40] We argue that Hurricane Irma creates random variation in insurance fragility. There are some Demotech insurers which happened to suffer major losses in the places that Irma hit; but this stress means they have limited means to pay out claims anywhere in their portfolio. Because many areas of Florida which are exposed to hurricane risk were not hit by the storm, there are also other Demotech insurers that are similar in financial and operational metrics and tend to operate in high risk areas which do not go insolvent. Therefore, we argue that Hurricane Irma induces random variation in insurance fragility. Table A.6 verifies this assumption by showing that borrowers in counties exposed to insolvent insurers are similar on observables to borrowers in counties that are not, including the insurance market characteristics. We can therefore look at how default after Hurricane Irma differs by exposure to insolvent insurers using a standard continuous-treatment difference-in-differences framework.

6.1.2. Conforming Loan Limit

In addition, we would also like to understand how securitization impacts the subsequent performance of the mortgage in places exposed to fragile insurers. We will therefore look

[40] 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.

at mortgages that are within narrow bands of the conforming loan limit. The identification assumption here is that borrowers just above or just below the conforming loan limit are are similar in unobservable characteristics, and only vary in their eligibility for securitization. We can therefore compare otherwise similar borrowers that happen to be conforming borrowers, and happen to be jumbo borrowers. Figure A.5 shows that defaults for conforming and jumbo loans within a 5% band of the conforming loan limit trend similarly prior to the storm, thereby validating this assumption.

6.1.3. Empirical Test and Hypotheses

We therefore consider the following continuous treatment difference-in-differences design:

$$Y_{l,c,o,t} = \beta_1(\text{Post Irma}_t \times \text{Insurance Fragility}_c) + \delta_c + \delta_t + \delta_o + \gamma' X_{l,c,t} + \varepsilon_{l,c,t}. \tag{5}$$

We consider mortgages originated five years prior to Irma, between 201208-201708, and track their annual performance two-years before the storm and two-years after the storm, from 201509 - 201909. We limit the sample to mortgages within a narrow band of the CLL (we limit to 10% and 5%) We then run the continuous treatment difference-in-differences for conforming loans (loans below the CLL) and jumbo loans (loans above the CLL) separately. Post Irma is a dummy that equals 1 after the landfall of Irma $InsuranceFragility$ is a continuous variable that we measure by obtaining the ex-ante share of premiums as of year-end 2016 in each county underwritten by an insurer that went insolvent after Irma. The idea of this variation is that households hit by Irma that are exposed to fragile insurers are less likely to have their insurance claims paid; for some of these borrowers, the size of the property damage is high enough to induce mortgage default.

The vector X includes borrower-level controls for FICO, DTI and LTV. We also include a control for the direct effect of property damage induced by the storm on default: Post Irma$_t \times$ log (damages), to isolate the effect coming from insurance fragility. Property damages are those incurred within 3 months after the hurricane and are calculated from SHELDUS. Our outcome variable Y is an indicator that equals one if the mortgage is in default at time t and never recovers. We include default, foreclosure, or REO, plus three missed payments which never become current again. We include county, year-month, and origination cohort fixed effects. Our coefficient of interest is β_1, which measures the increase in mortgage default after Irma in places with more insurance fragility relative to places with less insurance fragility.

We have two predictions. Our first prediction is that $\beta_1 > 0$ for conforming loans. Figure 6 shows that conforming borrowers match with Demotech insurers. If it is our contention that 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.

Our second prediction is that $\beta_1 \approx 0$ for jumbo loans. Even though these jumbo loans are in counties exposed to insolvent insurers, Figure 6 shows jumbo borrowers are far less likely to obtain insurance from Demotech companies. Therefore, it should be the case that default for jumbo borrowers should not vary with insurance market fragility, since they are not as likely to have Demotech insurance policies.

6.1.4. Results

Table 6 shows our results. Consistent with our hypothesis, we find that conforming loans default more after Irma in areas with fragile insurers. We see no significant change in default for jumbo borrowers. The results hold for both mortgages within 10% of the conforming loan limit, and within 5% of the conforming loan limit. This suggests that our results are driven by insurance market dynamics rather than any unobserved differences in borrower type or the independent effect of the storm (which is also unlikely to vary by conforming or jumbo).

The identifying assumption for this test is that there are parallel trends between counties with more exposure to insurer fragility and counties with less exposure to insurer fragility. That is, the change in default for borrowers in counties with low exposure to insurance market fragility is a valid counterfactual for those borrowers in counties with high exposure to insurance market fragility. Figure A.5 supports this assumption, showing that there are limited pre-trends in delinquencies prior to Hurricane Irma for either jumbo or conforming loans. The threat to identification is a time-varying, county-specific shock that affects default after Irma and may be correlated with county-level exposure to insolvent insurers. A natural worry in this context is 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 default rather than insurer fragility. Another concern is that worse quality borrowers may have chosen to have relationships with the insurers that went insolvent, or that the traditional insurers can cherry pick the best quality borrowers.

Table A.6 shows that the average characteristics of borrowers and insurance markets in places with both low and high insolvency exposure. We use households in 2015, two years prior to the storm, to show how characteristics vary. We find that borrower and insurance market characteristics are quite similar for both sets of counties. Furthermore, concerns that insolvent insurer share may be endogenous are also alleviated by the differential results for conforming loans and jumbo loans within the narrow band of the conforming loan limit. If all of our results were driven by areas exposed to insolvent insurers that have worse storm outcomes, with the insurer playing no role, we would also expect jumbo loans in such areas to experience heightened default. It is unclear why the direct effect of the storm would change around the conforming loan limit. Similarly, it is not clear that the conforming loan limit should impact how traditional insurers cherry pick policies; insurance behavior around the conforming loan limit is also unlikely to change. Because we see divergent patterns for conforming loans and jumbo loans, this suggests that our results are driven by insurance market fragility.

Taken together, our results suggest that insurance fragility caused a 27bps increase in defaults in the conforming segment. This is a sizeable fraction (70%) of the baseline default rate for conforming loans during the pre-period (38.6 bps). 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.[41] We quantify the exact size of the implicit transfer in subsection 6.3.

6.2. Excess Credit Supply

We will now seek to quantify the distortion in mortgage origination created by the GSE's policy to accept insurance counterparty risk without pricing for it. We are particularly interested in whether this policy choice leads to excess mortgage origination in the conforming segment compared to what would be optimal. Excess origination would have welfare implications, since that implies sub-optimal adaptation to climate risks via more lending in high risk areas. If households in the conforming segment do not face full risk-based pricing, they may have incentives to locate sub-optimally because they do not completely internalize the risks ex-ante– this can be thought of as a type of "ex-ante moral hazard."

However, quantifying the distortion in new mortgage origination is challenging. For example, we cannot use the Depopulation identification strategy from Section 5; for that strategy, we relied on an exogenous switch in insurers for *existing* mortgages that banks had already originated in prior periods. Ideally, what we would like to know is whether a bank would be more likely to deny a loan for the same borrower if she were randomly attached to a Demotech insurer instead of a traditional insurer. In the spirit of this intuition, we consider whether mortgage denials are more likely to be sensitive to Demotech share in the jumbo segment relative to the conforming segment, controlling for borrower characteristics. Table A.7 shows this exact test, and indeed we see that lender denial rates are insensitive to Demotech share in the conforming segment, and very sensitive to Demotech shares for the jumbo segment. There is, therefore, an unambiguous reduction in credit supply in the

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

jumbo segment in places that have a high Demotech presence, with no similar sensitivity for the conforming segment. However, what is challenging about this test is that there may be other unobservable characteristics about jumbo borrowers in Demotech counties that may be driving lender denial decisions. Extensive loan-level controls are limited for mortgage applications which are denied by lenders. It is therefore difficult to say that these denials are caused by insurance market risks. We therefore consider a more nuanced test for lender screening of insurance counterparty risk, which fixes the fundamentals of the borrower.

6.2.1. Insurance Fragility and Screening around the Conforming Loan Limit

We are interested in understanding whether lenders deny mortgage applications that are likely to be exposed to fragile insurers. This therefore requires a change in insurance market fragility that is exogenous to other borrower characteristics that may impact lender screening. We obtain this variation in two steps. First, we argue that insolvencies triggered by Hurricane Irma lead to a change in insurance market dynamics; that is, the realization of Hurricane Irma and insurance market stress brings an exogenous change in the willingness of different insurers to underwrite new policies in different areas. Places exposed in particular to insurers under stress or insolvency risk will likely see a change in insurance market dynamics. We therefore seek to understand two questions; a) who ends up underwriting insurance in those areas and whether it contributes to insurance market fragility, and b) what happens to mortgage screening.

The second component of the test also exploits the conforming loan limit. We want to understand in particular what happens *in the conforming segment*, and what happens in the jumbo segment. Lender behavior in the jumbo segment reveals optimal screening when they are forced to internalize the full risk of making a loan. We can therefore understand whether screening is lax in the conforming segment by comparing lending decisions in that segment to how lenders internalize risks in the jumbo segment. Because we are looking within a narrow band of the conforming loan limit, differences between the two can highlight how the ability to securitize the mortgage changes lender screening behavior rather than differences in borrower characteristics. This test is inspired by the literature (e.g. Ouazad and Kahn (2021); Adelino et al. (2023). We specifically test whether lender denial rates are sensitive to an exogenous measure of insurance fragility in the jumbo segment, and whether this differs in the conforming segment.

We also look at insurance market dynamics in each segment. Which insurers underwrite new policies for conforming borrowers after Irma in fragile areas; and whether they are different from the insurers underwriting new policies for jumbo borrowers after Irma. Insurance companies should not be influenced by the conforming loan limit, and so any specific changes around the conforming loan limit are likely to be outcomes driven by lenders' screening behavior.

6.2.2. Changes in New Underwriting in Insurance Markets

We consider the following continuous treatment difference-in-differences design. It is similar to Equation 5 with a few differences to account for the variables being considered and the setting:

$$DemotechShare_{c,t} = \beta_1(\text{Post Irma}_t \times \text{Insurance Fragility}_c) + \delta_c + \delta_t + \varepsilon_{c,t}. \tag{6}$$

For insurance markets, we consider two outcome measures of Demotech shares. We first consider the share of new insurance policies that are underwritten by Demotech insurers. Since we are interested in the flow of new credit origination, it therefore also makes sense to consider which companies underwrite insurance policies for these new borrowers. 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. We limit to policies underwritten between 2015-2018, two-years before the storm and one year after Irma.[42] Our specification includes county and year fixed effects.

We also seek to run the regression separately for conforming and jumbo individuals. Doing this split is less straightforward for insurance markets than for mortgages because we do not have individual-level data, meaning we cannot directly limit our insurance data to households that are actually conforming borrowers based on their loan amounts. We therefore rely on a proxy based on coverage-per-policy measures from the Quasar data. Insurers whose average coverage-per-policy in a county for new polices is below the conforming loan limit are more likely to be attached to conforming borrowers. Similarly, insurers whose average coverage-per-policy in a county for new policy is above the conforming loan limit are more likely to be attached to jumbo borrowers. We look within a 10% band of the conforming loan limit, but do not go below that threshold because the scope for misclassification is higher as one gets closer to the conforming loan limit band.

We have two predictions for this test. First, we expect $\beta_1 > 0$ for the segment that is likely to be conforming. This may seem surprising at first, because our shock comes from Demotech insurers going insolvent, which would have a direct effect of reducing their overall market share. However, after Irma when the insurance fragility event is "realized", we also expect there to be hesitation in the willingness of traditional insurers to underwrite new policies. This is consistent with the patterns in Figure 3, which shows traditional insurers limiting new

[42]We cannot look at two years after Irma because the reliability of our QUASAR data ends in 2018.

underwriting in Florida. If this is indeed the case, then we may actually expect Demotech market shares to increase for new policies. Second, we expect $\beta_1 < 0$ for the segment that is likely to be jumbo. This again may seem surprising because insurance companies have no reason to care about the conforming loan limit. However, if it is our contention that the realization of Hurricane Irma and subsequent stress in insurance markets is salient to banks, then it should be the case that lenders do not allow new jumbo borrowers to be insured by Demotech companies. That is, they either limit the insurance choices of borrowers to traditional insurers, or they deny loans that can only be insured by Demotech insurers. Either of these would manifest as Demotech share of new policies going down in the jumbo segment in equilibrium.

Table 8 shows the results from running this specification. Consistent with our predictions, 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. These results hold for coverage that lies within a 10% band of the conforming loan limit. 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.

These patterns are difficult to rationalize based on insurers' behavior alone, because it is not obvious why traditional insurance carriers would have differential preferences around narrow bands of the conforming loan limit. These results suggest that lender behavior is likely playing an important role in determining insurance product market outcomes.

6.2.3. Changes in Mortgage Denials in Insurance Markets

We now show the counterpart to Equation 6 by examining mortgage credit supply. We specifically consider the following specification:

$$\text{(7)} \qquad Denied_{l,c,t} = \beta_1(\text{Post Irma}_t \times \text{Insurance Fragility}_c) + \delta_c + \delta_t + \gamma' X_{l,c,t} + \varepsilon_{c,t}.$$

We limit our sample to mortgage applications made between 2015 and 2019, two-years before and after Hurricane Irma. We limit to mortgage applications within 10% and 5% of the conforming loan limit. Our variable $Denied_{l,c,t}$ is a dummy variable that equals one if the mortgage application was denied by the lender. We include county and year fixed effects. Our controls in X include loan-level borrower characteristics (log income, debt-to-income ratio), as well as a control for the direct effect of the storm ($PostIrma \times logdamages$). Our coefficient of interest, as earlier, is β_1, which measures how much mortgage denials increase after Irma in places where insurance markets are fragile. As earlier, we run this test separately for conforming and jumbo loans.

We have two predictions. For conforming loans, we expect $\beta_1 \approx 0$, because lenders have limited incentives to change their screening behavior for mortgages which can be securitized. For jumbo loans, however, we expect $\beta_1 > 0$, because lenders either have more incentives to screen for insurance counterparty risk or, given the increase in insurance market fragility associated with the landfall of Hurricanne Irma, lenders' tendency to screen would result in higher denials than before.

Table 7 shows the results. Consistent with the predictions, we see no change in lender screening behavior for mortgages which can be sold to the GSEs. If anything, mortgage denials exhibit less sensitivity to insurance market fragility after Irma. This result holds for mortgages regardless of which bandwidth we consider, and is robust to controlling for borrower incomes and debt-to-income ratios. However, for mortgages just above the conforming loan limit, we see that lenders significantly tighten credit after Hurricane Irma, particularly in places that are exposed to insurance market fragility. We see that mortgage denials significantly increase in the jumbo segment in fragile areas, regardless of which bandwidth we consider around the conforming loan limit.

6.2.4. Understanding the Flow of New Mortgages and New Insurance Policies

What explains the two sets of results in Table 8 and Table 7? The picture that emerges is that, in the segment of the mortgage market where lenders have limited incentives to actively screen for risks, we see a growth in the market share of fragile insurers, even after the insurance fragility event is realized. That is, right after the Hurricane hits and insurance markets undergo stress, we see no change in mortgage origination in those areas, even though we see the market share of fragile insurers expand. However, in the segment of the mortgage markets where lenders have large incentives to actively screen, we see a significant reduction in credit supply, as well as a reduction in the market share of fragile insurers. That is, we actually see a statistically significant change in lender screening behavior. The two pieces together suggest that jumbo borrowers are likely being encouraged by banks to obtain insurance from traditional insurers, and that those jumbo mortgage borrowers that may only have had access to fragile insurers were denied a mortgage.

These results are unlikely to be driven by the choices of insurance companies choosing "better" risks, since the conforming loan limit does not impact insurers. As earlier, this is also unlikely to be driven by the direct effect of the storm, since that is unlikely to impact conforming borrowers differently from jumbo borrowers. We take this evidence to suggest that credit supply is distorted in the conforming segment, and that the limited incentives of lenders to screen in this segment has enabled the growth of Demotech insurers in Florida. In the 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.

6.3. Quantification

.

6.3.1. Implicit Transfer

In this Section, we provide a back-of-the-envelope estimation of how insurance fragility translates into direct losses for the GSEs and thus the overall size of the implicit transfer. Our calculation uses the following main inputs: default rates and loss given defaults (LGDs) in two scenarios (hurricane with fragile insurance and no hurricane), and the probability of a hurricane. GSEs expected losses can be written as

$$\mathbb{E}(\text{Losses}) = \underbrace{\delta_B LGD_B}_{\text{Baseline}} + \underbrace{P_H P_{INS}(\delta_{INS}) \times LGD_H}_{\text{Insurance Fragility}}. \tag{8}$$

Equation 8 says that GSEs expected losses are given by the baseline expected losses plus a second term due to insurance market fragility induced after a hurricane. The baseline expected losses are a product of baseline default rate (δ) and the baseline LGD. The second term denotes the additional expected losses due to insurance market fragility, which can be large if the probability of hurricane (P_H) is substantial, borrowers are more exposed to insolvent insurers (P_{INS}), the defaults induced by the storm due to insurance market fragility (δ_{INS}) are meaningfully large, and the LGDs conditional on a hurricane (LGD_H) are large.

To estimate GSEs' exposures, we extrapolate from the default dynamics observed during hurricane Irma. The implicit assumption is that the insurer insolvency dynamics is the same for each hurricane of similar severity as observed after Irma. We calibrate $\delta_B = 38.6$ bps, which is the baseline default rate prior to the hurricane for conforming loans. As Irma was a Category 3/ 4 hurricane,[43] we assume $P_H = 27.3\%$, which is the probability of a major hurricane (Category 3, 4, 5).[44] We assume $P_{INS} = 4\%$, which is the ex-ante market share of insolvent insurers in the average county and indicates the probability that a borrower may be exposed to a fragile insurer. $\delta_{INS} = 6.8\%$ is the estimated increase in default for conforming loans from Table 6. Following An and Cordell (2019), we assume LGD_B to be 40%. As there are no reliable estimates of LGD_H available, to be conservative, we assume

[43] Irma made landfall as a category 4 hurricane in the Florida Keys and struck southwestern Florida at category 3 intensity (NOAA report).

[44] Colorado State University Tropical Cyclone Impact Probabilities report estimates the average probability of a major hurricane impact is 29% for Florida. This translates to a probability that Florida is hit by a major hurricane every 3-4 years.

it to also be 40%, which is very likely a lower bound.

Overall, we find that about 16.1% of GSEs expected losses are due to local insurance market fragility. There are a number of reasons why our expected loss estimates may provide a lower bound on GSEs insurance market exposures. First, we only consider the effects of defaults and not delinquencies, which also pose large losses for the GSEs especially those that remain in unpaid status for long period of time. Second, we assume LGD in a hurricane to be the same as in the baseline scenario. However, it is likely that LGDs would be higher after a natural disaster because of damage to the property and potential decline in home values. Third, we extrapolate the default rates from a Category 3/4 hurricane. The actual defaults could be higher for a more serious storm. Fourth, insurance market fragility has likely gotten worse since 2017, as evidenced by series of insurer insolvencies after Hurricane Ian in 2022.

6.3.2. Excess Credit Supply

In this Section, we provide a back-of-the-envelope estimate of how many extra mortgages are originated because the GSEs accept unpriced insurance counterparty risk. We first estimate excess mortgage origination around the CLL and then extrapolate to all mortgages. Our calculation requires the following main inputs: Number of applications and denial rates in the conforming and jumbo segments, and an estimate of the excess denial rate in the jumbo segment.

Excess conforming origination is given by

$$\text{Excess conforming loans} = \frac{N_{Conforming}}{N_{Jumbo}} \Big(\underbrace{\frac{\alpha^C}{\alpha^J}}_{\text{Observed}} - \underbrace{\frac{\alpha^C}{\alpha^J + \alpha^\Delta}}_{\text{Efficient}} \Big). \tag{9}$$

Equation 9 says that the excess conforming loans measured per unit of jumbo loans is given by the ratio of number of conforming ($N_{Conforming}$) to jumbo (N_{Jumbo}) applications in each segment multiplied by the excess approval in the conforming segment relative to that in the jumbo segment, which is the second part of the Equation in the parenthesis. The second part has two components. $\frac{\alpha^C}{\alpha^J}$ denotes the observed ratio of approvals, where as $\frac{\alpha^C}{\alpha^J+\alpha^\Delta}$ denotes the ratio of approvals under an efficient benchmark where lenders internalized risks in the conforming segment to the same extent as they do in the jumbo segment.

We calibrate $\alpha^C = 87.3\%$ and $\alpha^J = 84\%$, which are the approval rates for conforming and jumbo loans around the CLL in the two years prior to hurricane Irma. We estimate α^Δ, which denotes the additional approval in the jumbo segment in case lenders behaved the same way as they did in the conforming segment, $= 2.71\%$ which is the increase (decrease) in the denial (approval) rate for jumbo loans in the average county. We also calibrate $\frac{N_{Conforming}}{N_{Jumbo}}$ to 18.7, which is the ratio of applications for conforming and jumbo loans on average in the two years prior to hurricane Irma. Overall, we find that there are ∼0.5 extra conforming loans originated for every jumbo loan application, translating to over 8,000 additional conforming loans and ∼$2 billion in excess origination per year.

7. Conclusion

This paper explores how insurance markets have responded to growing climate losses, and how these dynamics impact mortgage markets. We show that there has been a dramatic decline in the quality of insurance provision. The market share of traditional insurers has declined, driven by their exit from underwriting, particularly in higher risk areas. The gap created by their exit is being filled by new insurers that receive their financial stability rating emerging rating agencies, such as Demotech. Second, these new insurers are of significantly lower quality than traditional insurers across most observable measures of financial and operational risk: they have riskier liabilities, are less diversified, have more risky and concentrated reinsurance exposures, and have higher leverage and less risk-based capital. Our rating replication model suggests that the vast majority of these insurers would likely be rated "junk" if they received their rating from a traditional rating agency rather than Demotech. In fact, we find that their counterfactual ratings would be so low that they would no longer meet the GSE's requirements for securitization.

In the second part of the paper, we show that this deterioration in insurance quality leads banks to offload more mortgages with the GSEs. We show this correlation holds by looking at overall market shares, as well as in an identified natural experiment that addresses the possibility of adverse borrower selection. In particular, in studying Florida's Depopulation program, we find that a 1% increase in policies transferred to Demotech insurers in a given county brings a .03% increase in mortgages that are sold to the GSEs. These findings highlight the importance of a well-functioning insurance market for mortgage markets, and the increased counterparty risk offloaded to the GSEs.

Lastly, in the third part of the paper, we show that there is surge in serious delinquencies following large climate shocks, and that the effects are worse in counties that are more exposed to fragile insurers. The effect on delinquencies allows us to compute the direct exposure and losses stemming from the interaction of climate risk and fragility in insurance markets.

The paper suggests a few key drivers of the decline in quality across Florida's insurance markets. The first comes from the market for ratings. Insurers have an incentive to minimize and adequately manage risk exposures in order to maintain a good financial rating, which is key for both GSE eligibility and consumer demand. However, we show that there is a significant heterogeneity in methodologies across agencies, which allows lower quality insurers obtain favorable ratings that maintain their eligiblility for GSE purchase and securitization. Second, financial regulation can play a powerful role in weeding out poor quality insurers. However, we find significant regulatory forbearance both in financial supervision and in market conduct supervision. We see that forbearance has increased over time–likely due to regulators attempts to increase availability of insurance. Third, Florida's Depopulation program is ongoing and expanding, as the state seeks to manage its fiscal exposures and limit taxpayer underwriting of insurance markets. As losses from climate change worsen, the financial stability risks of insurers is likely to become even more pronounced, calling into question the optimal design of such programs. We are likely to see policymakers face difficult tradeoffs in maintaining affordability, availability, and reliability of insurance markets.

Tables and Figures

Figures

Figure 1: Demotech Market Share Across US States

The figure shows the market share of Demotech-rated insurers over time in the top 10 states by climate losses relative to all remaining states.

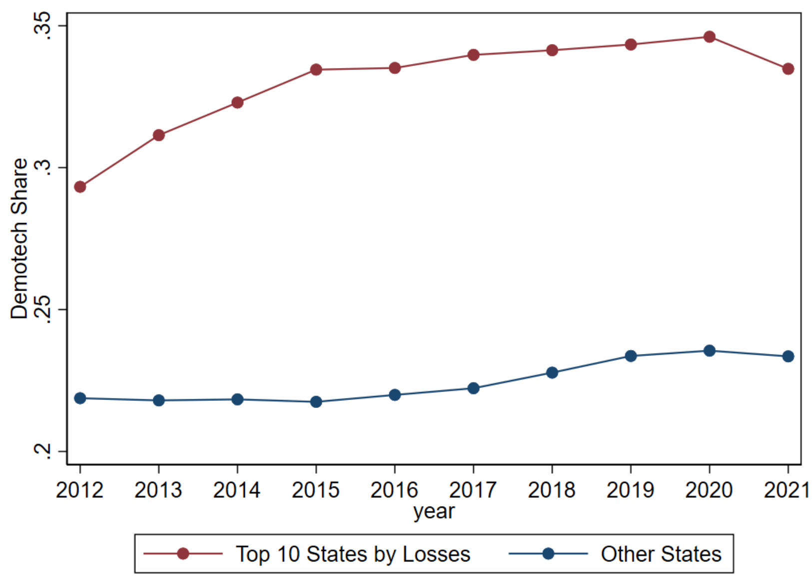


Figure 2: Evolution of Homeowners' Insurance Market in Florida

The figure shows the evolution of homeowners' 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 are insurers that are rated by traditional rating agencies (AM Best and S&P). Total premiums are in thousands of dollars. Data are taken from insurers' statutory filings. Start and end dates are dictated by data availability of the QUASAR database.

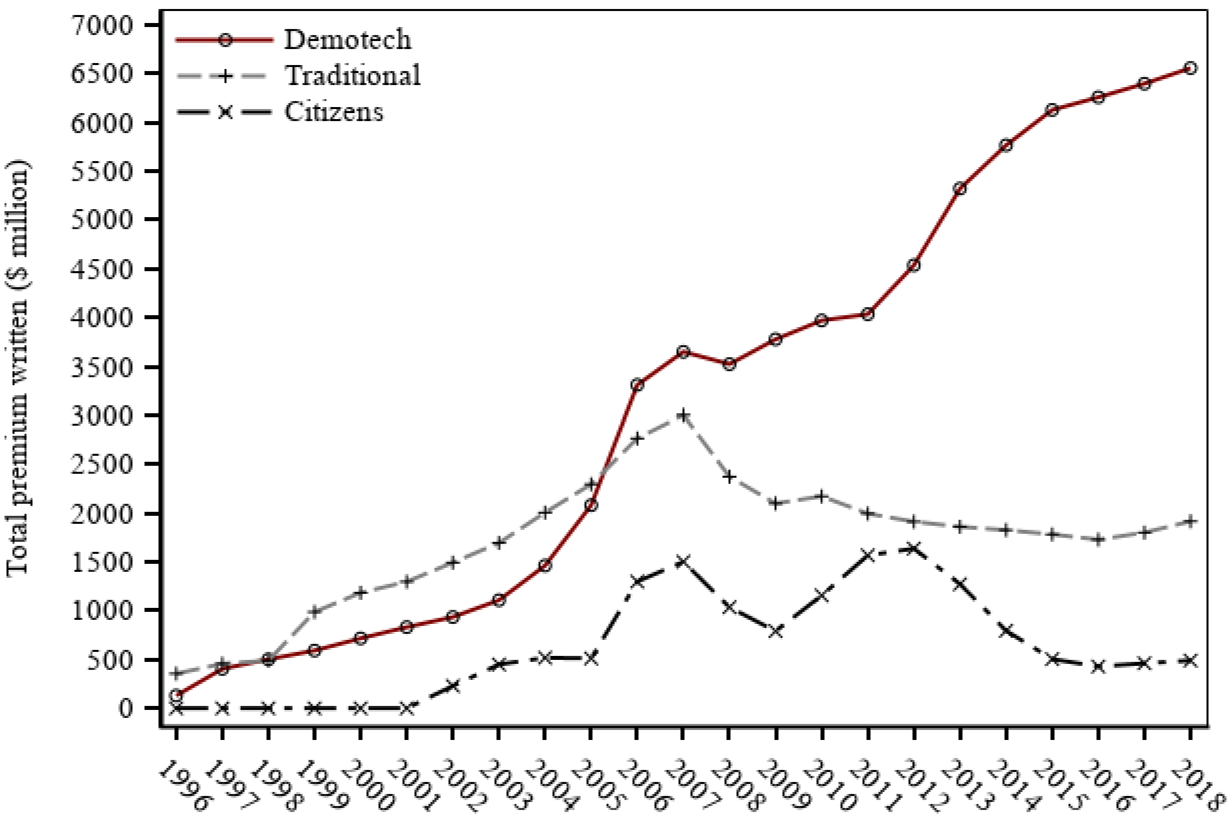
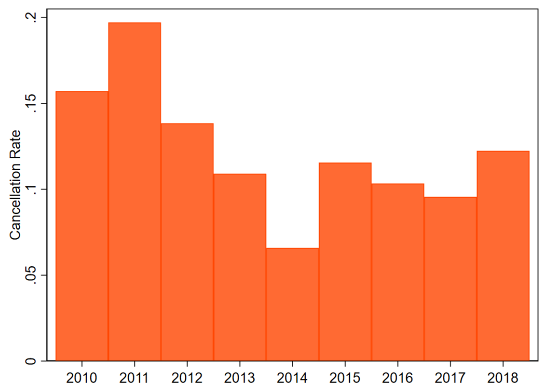


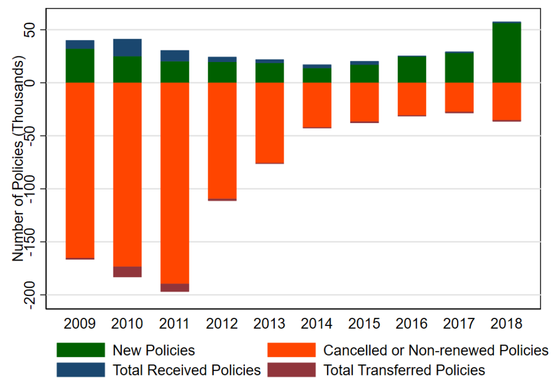
Figure 3: Cancellations and Non-renewals of Insurance Policies by Traditional Insurers

Panel A shows the percent of policies in force that are cancelled or not renewed each year for policies underwritten by traditional insurers, defined as those that receive a financial stability rating from the traditional rating agencies (AM Best or S&P). Panel B decomposes the flows of policies into new policies, cancelled or non-renewed policies, policies transferred to traditional insurers, and policies transferred from other insurers to traditional insurers. Panel C shows how traditional insurer cancellation rates vary by FEMA's climate risk index in 2015.

(a) Cancellation Rate



(b) Overall Policy Flows



(c) Cancellation Rate by Climate Risk (2015)

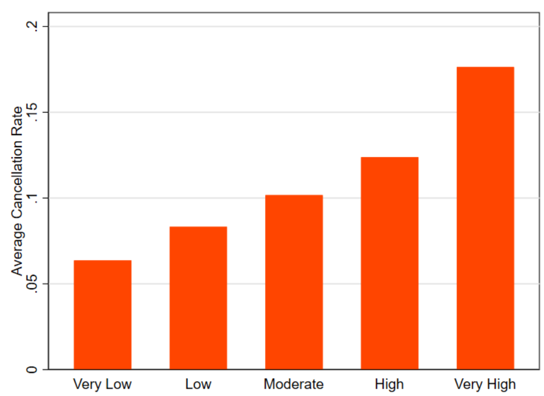
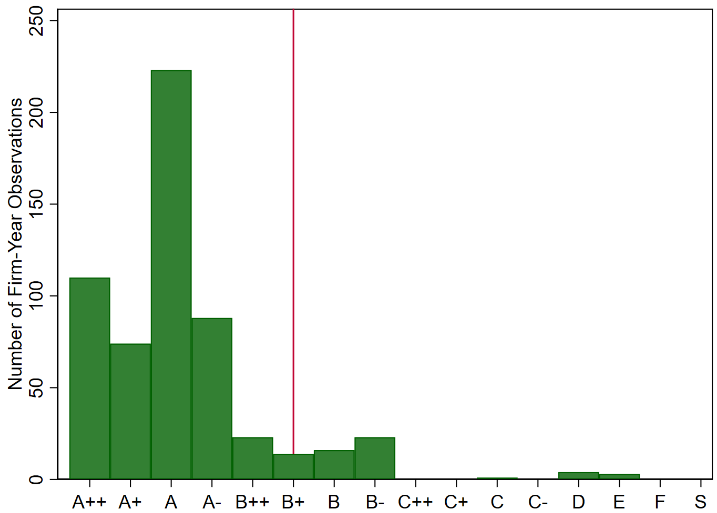


Figure 4: Histograms of Financial Stability Ratings

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

(a) AM Best Financial Stability Ratings



(b) Demotech Financial Stability Ratings

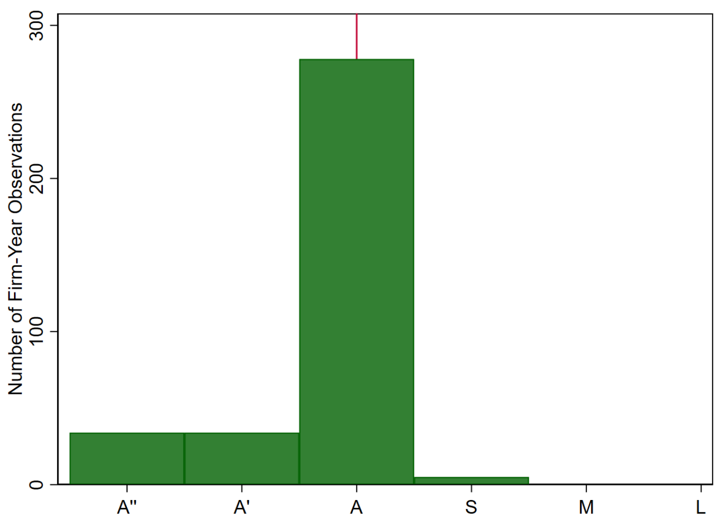


Figure 5: Counterfactual AM Best Ratings of Demotech Insurers

The figure shows the counterfactual AM Best financial stability ratings of Demotech insurers. The AM Best replicating model is described in the appendix. We compute 90% confidence intervals by bootstrapping the predicted ratings. The red line shows the GSE eligibility cutoff for Freddie Mac and the blue line shows the GSE eligibility cutoff for Fannie Mae.

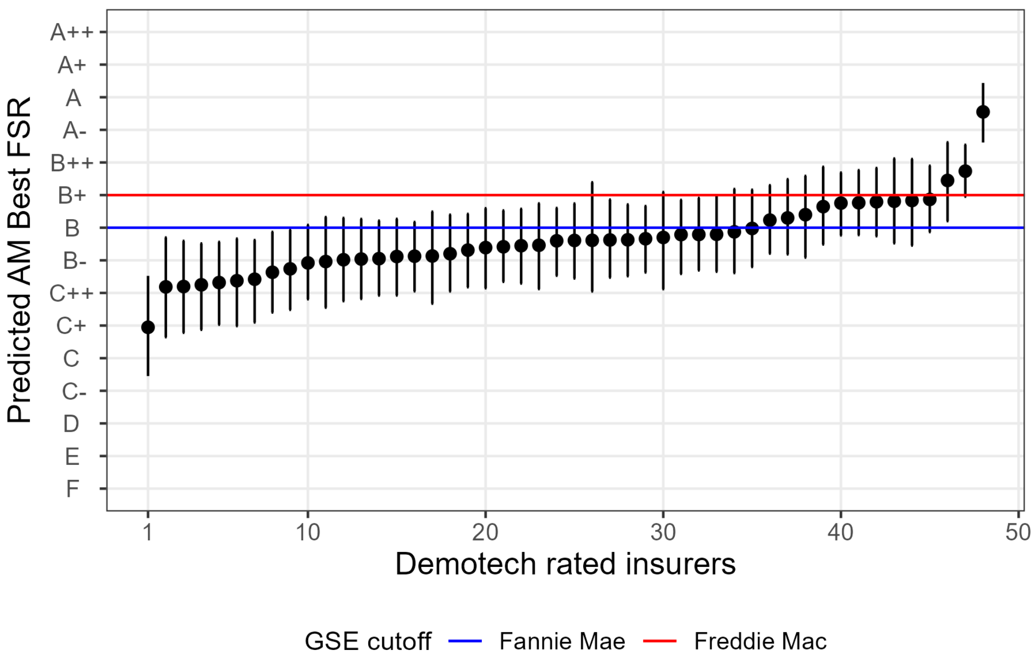


Figure 6: Demotech Market Shares By Coverage Per Policy

The figure shows the market share by number of policies for Demotech insurers in each coverage-per-policy category.

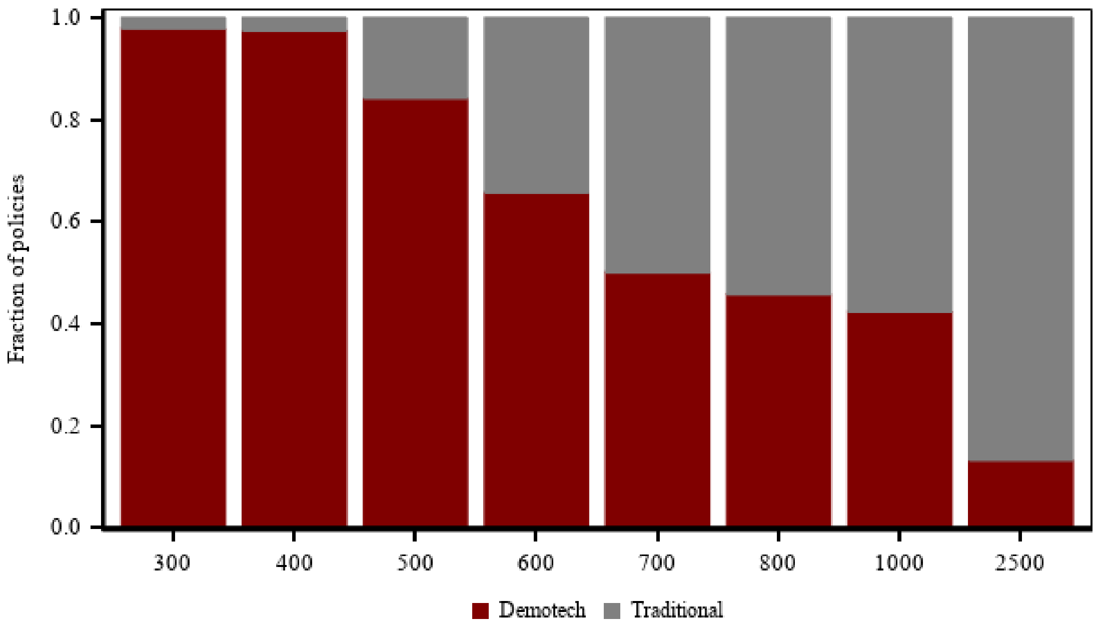


Figure 7: Participation in Citizens' Depopulation Program

The figure shows the fraction of insurers that 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.

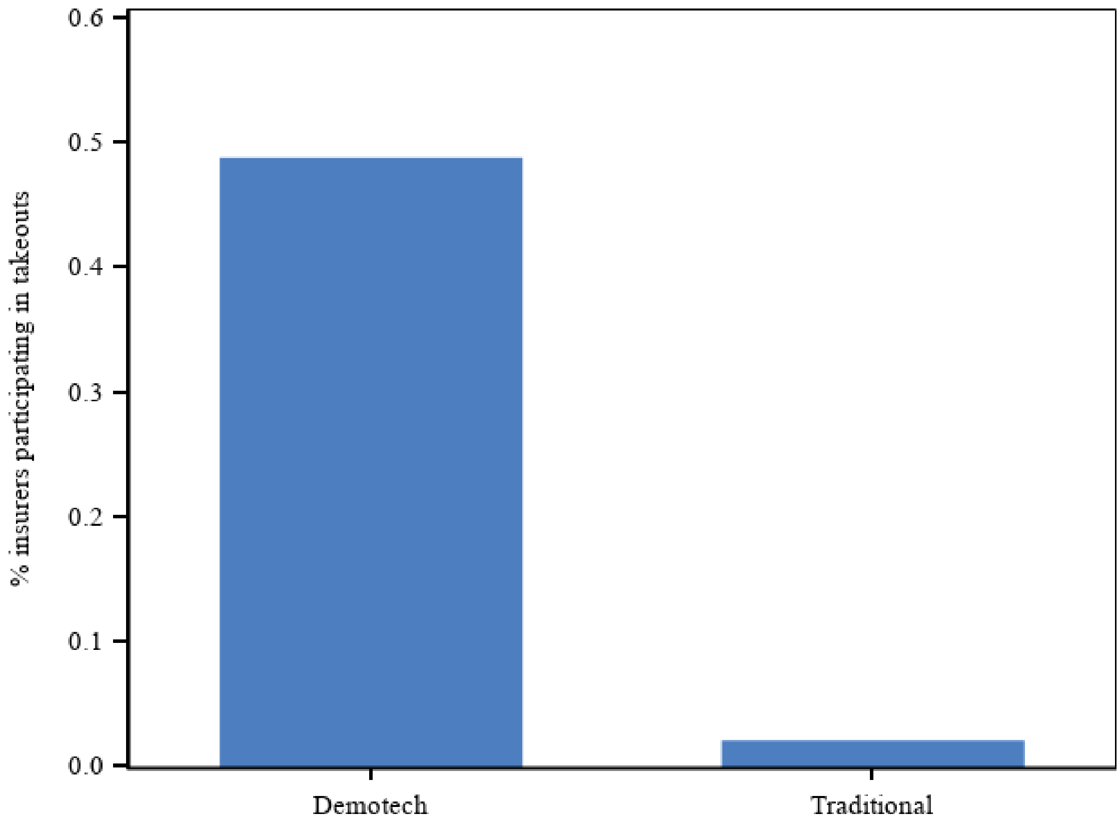
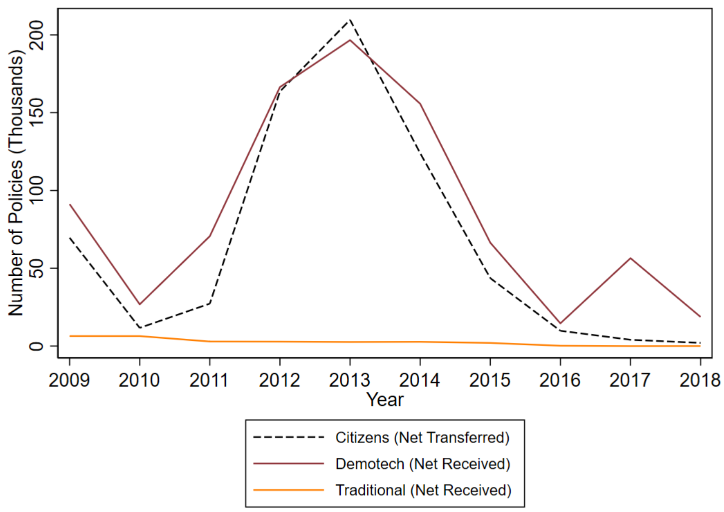


Figure 8: Citizens' Depopulation and Policy Flows

The figure shows the total number of policies away transferred from Citizens insurance, and the total number of policies received by private insurers. We categorize insurers by who provides their financial stability rating. Policies data comes from FLOIR's QUASAR database. Panel A shows overall flows by year, and Panel B shows policy flows at the county-year level.

(a) Annual Flows



(b) Policy Flows from Citizens to Demotech Insurers

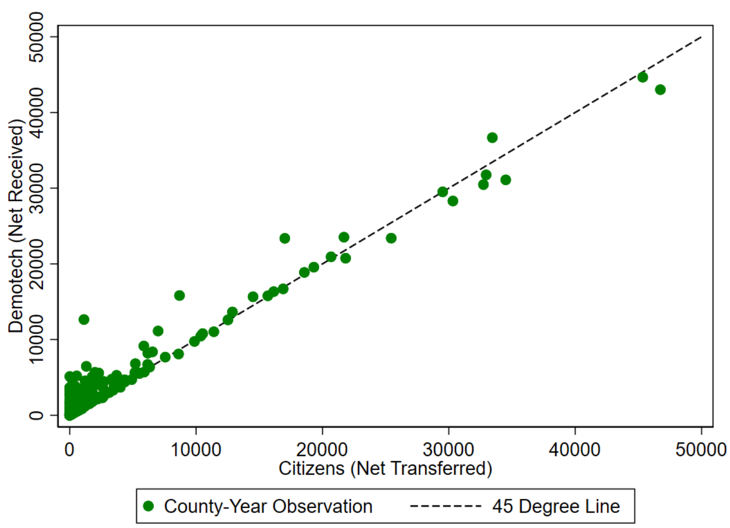


Figure 9: Default Rates around Hurricane Irma, above and below conforming loan limit.

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 consist of default, foreclosure, or REO. We limit mortgages to those within 10% bands of the conforming loan limit.

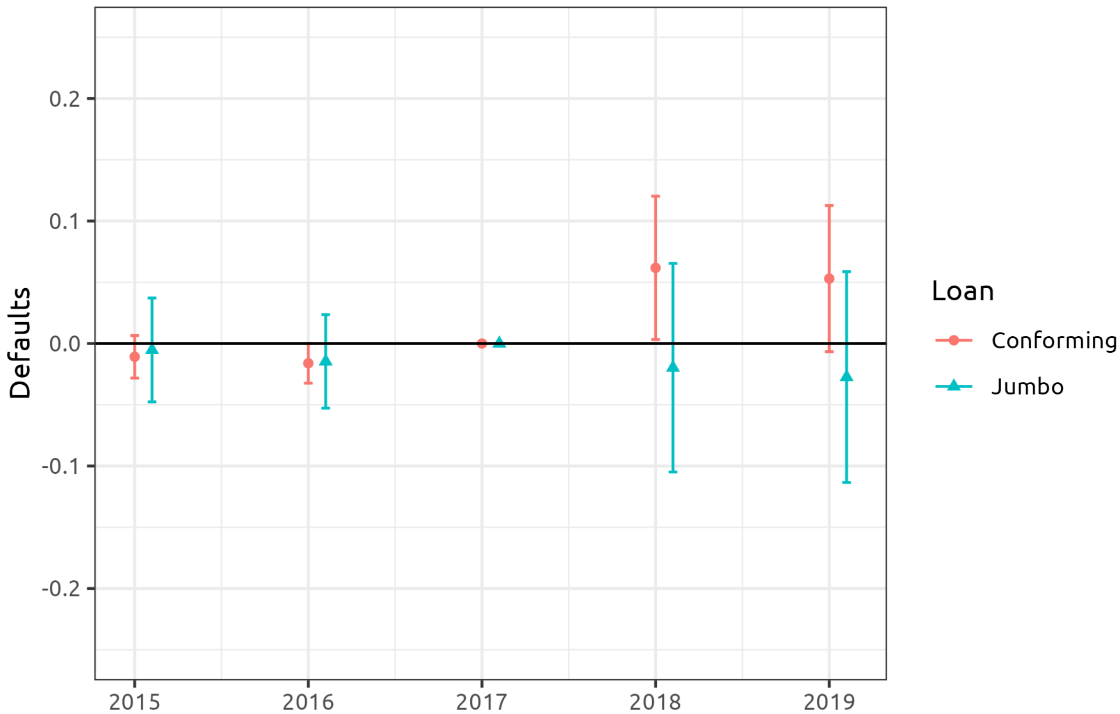


Figure 10: Default Rates around Hurricane Irma, above and below conforming loan limit for high insolvency counties

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. We limit mortgages to those within 10% bands of the conforming loan limit. We estimate the average default rate for conforming and jumbo rates for counties with high insolvency rates (above the median rate).

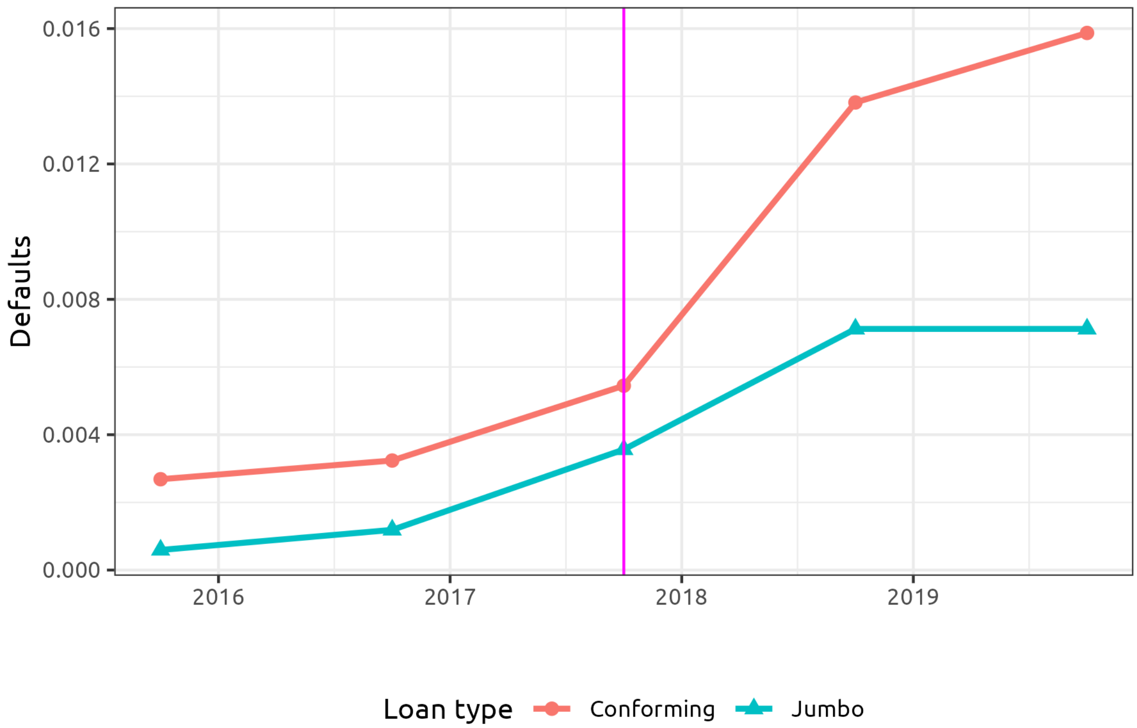


Table 1: Minimum Required Insurance Financial Stability Ratings for Mortgages

The table reports the minimum financial stability rating required of homeowners 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 nationally recognized statistical rating organization (NRSRO) by the SEC.

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 the Appendix. 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) Balance sheet 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) Assets			
% 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 the fraction of insurers that get liquidated and the share of liquidations by insurer type. Data on liquidations come from National Association of Insurance Commissioners (NAIC) Global Receivership Information Database (GRID). We track liquidations between 2009 and 2022.

	Demotech (1)	Traditional (2)
% of insurers that get liquidated	18.7%	0%
% Liquidated insurers by type	100%	0%

Table 4: Regulatory Supervision by Insurer Types

We compare regulatory strictness and consumer complaints among different. Panel A shows differences in overall regulatory strictness between the period 2009 to 2013 and 2014 to 2018. Panel B shows differences in regulatory strictness across various insurer types. Panel C shows differences in consumer complaints across various insurer types. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a) Regulatory supervision over time	2009-2013	2014-2018	Difference
	(1)	(2)	(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	Traditional	Difference
	(1)	(2)	(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	Traditional	Difference
	(1)	(2)	(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 5: Insurer Quality and GSE Mortgage Purchases: Depopulation Experiment

This table shows the results of estimating Equation 4 in the text. The dependent variable is the log of the dollar volume of mortgages sold to the GSEs that were originated in prior years. The independent variable is the log of the net number of policies transferred to Demotech-rated insurers. The control variables here refers to the average borrower income of mortgages borrowers that are sold in that calendar year. County and year fixed effects are included where indicated. Standard errors are clustered at the county level and reported in parentheses. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	log(GSE)	
	(1)	(2)
log(Depopulated)	0.0343**	0.0331**
	(0.0157)	(0.0162)
County FE	Y	Y
Year FE	Y	Y
Controls	N	Y
Sample Period	2009-2018	2009-2018
Number of Observations	619	618
Adjusted R-squared	0.974	0.974

Table 6: Default After Hurricane Irma by Mortgage Market Segment

This table shows the results of estimating Equation 5 in the text. The dependent variable is an indicator for whether a loan application is denied. The independent variable is an interaction between (1) a post-Irma indicator which is one for all month-years after September 2017 and (2)insurance fragility, a continuous variable that we measure by obtaining the ex-ante share of premiums as of year-end 2016 in each county underwritten by an insurer that went insolvent after Irma. The control variables here refers to debt to income ratio, log income, and interaction between post irma indicator and log damages at the county level due to Irma. County and year fixed effects are included where indicated. Standard errors are clustered at the county level and reported in parentheses. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Mortgage Defaulted (Y/N)			
	± 10% CLL		± 5% CLL	
	Conforming	Jumbo	Conforming	Jumbo
	(1)	(2)	(3)	(4)
Post Irma × Insurer Fragility	0.068**	−0.032	0.066**	−0.039
	(0.030)	(0.046)	(0.029)	(0.082)
Loan controls	Yes	Yes	Yes	Yes
County Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Origination Fixed Effect	Yes	Yes	Yes	Yes
Observations	122,785	17,105	71,730	9,395
Adjusted R^2	0.011	0.027	0.012	0.054

Table 7: Impact of Hurricane Irma on Credit Supply 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. We limit mortgages to those with amounts within a ±10% or a ± 5 % window of the conforming loan limit (CLL). We limit to mortgages applications within two years of the storm (2015-2019), and drop any loan amounts exactly at the CLL boundary (due to the issues with rounding in HMDA). Insurer 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 for debt-to-income ratios and log income are also included, as well as county fixed effects and year fixed effects. Standard errors are clustered at the county level. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Mortgage Denied (Y/N)			
	± 10% CLL		± 5% CLL	
	Conforming	Jumbo	Conforming	Jumbo
	(1)	(2)	(3)	(4)
Post Irma=1 × Insurer Fragility	-0.221	0.498**	-0.525*	0.461*
	(0.164)	(0.215)	(0.294)	(0.246)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Number of Observations	25571	10118	12447	6810
Adjusted R-squared	0.0231	0.0349	0.0268	0.0343

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

This table shows the difference-in-differences regression studying the effect of Hurricane Irma on 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 conforming loan limit (CLL). We limit the sample to 2015-2018 (two years prior to the storm, and only one year after due to the QUASAR data limits). Insurer Fragility refer 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 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 of New Policies		Demotech Share of All Policies	
	Conforming	Jumbo	Conforming	Jumbo
	(1)	(2)	(3)	(4)
Post Irma=1 × Insurer Fragility	2.109***	-1.907**	1.325**	-1.362*
	(0.622)	(0.951)	(0.613)	(0.772)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	N	N	N	N
Number of Observations	265	254	268	263
Adjusted R-squared	0.768	0.730	0.820	0.762

References

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.

Baldauf, M., L. Garlappi, and C. Yannelis (2020, March). Does Climate Change Affect Real Estate Prices? Only If You Believe In It. *The Review of Financial Studies 33*(3), 1256–1295.

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

Bernstein, A., M. Gustafson, and R. Lewis (2019, November). Disaster on the Horizon: The Price Effect of Sea Level Rise. *Journal of Financial Economics 134*(2), 253–272.

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*.

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

Cortés, K. R. and P. E. Strahan (2017, July). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics 125*(1), 182–199.

Davenport, F. V., M. Burke, and N. S. Diffenbaugh (2021, January). Contribution of historical precipitation change to US flood damages. *Proceedings of the National Academy of Sciences 118*(4).

Demyanyk, Y. and O. Van Hemert (2011). Understanding the Subprime Mortgage Crisis. *The Review of Financial Studies 24*(6), 1848–1880. Publisher: [Oxford University Press, Society for Financial Studies].

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.

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]*.

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.

Froot, K. A. F. and J. Stein (1991). Exchange rates and foreign direct investment: An imperfect capital markets approach. *Quarterly Journal of Economics 106*(Nov.), 1191–1217.

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.

Garbarino, N. and B. Guin (2021, June). High water, no marks? Biased lending after extreme weather. *Journal of Financial Stability 54*.

Garmaise, M. J. and T. J. Moskowitz (2009). Catastrophic Risk and Credit Markets. *The Journal of Finance 64*(2), 657–707.

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 (2021). Trust and insurance contracts. *The Review of Financial Studies [Forthcoming]*.

Gibson, M. and J. T. Mullins (2020, November). Climate Risk and Beliefs in New York Floodplains. *Journal of the Association of Environmental and Resource Economists 7*(6), 1069–1111. Publisher: The University of Chicago Press.

Giglio, S., M. Maggiori, K. Rao, J. Stroebel, and A. Weber (2021, August). Climate Change and Long-Run Discount Rates: Evidence from Real Estate. *The Review of Financial Studies 34*(8), 3527–3571.

Gropp, R., F. Noth, and U. Schüwer (2019). What Drives Banks' Geographic Expansion? The Role of Locally Non-Diversifiable Risk. *SSRN Working Paper No. 3347766*.

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.

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.

Keenan, J. M., T. Hill, and A. Gumber (2018, April). Climate gentrification: from theory to empiricism in Miami-Dade County, Florida. *13*(5), 054001. Publisher: IOP Publishing.

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., H. Kunreuther, M. LaCour-Little, and S. Wachter (2020). Flood Risk and the U.S. Housing Market. *Journal of Housing Research 29*(sup1), S3–S24. Publisher: Routledge _eprint: https://doi.org/10.1080/10527001.2020.1836915.

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*.

Mulder, P. and B. Keys (2020, October). Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise. *NBER Working Paper #27930*.

Murfin, J. and M. Spiegel (2020, March). Is the Risk of Sea Level Rise Capitalized in Residential Real Estate? *The Review of Financial Studies 33*(3), 1217–1255.

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*.

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*.

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. R. (2022). Adaptation and adverse selection in markets for natural disaster insurance. *American Economic Journal: Economic Policy 14*(3), 380–421.

A. Additional Tables and Figures

Figure A.1: Percent of premiums written by insurers not reported in QUASR

The figure shows the fraction of homeowners' premiums written in Florida by insurers missing from the QUASAR database. QUASAR premiums are benchmarked against premiums reported in statutory filings obtained from S&P MI.

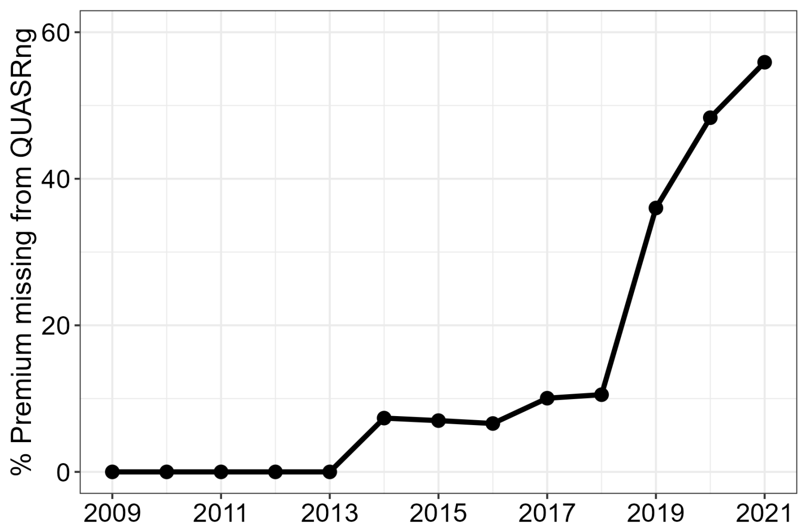


Figure A.2: Top 6 States by Market Share of Demotech-rated firms

The figure shows the fraction of the homeowners insurance premiums written by insurers rated by Demotech in the top six states that Demotech operates in.

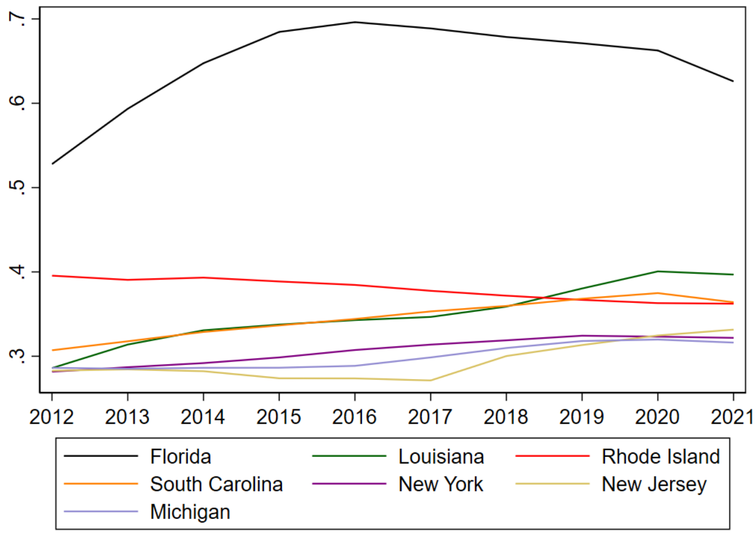


Figure A.3: Histogram of Demotech Insurers' Premium Shares in 2009 versus 2018

The figure shows two histograms of Demotech insurer premiums shares in each county. The white bars reflect the histogram in 2009, and the green bars show the histogram in 2018. Demotech insurers are defined as those that receive a financial stability rating at any point from the Demotech rating agency.

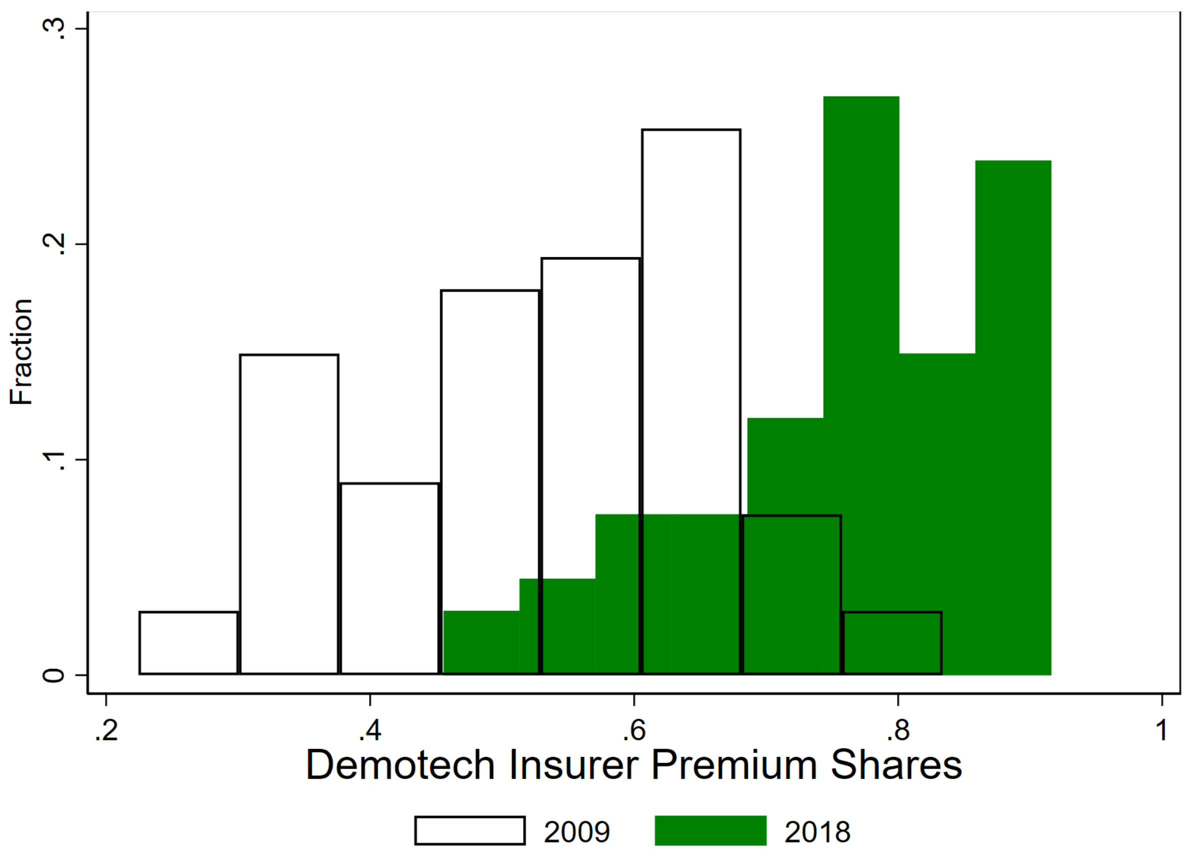
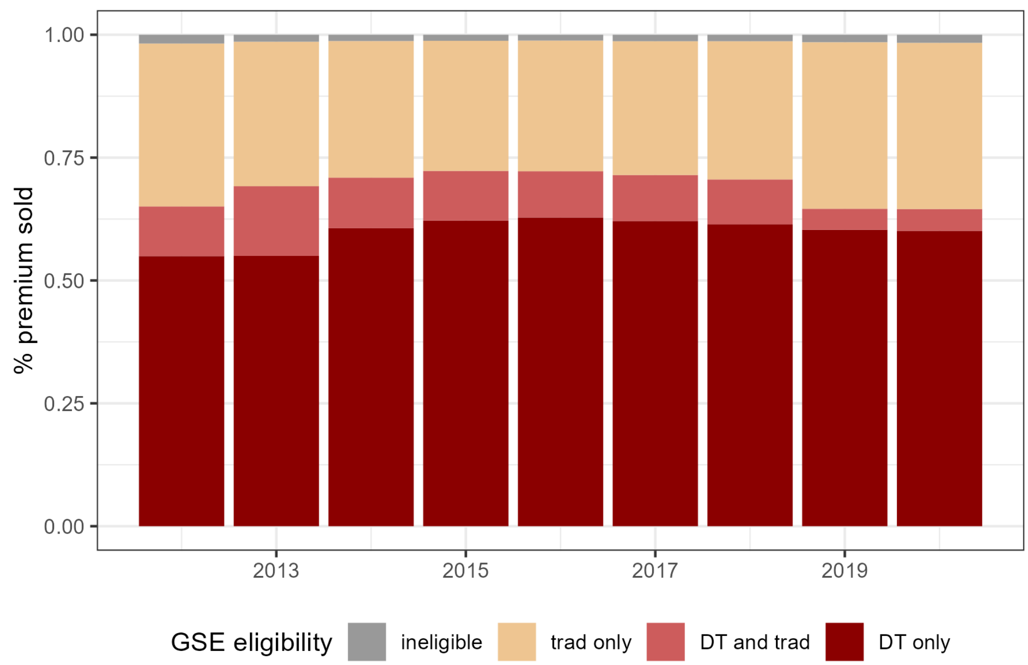


Figure A.4: GSE eligibility of insurers in Florida

We estimate the amount of homeowner insurance sold in Florida that was not eligible under GSE standards, and that was eligibible due to ratings by traditional insurers (trad only), Demotech (DT only), or trough both (DT and trad). In the top panel, the proportions were estimated using total premium sold, and in the bottom panel – using number of policies.



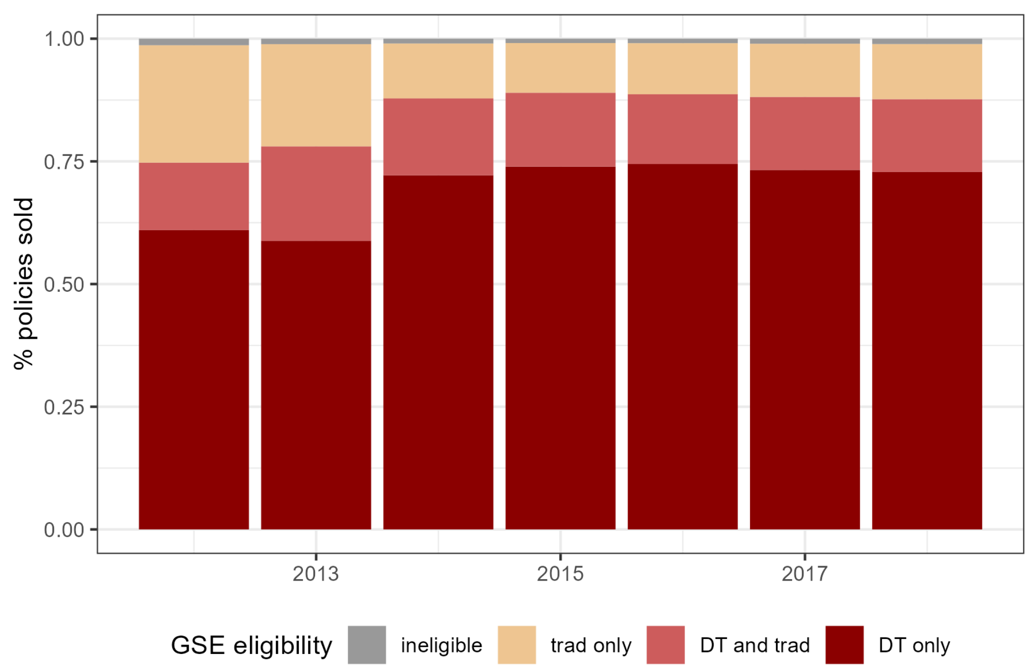


Figure A.5: Default Rates around Hurricane Irma, above and below conforming loan limit

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. We limit mortgages to those within 10% bands of the conforming loan limit. We estimate the average default rate for jumbo and conforming loans.

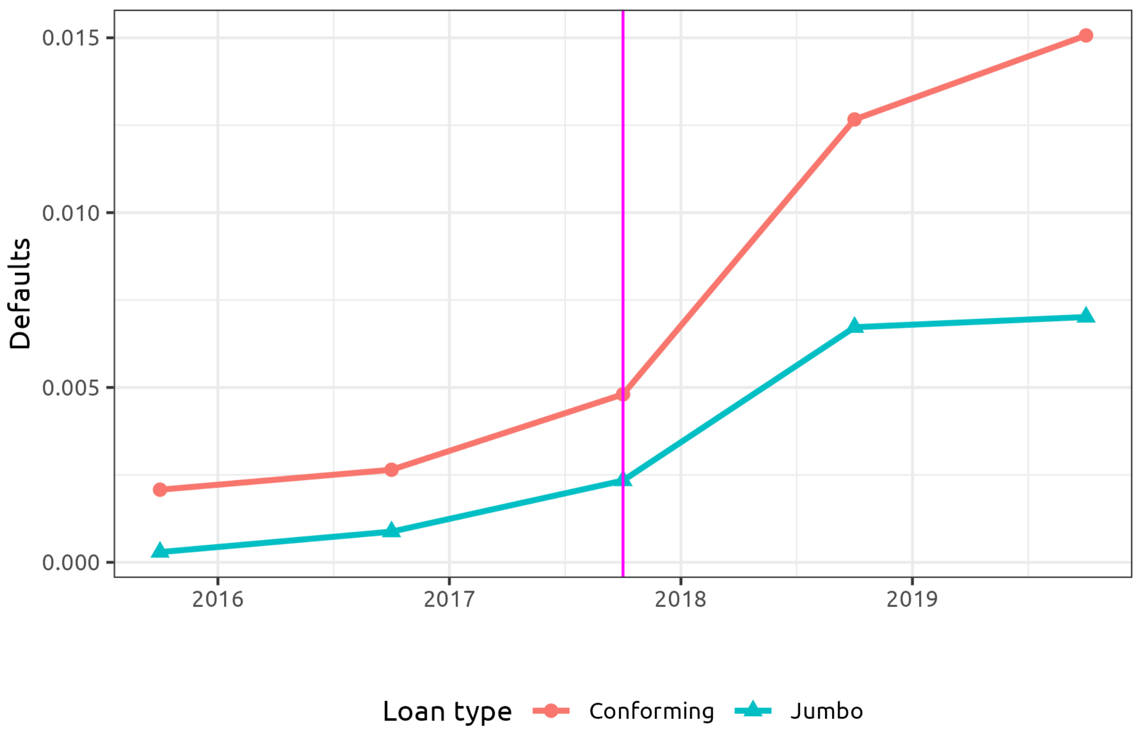


Figure A.6: Differential Impact of Hurricane Irma on Credit Supply

This figure shows the coefficient from a continuous treatment triple difference-in-differences regression that shows how the effect of Hurricane Irma varies by mortgage market segment (jumbo and conforming). The design runs the fully saturated model with all interactions between $PostIrma = 1$, $InsolventInsurerShare$, and $Conforming = 1$. The figure plots the coefficient on the triple interaction $PostIrma = 1 \times InsolventinsurerShare \times Jumbo$. We run the triple difference-in-differences regression for three different samples. The first limits to mortgages within a ±15% window of the conforming loan limit (CLL). The second restricts the window to 10%, and the third restricts to 5%. We also include county and year fixed effects, as well as controls for borrower debt-to-income ratios and log income, and the term $post = 1\times$ *log property damages from SHELDUS*. Standard errors are clustered at the county level.

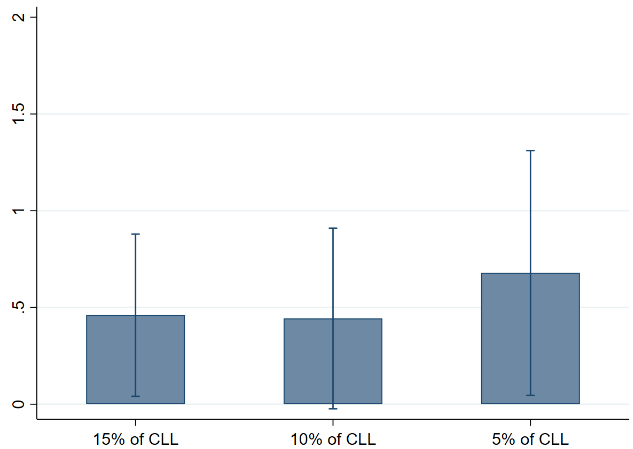


Table A.1: Financial Risks, Operational Risks, and Insolvency Rates by Insurer Types (Broader Evidence)

The table reports the key characteristics for the different insurer types: Demotech (1) and Traditional (2). The sample includes all insurers that have sold homeowners insurance in any of the top 10 states by climate losses between 2009 and 2018. The top 10 states are Arkansas, California, Florida, Georgia, Kansas, Louisiana, Mississippi, Nebraska, Oklahoma and Texas. "Demotech" refers to 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 the Appendix. 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) Balance sheet 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 A.1: 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) Assets			
% 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 get liquidated	11.9%	2.55%	

Table A.2: Risk Exposures by Insurer Types

This table uses data at the firm-year level to assess how firm-level 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 firm's financial stability 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)
Observations	924	924	924
Adjusted R^2	0.022	0.025	0.017
year_fe	Y	Y	Y

Table A.3: AM Best Rating Replication Model

We estimate the relationship between AM Best rating and various insurers characteristics, as shown in Equation 1. Column I shows the full model, which includes all relevant characteristics. Column II shows characteristics selected using the LASSO technique. Column III 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 A.4: 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) it 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
Year FE	Y	Y	Y	Y
County FE	N	Y	N	Y
Risk controls	N	Y	N	Y
N	46,313	46,311	39,555	39,554

Table A.5: Insurer Quality and GSE Mortgage Purchases: Overall Stock

This table shows the results of estimating Equation 3 in the text. 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-rated firms. Loan-level controls from HMDA include log income and debt-to-income. 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

	(1) GSE Share	(2) GSE Share	(3) GSE Share	(4) GSE Share
Demotech Share	0.291***	0.224***	0.0820**	0.0768**
	(0.0388)	(0.0599)	(0.0403)	(0.0365)
County FE	N	N	Y	Y
Year FE	N	Y	Y	Y
Controls	N	N	N	Y
Number of Observations	670	670	670	651
Adjusted R-squared	0.255	0.283	0.746	0.787

Table A.6: Borrower and Insurance Characteristics by Insurance Fragility Prior to Irma

This table presents average characteristics from 2015 for borrowers in counties with low exposure to the insolvent insurers and for borrowers in counties with high exposure to the insolvent insurers. Florida counties are divided into the two groups based on the county's pre-Irma exposure to insurers which went insolvent after Irma. County-level variables are weighted by the number of loans in each county, to be comparable with the loan-level data. Borrower data comes from HMDA and McDash; insurance data comes from QUASAR.

	(1) High Fragility Mean	(2) Low Fragility Mean
Panel A: Loan Applications:		
Denied (Y/N)	0.16	0.18
Loan Amount (000s)	228.1	218.4
Borrower Income (000s)	95.3	89.6
Conforming (Y/N)	0.95	0.95
Observations (Applications)	186,501	81,221
Panel B: Originated Loans:		
Loan Amount (000s)	230.6	219.9
Borrower Income (000s)	98.0	91.5
Conforming (Y/N)	0.93	0.94
Debt-to-income ratio	32.4	31.3
FICO Credit Score	685.5	660.0
Loan-to-value ratio	81.1	79.6
Property Value (000s)	275.2	265.0
Observations (Loan Originations)	150,273	64,121
Panel C: Insurance Markets:		
Demotech Premiums Share	0.82	0.76
Demotech Policies Share	0.88	0.82
Traditional Insurer Cancellation Rate	0.13	0.11
Exposure to Insolvent Insurers (2016)	0.056	0.018

Table A.7: Demotech Market Share and Credit Supply

This table estimates how mortgage denial rates vary across counties depending on the premium share of Demotech insurers in the county and the mortgage type, i.e. conforming vs. jumbo loans. The dependent variable across all specifications is 1 if a mortgage is denied and 0 otherwise. Fixed effects are included where indicated. Standard errors are clustered at the county level.

	Mortgage Denied (Y/N)	
	(1)	(2)
jumbo=1	-0.0265*	-0.0279*
	(0.0152)	(0.0144)
Demotech Premium Share	-0.0166	-0.0152
	(0.0164)	(0.0161)
jumbo=1 × Demotech Premium Share	0.0526**	0.0521**
	(0.0208)	(0.0201)
County FE	Y	Y
Year FE	Y	Y
Controls	N	Y
Number of Observations	2,275,138	2,250,777
Adjusted R-squared	0.0112	0.0131

B. 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 operating companies' 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* are 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 per years the firm 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 and were regulated by the Florida office of insurance regulation.

21. *% exams with restatements*: Percent of financial exams which resulted in restatement among the financial exams of all Florida domiciled 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. Data comes from FLOIR annual reports, 2009 to 2018.

23. *Likelihood of any complaints in a year (%)*: We estimate for each insurer the average likelihood for at least one complaint ina 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.