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

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Abstract

This paper studies how homeowners insurance markets respond to growing climate losses and how this impacts mortgage market dynamics. Using Florida as a case study, we show that traditional insurers are exiting high risk areas, and new lower quality insurers are entering and filling the gap. These new insurers service the riskiest areas, are less diversified, hold less capital, and 20 percent of them become insolvent. We trace their growth to a lax insurance regulatory environment. Yet, despite their low quality, these insurers secure high financial stability ratings, not from traditional rating agencies, but from emerging rating agencies. Importantly, these ratings are high enough to meet the minimum rating requirements set by government-sponsored enterprises (GSEs). We find that these new insurers would not meet GSE eligibility thresholds if subjected to traditional rating agencies' methodologies. We then examine the implications of these dynamics for mortgage markets. We show that lenders respond to the decline in insurance quality by selling a large portion of exposed loans to the GSEs. We quantify the counterparty risk by examining the surge in serious delinquencies and foreclosure around the landfall of Hurricane Irma. Our results show that the GSEs bear a large share of insurance counterparty risk, which is driven by their mis-calibrated insurer eligibility requirements and lax insurance regulation.

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

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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. 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 flesh out how exactly insurance markets are evolving in the face of growing natural disaster losses. We show that the well-established traditional insurers are cancelling policies and exiting high risk areas. Instead of insurance disappearing completely, as is widely believed, the gap left by traditional insurers is filled by poor quality insurers, who disproportionately service the riskiest areas. Despite being low quality, these insurers secure good financial stability ratings on their liabilities from emerging rating agencies which we show have laxer standards for high ratings than the traditional ones.[2] Second, we examine how banks respond to the changing insurance market dynamics. We find that banks manage the increase in counterparty risk from insurers by selling a large portion of loans to GSEs, whose eligibility criteria, as we argue, are not sufficiently sensitive to insurer quality. The high financial stability ratings obtained by these low quality insurers are often high enough to meet the GSE's minimum rating requirements for purchase and securitization. Third, we show that insurer fragility amplifies the effect of climate shocks on

[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.

mortgage delinquencies.

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 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

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

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 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 find that, on average, a 1

[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.

percentage point increase in the market share of Demotech insurers is associated with an 0.08 percentage point increase in the share of mortgages that are securitized. Our specification includes county and year specific effects, and the estimate is robust to controlling for average loan characteristics including borrower income, FICO credit score, and property values. This result suggests that the GSE's have large exposures to Demotech insurers.

However, this specification does 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 versus 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 which 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. To interpret the magnitude of this elasticity, we consider a counterfactual program where

Citizens conducts a takeout of 100,000 policies in 2020, similar to the depopulation efforts in 2013 or 2014. Our elasticity suggests that such a program would lead to a 24% increase in the dollars securitized with 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 the counterparty risk brought by the interaction of climate events and insurer insolvencies by examining how delinquency rates evolve for counties exposed to fragile insurers. We find that, on average, counties with a higher share of premiums underwritten by insurers that go insolvent in the following year have significantly higher delinquency rates, and this is robust to the inclusion of county and year fixed effects. We then examine the landfall of Hurricane Irma using an event study design. Serious delinquencies increased three times from 1.2% to 3.5% in exposed counties, and remained elevated in the years following the landfall, relative to counties that were not directly hit by the hurricane. We connect the climate event to insurer insolvency risk by exploring heterogeneous effects by both exposure to the hurricane and exposure to insurers that go insolvent after the hurricane. We find that counties highly exposed to insolvent insurers experience a 4.6 times higher increase in delinquency rate after the hurricane than counties less exposed to fragile insurers. In other words, mortgage delinquencies increase after hurricanes, and

[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

the immediate effects are exacerbated by fragile insurers. These results suggest that further increases in insurer fragility could cause a surge in serious mortgage delinquencies.

A key question is what sustains the emergence of fragile insurers in Florida. We provide three pieces of the puzzle. First, we show that the GSE eligibility requirements are not properly calibrated across rating agencies. In particular, our rating replication exercise suggests that the ratings of emerging rating agencies appear to be lax relative to traditional rating agencies such as AM Best and S&P. Poor quality insurers are likely to select into the emerging rating agencies, allowing them to meet the GSE's eligiblity thresholds. Second, we show that insurance regulation is lax on two fronts. (i) Demotech insurers experience similar levels of supervision as traditional insurers despite observable differences in quality. (ii) The risk-based capital ratios do not adequately capture the risks embedded in the liabilities of under-diversified insurers that operate in fewer states. Third, we document that the office of insurance regulation provides direct cash incentives to the private sector bringing down their required returns for operating in the riskiest areas of Florida.

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

[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).

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 characteristics (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.

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

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 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

[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 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.

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 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

[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.

[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.

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]

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.

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

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 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.

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

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

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).

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

[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.

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.

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

[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.

(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

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

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 3 shows that Demotech insurers have higher exposure to riskier counties in Florida by all three measures.[29] Finally, Table 2 Panel 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

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

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%).

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 4 shows that 19% of Demotech insurers entered rehabilitation proceedings in this period. None of the traditional insurers were liquidated.

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 4.[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.

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

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

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 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.1 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.

[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.

Figure 5 shows the counterfactual AM Best ratings for all Demotech insurers. For each model in Table A.1, 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). 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 5 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.

5. Depopulation and Mortgage Securitization 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. *Incentives to Offload 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.[33] 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 6 reports the results of estimating Equation 3. Column (1) of Table 6 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.

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

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.

There are a number of competing explanations for the correlation between GSE share and Demotech share. There are two in particular that we would like to tease apart: a) that lenders strategically try to reduce their exposure to Demotech insurers by selling the mortgages to the GSEs, or b) lenders strategically reduce their exposure to higher risk borrowers by selling to the GSEs, and being a high risk borrower is correlated with obtaining an insurance policy from Demotech insurers. We try to address the possibility that a changing borrower composition drives our results by including time-varying county controls for average log income, FICO credit score, and property value of new mortgage borrowers.[34] As Column (4) of Table 6 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.

5.2. Citizens Depopulation Natural Experiment

We also use a natural experiment to more directly address 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 6 shows that almost 50% of all Demotech insurers participate in the depopulation scheme. By

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

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 7, we see that at its peak in 2013, Citizens transferred on net more than 200,000 policies. Figure A.5 shows that Citizen's depopulation was concentrated in counties classified by FEMA as being high risk. 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.[35] 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.[36] 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.

Identifying Assumptions: With this specification, we seek to isolate variation coming

[35] 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.

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

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 7, 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 7 shows the results of estimating Equation 4. Column (1) shows that there is a statistically significant raw correlation between policies transferred to Demotech and mortgages sold to the GSEs. A 1% increase in policies sold on average brings a 0.79 percent increase in mortgages sold to the GSEs. This number increases slightly in Column (2) when we include year fixed effects. In Column (3), the coefficient shrinks to a 0.03 percent increase after including county fixed effects. This suggest that between-county variation is important for explaining the raw correlation in Column (1). Finally, the coefficient estimate does not change much in Column (4) after including a control 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).[37] 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. Insurance Counterparty Risk and Mortgage Delinquencies

In Section 5, we show that lenders are more likely to manage ex-ante exposures to low quality insurers by strategically offloading mortgages to the GSEs. In this section, we explore the flip side of this question by looking at the link between insurance fragility and mortgage delinquencies and default.

6.1. Fragile Insurance Markets

As a first step, we evaluate the relationship between insurer fragility and mortgage delinquencies. To do so, we run the following specification:

$$SeriousDelinquencyRate_{c,t} = \alpha + \beta InsolventShare_{c,t} + \delta_c + \delta_t + \varepsilon_{c,t}. \tag{5}$$

We calculate our dependent variable, $SeriousDeliqnuencyRate_{c,t}$ as follows: we find all mortgages in county c that were originated within five years prior to period t, and compute the share of those which are seriously delinquent as of period t. Serious delinquency is defined as whether the mortgage is more than 90-days delinquent, in pre-sale or post-sale foreclosure, or in REO.[38] Our independent variable $InsolventShare_{c,t}$ is defined as the share of all insurance premiums in county c in period t provided by insurers which go into liquidation in period $t+1$. The idea behind this measure is that the insurance liquidation process has a lag,

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

[38] We focus on mortgages originated within 5-years since these mortgages are the ones where the lender bears the most potential losses from a default.

and so insurers which are in trouble in period t will only be put into liquidation in period $t+1$ at the earliest. We include county and year fixed-effects, δ_c and δ_t, respectively to absorb any time-invariant county shocks and any Florida state-wide aggregate trends. Standard errors are clustered at the county level. The coefficient of interest is β, and should be interpreted to mean that a 1 percentage point increase in insolvent insurer share is associated with a β percentage point increase in serious delinquency.

Table 8 shows the results from running this specification. In Column (1), with no fixed effects, we see a statistically significant and high correlation between insolvency shares and delinquency. The coefficient is muted in Column (2), with the inclusion of county and year fixed effects, but still very large. The coefficient in column (1) can be interpreted to mean that the counties where insolvent insurers were relatively more important are also the counties which experienced more mortgage delinquency. Column (2) shows that as a county experienced more insurer fragility, it also tended to experience more mortgage delinquencies. While these are not causal estimates, we do find strong correlation between insurance fragility and mortgage delinquency.

6.2. Event Study Around Hurricane Irma

We now turn to an event study to try an obtain a causal link between insurer insolvency and mortgage delinquency. We focus specifically on Hurricane Irma, which made landfall in Southern Florida on August 30, 2017, and lasted for nine days. We first explore the effect of this hurricane on mortgage delinquency, and then consider how these effects vary by the fragility of the local insurance market.

Event Study Design: We start by showing how delinquencies evolve in the aftermath of hurricane Irma relative to the months before the storm. Figure 8 shows the serious delinquency rates for two types of counties: exposed, i.e. counties which receive a Presidential Disaster Declaration, indicating that they were directly hit by the hurricane, and not exposed, i.e. counties that do not receive such a declaration. We observe a large spike in serious delinquencies following Irma. For example, the average delinquency rate was around 1.2% in both types of counties one year prior to Irma, however it increases three times to about 3.5% in exposed counties in the months following Irma, and remains elevated. We also observe that delinquencies rise in not exposed counties, suggesting that these counties also experienced some effects of the hurricane, although not large enough to receive a Presidential Disaster Declaration.

To obtain a causal effect of the storm on delinquencies, we run the following difference-in-differences specification:

$$(6)\qquad SeriousDelinquencyRate_{c,t} = \beta_1(PostIrma_t \times logDamages_c) + \delta_c + \delta_t + \varepsilon_{c,t}.$$

The variable $logDamages_c$ is the log of the property damages per capita experienced by a county within 3 months after Hurricane Irma. We use a continuous measure to identify exposed counties because we would like to know not only whether a county was directly hit by the hurricane, but also the extent of damages it incurred. This is important because losses tend to be non-linear and two counties that received a Presidential Disaster Declaration could have suffered different levels of losses. As earlier, our dependent variable, $SeriousDeliqnuencyRate_{c,t}$, is the share of all mortgages in county c that were originated within five years prior to period t which are seriously delinquent as of period t. Serious delinquency is defined as whether the mortgage is more than 90-days delinquent, in pre-sale or post-sale foreclosure, or in REO. δ_c and δ_t capture county- and year-month fixed effects, respectively. The variable $PostIrma_t$ equals 1 after September 2017, when Irma made landfall. Standard errors are clustered at the county level.

The coefficient β_1 is the difference-in-differences estimator, and captures the extent to which the increase in delinquencies after Irma is correlated with the size of damages experienced by a county. The key identifying assumption for this specification is parallel trends– that delinquencies in the high damages (higher treatment) counties would have moved in parallel to the low damages (lower treatment) counties in the absence of the hurricane. The evidence supporting this assumption can be seen in Figure 8, which shows that serious delinquency rates indeed move in parallel for both counties that are more and less exposed to the storm in the year prior to the storm.

To quantify how delinquencies vary by the fragility of the local insurance market, we additionally consider the following specification:

$$\begin{aligned}(7)\qquad SeriousDelinquencyRate_{c,t} = {} & \beta_1(PostIrma_t \times logDamages_c) \\ & + \beta_2(PostIrma_t \times InsolventInsurerShare_c) \\ & + \delta_c + \delta_t + \varepsilon_{c,t}.\end{aligned}$$

The additional independent variable, $InsolventInsurerShare_c$, refers to the premiums shares in 2016, the year prior to the storm, of insurers which subsequently become insolvent after the landfall of Hurricane Irma and measures how exposed is a given county to fragile insurers. The coefficient β_2 allows us to quantify the extent to which counties that have more insurance market fragility also have worse mortgage market outcomes, controlling for the extent of property damages due to the hurricane using $PostIrma_t \times logDamages_c$. A positive β_2 would imply that fragility of the local insurance market amplifies delinquencies when comparing two counties that are similarly exposed to the hurricane.

Results: Table 9 shows the results from estimating Equations 6 and 7. In the year prior to the storm, on average the serious delinquency rate in Florida was around 1.2% (or 120 bps). Column (1) shows that β_1 is positive and statistically significant, implying that counties that are more exposed to the hurricane also experience a strong increase in delinquencies. The magnitudes are sizeable. For example, counties at the 25th percentile of the damages experience an increase of 17bps in delinquencies in the year after the storm, which is already about 10% of the baseline rate of 120 bps. However, counties at the 75th percentile of the damages experience an increase of 48bps in delinquencies or about 3 times the increase in counties at the 25th percentile.[39] Extending the sample further to up to 5 years in column (2) we see that β_1 is still positive and statistically significant. This implies that serious delinquencies are persistent and large, with more exposed counties (75th percentile) experiencing 34 bps and less exposed counties (25th percentile) experiencing 12 bps higher delinquency rates over the longer term.

Column (3) and (4) show the effects of insurer fragility on delinquency rates at a univariate level. We find that β_2 is positive, statistically significant, and economically large. Thus, delinquency rates were even higher in counties exposed to fragile insurers in the year around the storm. Moreover, column (4) shows that the effect persists over the longer-term. In columns (5) and (6) we show that the effect of insolvent insurers is robust to controlling for the direct effect of Irma using property damage, $PostIrma_t \times logDamages_c$. We test whether the identifying assumption of parallel trends– that delinquencies in the high and low insolvency share counties would have moved in a parallel fashion in the absence of the hurricane– holds by estimating a dynamic version of Equation 7. Figure A.6 (a) and (b) show the dynamic treatment effects of exposure to fragile insurers on delinquencies at a univariate level and after controlling for property damages. The difference between high and low insolvency share counties in statistically zero throughout the pre-period, implying the absence of different trends.

The interpretation of the coefficient in column (5) is that a 1 percentage point increase in exposure to insolvent insurers increases delinquencies by .085 percentage points. To contextualize this result, our estimates suggest that counties at the 25th percentile of exposure to insolvent insurers experience an increase of 7.6bps in delinquencies in the year after the storm. However, counties at the 75th percentile of exposure to insolvent insurers experience

[39] The cross-sectional average $logDamages$ is 3.2 and 25th and 75th percentiles are 1.8 and 5.2, respectively.

an increase of 35bps in delinquencies, which is a 4.6 times higher increase in delinquency rates after the hurricane than counties at the 25th percentile of exposure to fragile insurers. This is also a large result considering that on average delinquency rates are around 1.2%, meaning that a 28bps change represents about 25% of the average delinquency rate.

Taken together, the results show that mortgage delinquencies do increase after hurricanes, and the immediate effects are exacerbated by fragile insurers. These results suggests that further increases in insurer fragility could therefore lead to a direct increase in serious mortgage delinquency.

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.

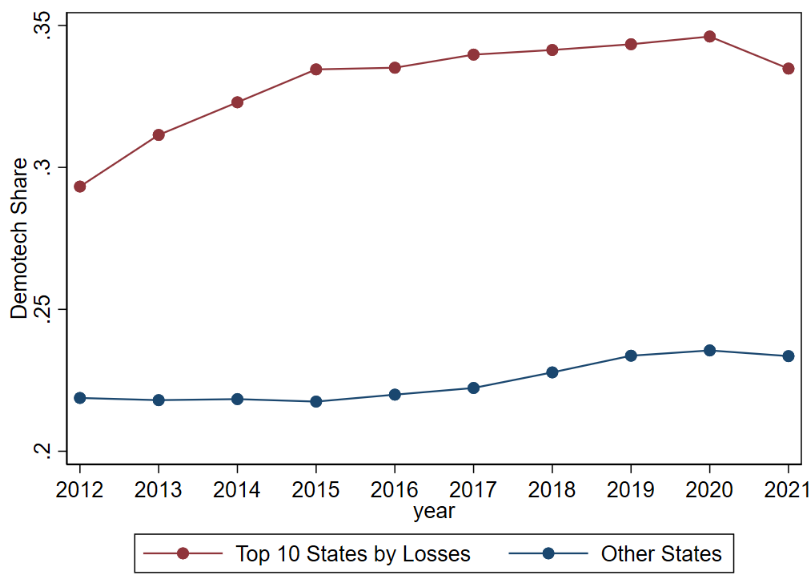


Figure 2: Evolution of Homeowners' Insurance Market in Florida

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.

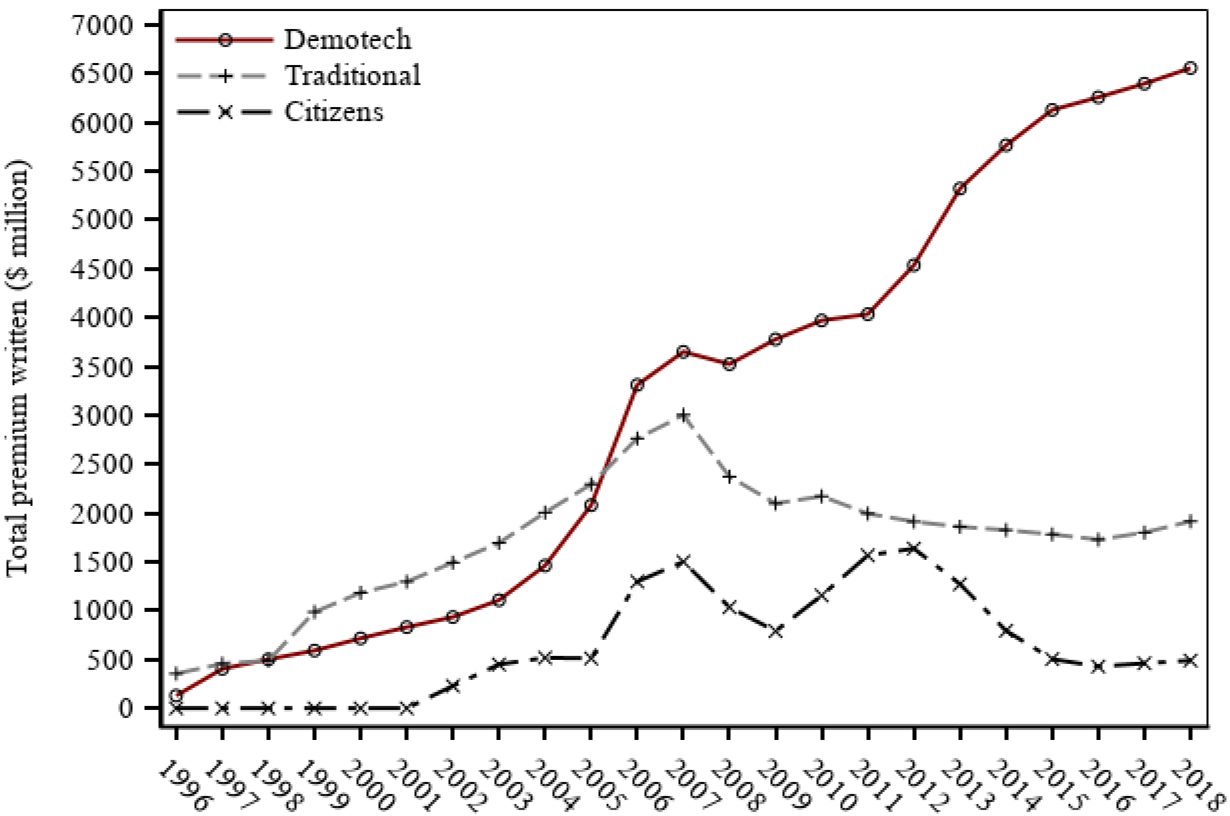
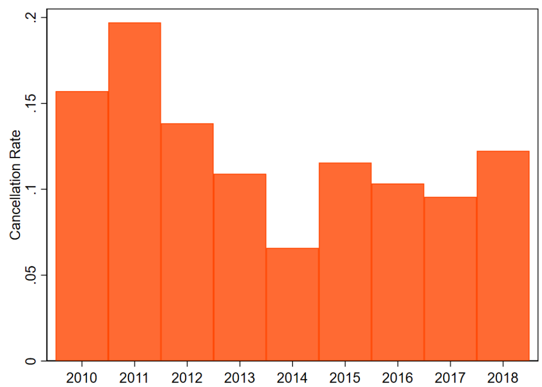


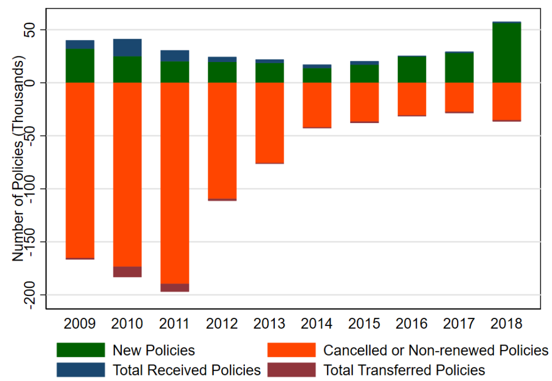
Figure 3: Cancellations and Non-renewals of Insurance Policies by Traditional Insurers

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)

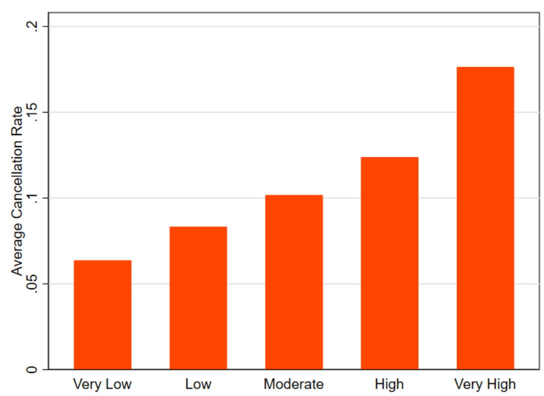
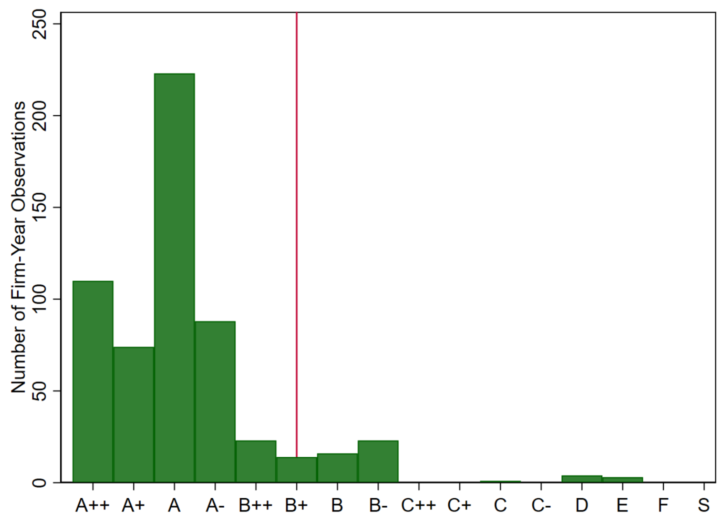


Figure 4: Histograms of Financial Stability Ratings

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

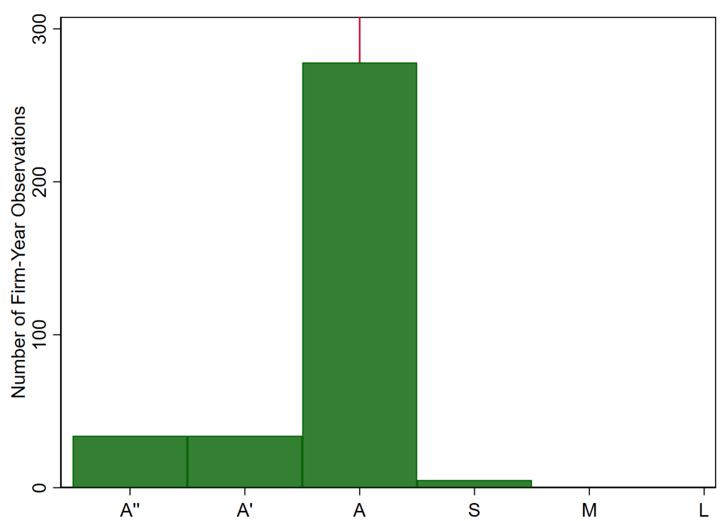


Figure 5: Counterfactual AM Best Ratings of Demotech Insurers

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.

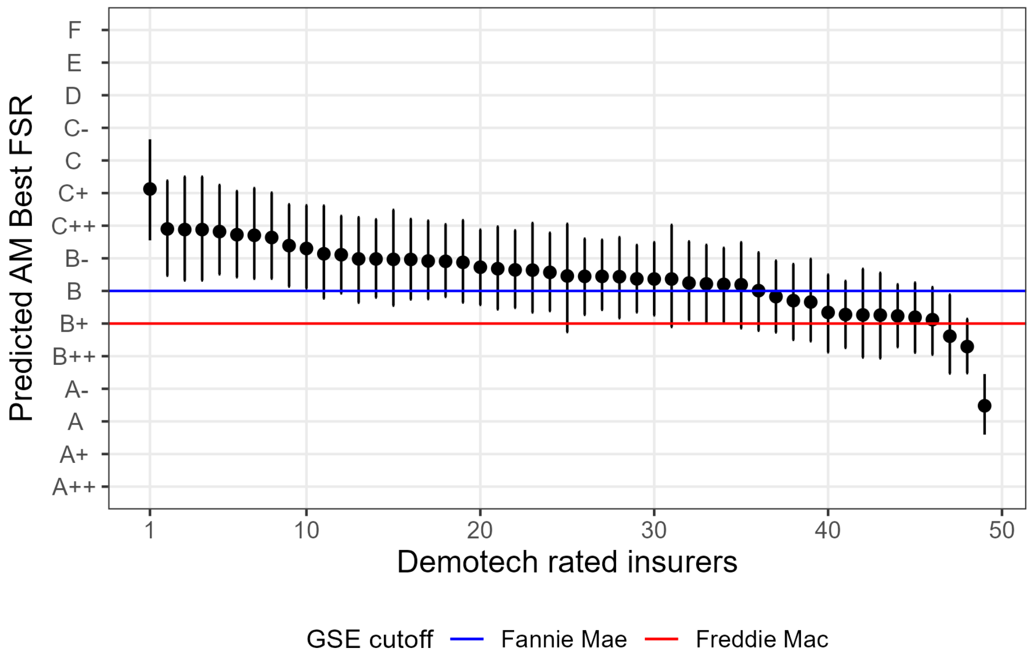


Figure 6: Participation in Citizens' Depopulation Program

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.

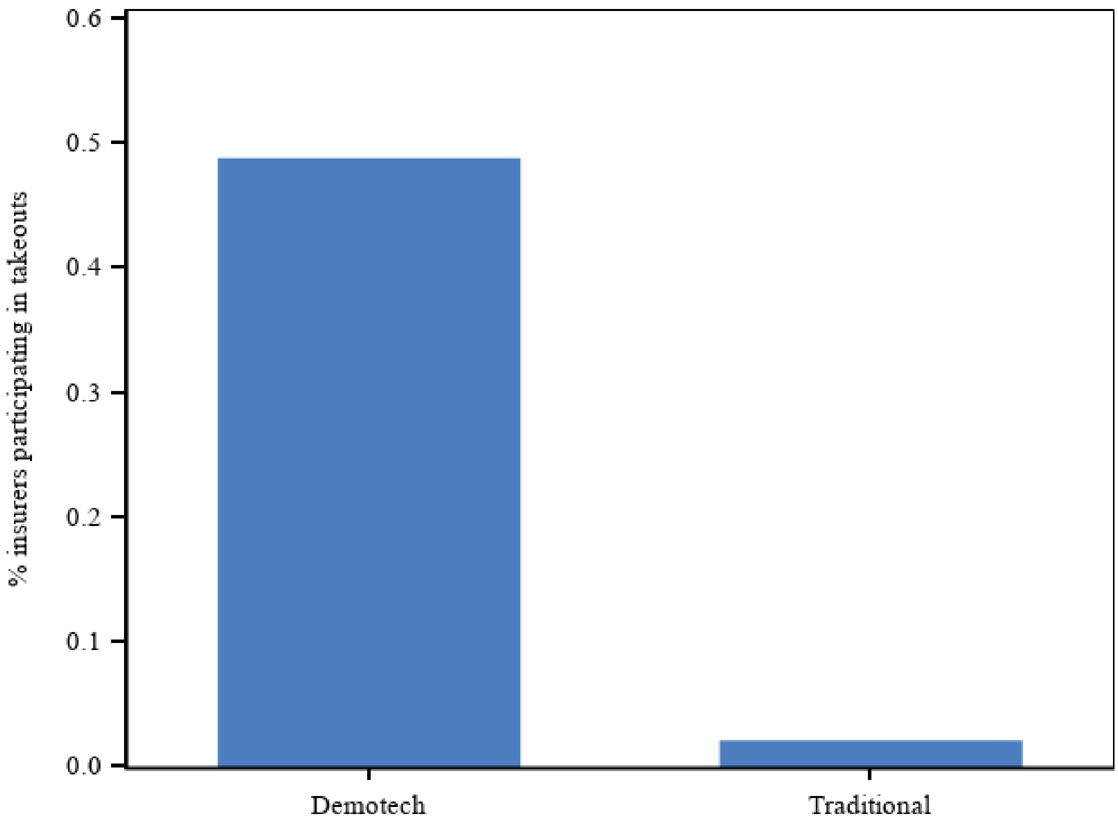
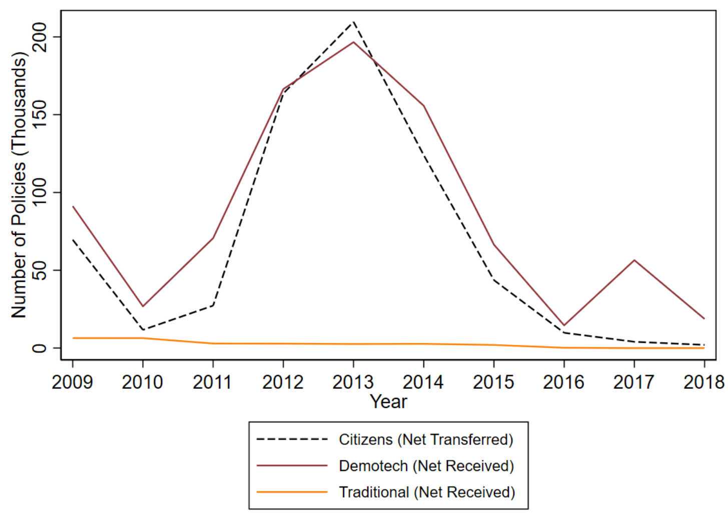


Figure 7: Citizens' Depopulation and Policy Flows

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

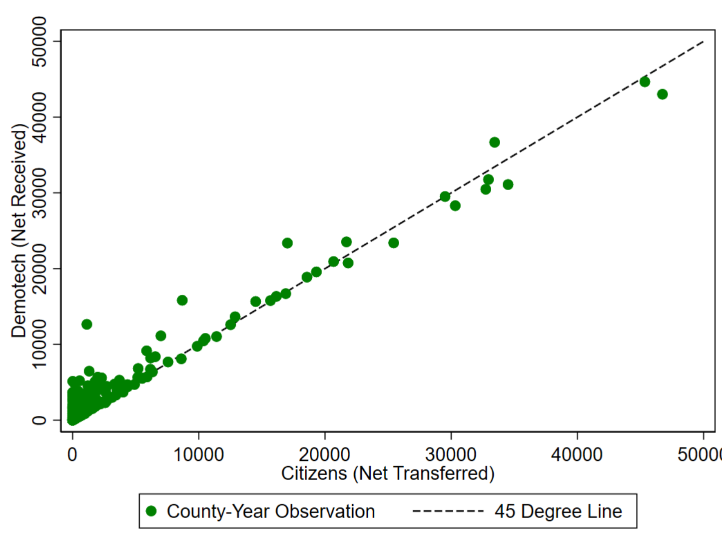
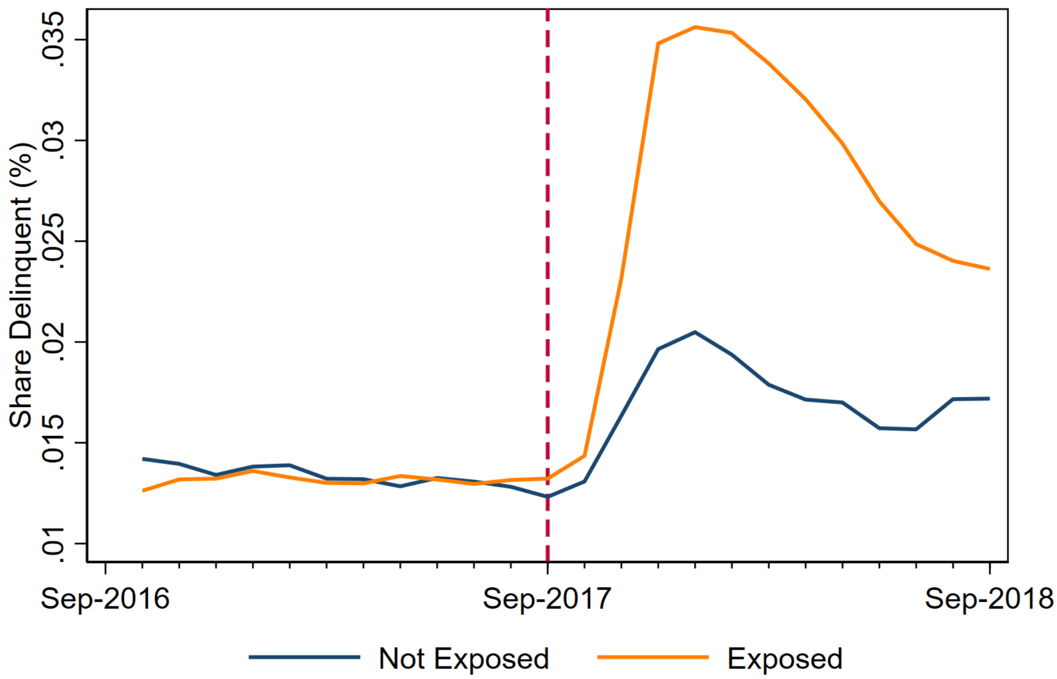


Figure 8: Delinquency Rates around Hurricane Irma

This figure shows serious delinquency in the one year before and after Hurricane Irma. Exposed counties are those that receive a Presidential Disaster Declaration. Serious Delinquency is defined as whether the mortgage is more than 90 days delinquent, is in pre-sale or post-sale foreclosure, or in REO.



Tables

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.

Type	Rating Agency	Fannie Mae	Freddie Mac
Traditional	AM Best	"B" or better	"B+" or better
Traditional	S&P Global	"BBB" or better	"BBB" or better
Emerging	Demotech, Inc.	"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: Risk Exposures and Pricing by Insurer Types

This table uses data at the firm-year level to assess how firm-level exposures and pricing 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. In Panel (A), 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). In Panel (B), we look at firm pricing behavior, where price is defined as premiums per every $10,000 of coverage. Column (1) shows the average price in high risk counties, (2) shows average price in low risk counties, and (3) shows the average price in high risk counties minus the average price in low risk counties. In both panels, we regress each dependent variable on an 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 the omitted category. All specifications include year fixed effects. We report heteroskedasticity robust standard errors in parentheses. Note that there are 44 insurers which do not operate at all in low risk counties. This explains the difference in observations in Panel B, columns (2)-(3). Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Climate Risk Exposure			
	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

Panel B: Pricing of Climate Risk			
	Premiums per $10,000 of Coverage		
	High Risk Counties	Low Risk Counties	High - Low Risk
	(1)	(2)	(3)
Demotech	10.19***	5.646***	4.521***
	(0.826)	(0.710)	(0.588)
Observations	924	880	880
Adjusted R^2	0.160	0.104	0.051
year_fe	Y	Y	Y

Table 4: 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 5: 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 (1)	2014-2018 (2)	Difference (1) - (2)
Likelihood of exam in a year (%)	36.2	28.1	8.1
% insurers ever restated	34.4	24.6	9.8
% exams with restatements	37.6	21.3	16.3**
(b) Regulatory supervision across insurers	**Demotech (1)**	**Traditional (2)**	**Difference (1) - (2)**
Likelihood of exam in a year (%)	32.6	25.7	6.9
% insurers ever restated	35.5	28.6	6.9
% exams with restatements	30.8	21.4	9.4
(c) Consumer complaints	**Demotech (1)**	**Traditional (2)**	**Difference (1) - (2)**
Share of complaints	87.9	12.1	75.9***
Likelihood of any complaints in a year (%)	79.7	48.5	31.2***

Table 6: 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. Controls are county-by-year averages from HMDA and McDash, and include log income, FICO score, LTV, and log property value at origination. County and year fixed effects are included where indicated. Our McDash sample ends in 2016, explaining the different number of observations in Column (4). Standard errors are clustered at the county level and reported in parentheses. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	GSE Share	GSE Share	GSE Share	GSE Share
Demotech Share	0.291***	0.224***	0.0820**	0.0837**
	(0.0388)	(0.0599)	(0.0403)	(0.0399)
County FE	N	N	Y	Y
Year FE	N	Y	Y	Y
Controls	N	N	N	Y
Sample Period	2009-2018	2009-2018	2009-2018	2009-2016
Number of Observations	670	670	670	536
Adjusted R-squared	0.255	0.283	0.746	0.767

Table 7: 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	log(GSE)	log(GSE)	log(GSE)	log(GSE)
log(Demotech)	0.795***	0.929***	0.0343**	0.0331**
	(0.0367)	(0.0346)	(0.0157)	(0.0162)
County FE	N	N	Y	Y
Year FE	N	Y	Y	Y
Controls	N	N	N	Y
Sample Period	2009-2018	2009-2018	2009-2018	2009-2018
Number of Observations	619	619	619	618
Adjusted R-squared	0.580	0.762	0.974	0.974

Table 8: Mortgage Delinquency and Insurer Insolvency

This table shows the correlation between insurer insolvency and mortgage delinquency. The dependent variable is the share of all originations made in the prior five years which are seriously delinquent at the county-year observation, obtained from McDash. Serious Delinquency is defined as whether the mortgage is more than 90 days delinquent, is in pre-sale or post-sale foreclosure, or in REO. The independent variable "Insolvent Firm Premium Share" is the share of all premiums underwritten by firms which go insolvent in the following year. County and year fixed effects are included where indicated. Standard errors are clustered at the county level.

	(1)	(2)
	Seriously Delinquent Rate	
Insolvent Firm Premium Share	1.487***	0.486**
	(0.395)	(0.208)
Constant	0.0410***	0.0429***
	(0.00140)	(0.000400)
County FE	N	Y
Year FE	N	Y
Number of Observations	670	670
Adjusted R-squared	0.0617	0.802

Table 9: Delinquency Event Study Around Hurricane Irma

This table shows the difference-in-differences regression studying the effect of Hurricane Irma on mortgage delinquency. The dependent variable across all specifications is the share of mortgages originated in the prior five years which are seriously delinquent. Serious delinquency is defined as whether the mortgage is more than 90 days delinquent, is in pre-sale or post-sale foreclosure, or in REO. Insolvent Insurer Shares 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. Log Damages refers to the log of the property damages per capita, as reported in SHELDUS, incurred within 3 months after Hurricane Irma. County and year-month fixed effects are included where indicated. Columns (1), (3) and (5) restrict the window to one-year before and after the storm. Columns (2), (4), and (6) include an extended window following the storm to capture long-run effects. The sample for all six specifications is restricted to the 50 counties with nonzero property damage. Standard errors are clustered at the county level.

	Seriously Delinquent Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Post Irma=1 × Log Damages	0.000919**	0.000653**			0.000635**	0.000450*
	(0.000345)	(0.000289)			(0.000294)	(0.000267)
Post Irma=1 × Insolvent Insurer Shares			0.106***	0.0760***	0.0853***	0.0612**
			(0.0291)	(0.0242)	(0.0280)	(0.0241)
County FE	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y
Number of Observations	1250	3800	1250	3800	1250	3800
Adjusted R-squared	0.773	0.813	0.780	0.814	0.788	0.815
Time Period	9/2016-9/2018	9/2016-12/2022	9/2016-9/2018	9/2016-12/2022	9/2016-9/2018	9/2016-12/2022

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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.

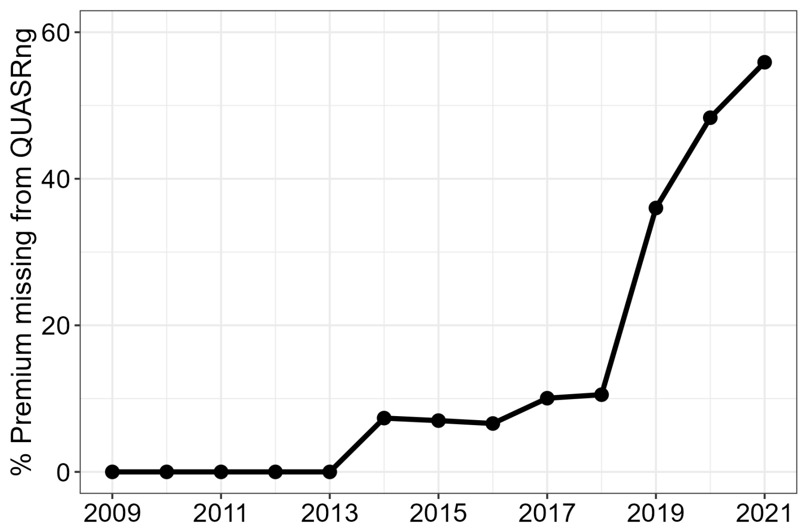


Figure A.2: Top 6 States by Market Share of Demotech-rated firms

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.

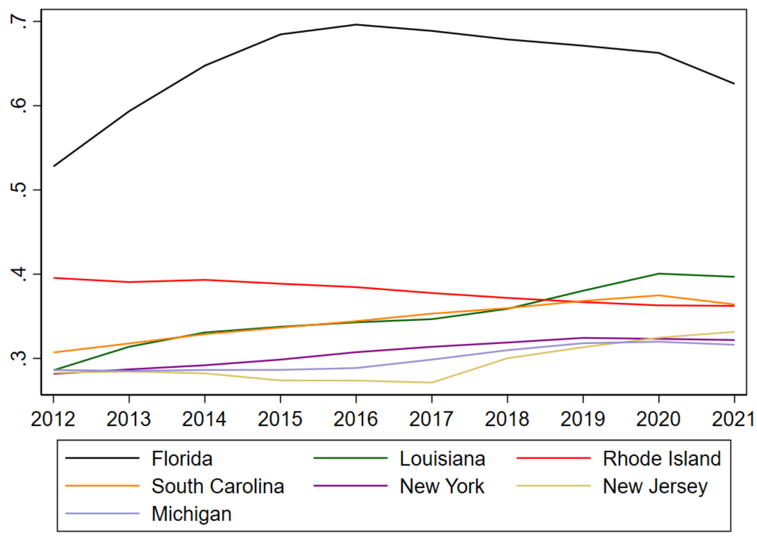


Figure A.3: Histogram of Demotech Insurers' Premium Shares in 2009 versus 2018

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.

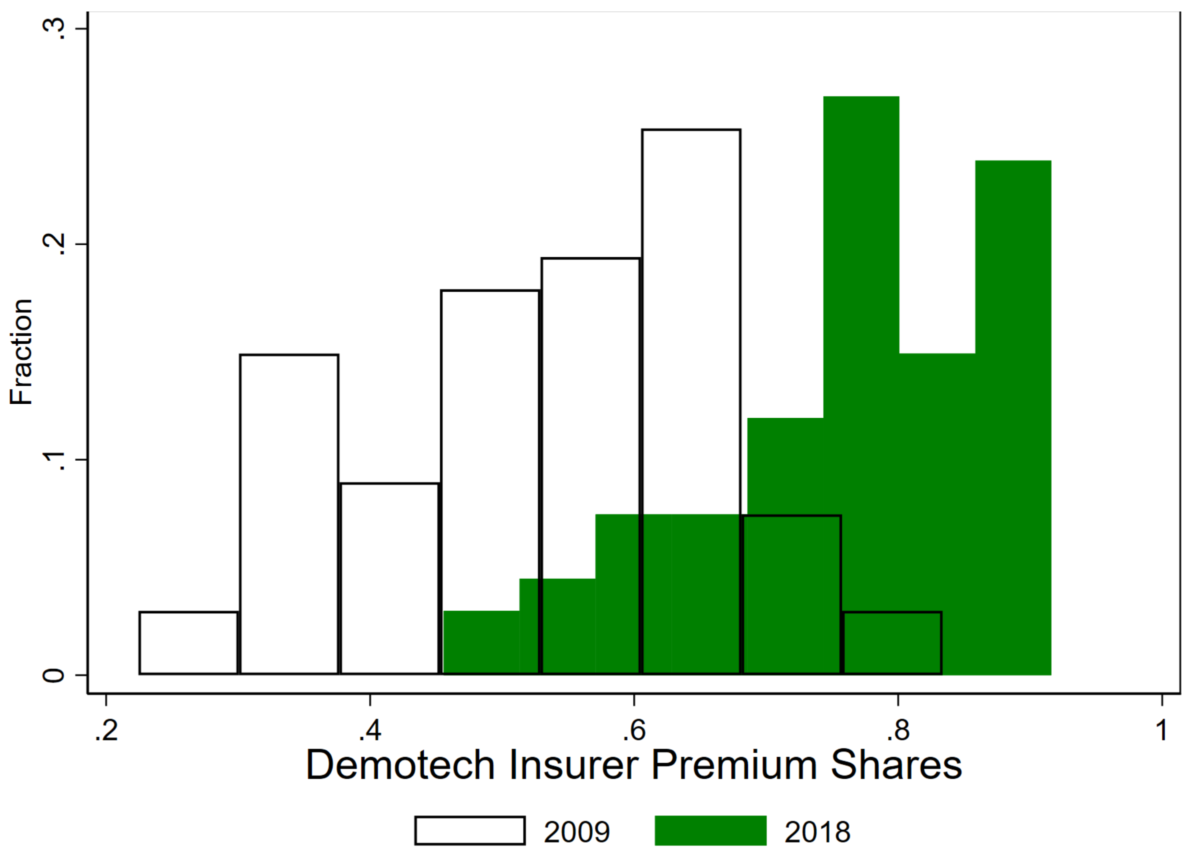


Figure A.4: GSE eligibility of insurers in Florida

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.

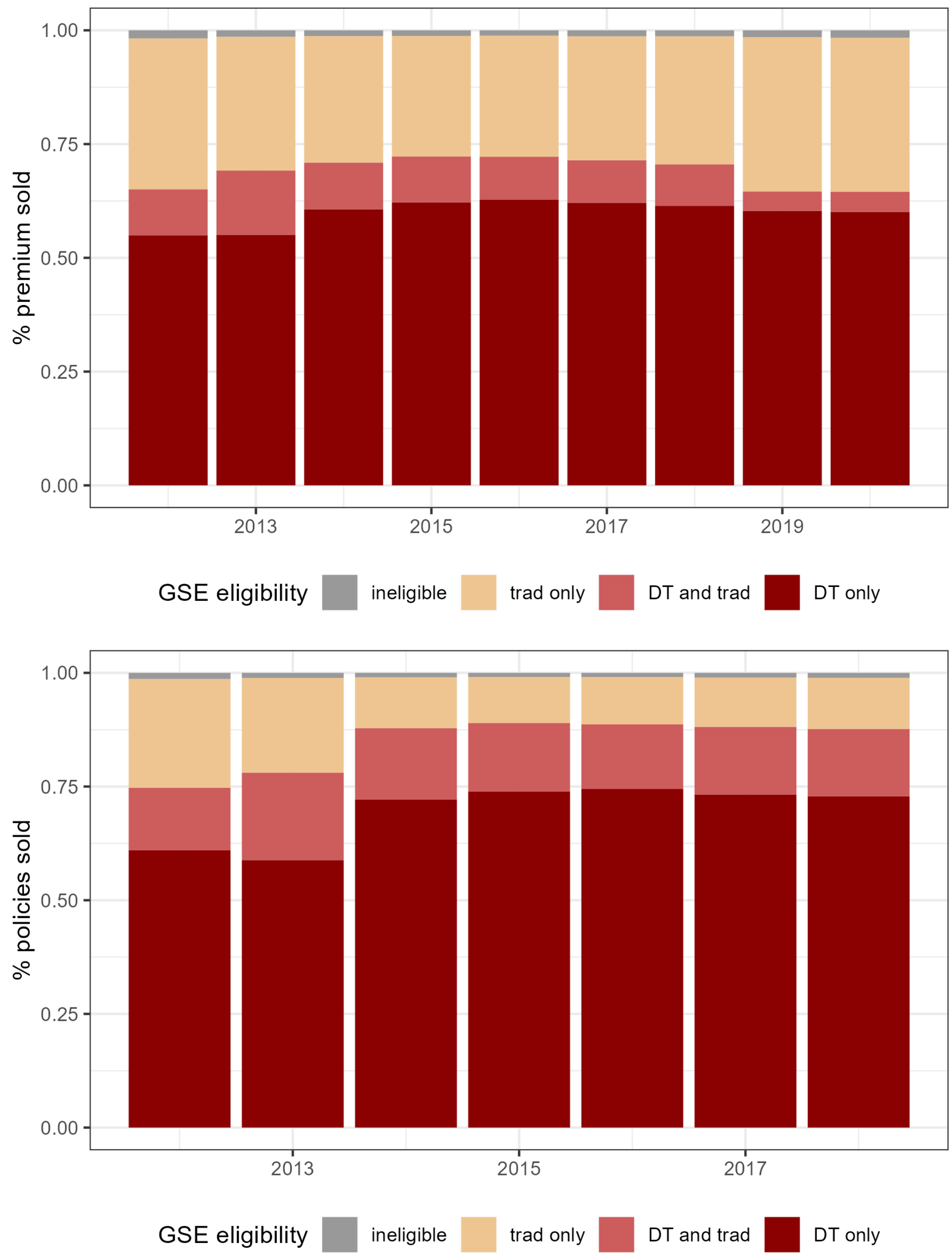


Figure A.5: Citizens' Depopulation and Climate Risk

The figure shows how Citizens' depopulation across counties varied by FEMA's climate risk categorization. Panel A shows counties classified as low risk, which are categories 1 and 2. Panel B shows counties classified as high risk, which are categories 3, 4, 5.

(a) FEMA Low Risk Counties

(b) FEMA High Risk Counties

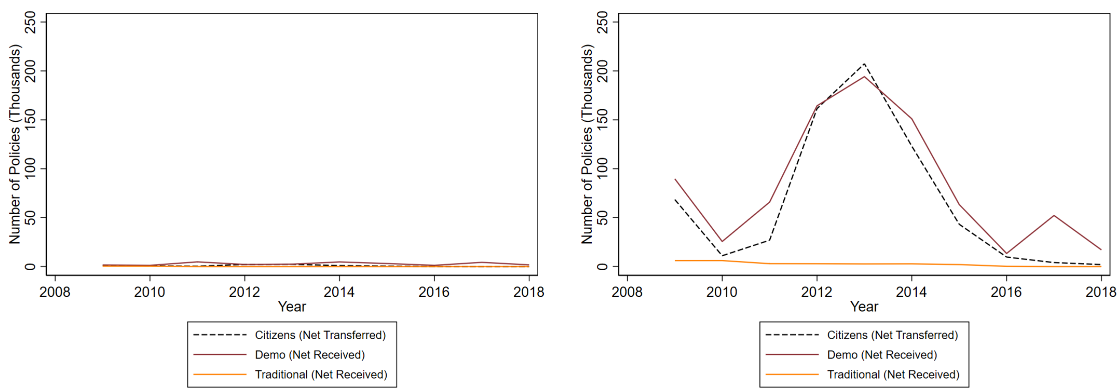
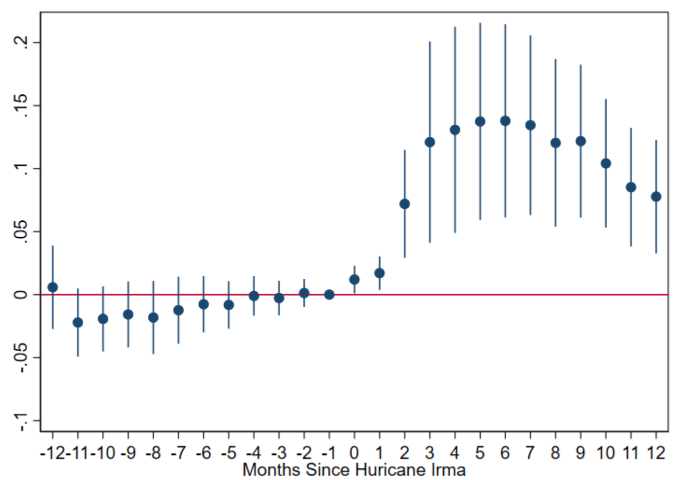


Figure A.6: Dynamic Treatment Effects of Delinquency around Hurricane Irma

This figure shows the coefficients from from the continuous treatment difference-in-differences regression that allows the effect to vary by month relative to the landfall of Hurricane Irma in September 2017. The dependent variable is the share of mortgages originated within 5 years that are seriously delinquent. Serious Delinquency is defined as whether the mortgage is more than 90 days delinquent, is in pre-sale or post-sale foreclosure, or in REO. The treatment varies by insolvent insurer share, a continuous varibale that 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. In Panel A we should the difference-in-difference results with no controls, and in Panel B we also include the interaction term of year-month × log damages as a control variable. Log Damages refers to the log of the property damages per capita as reported in SHELDUS incurred within 3 months after Hurricane Irma. The sample for both figures is restricted to the 50 counties with nonzero property damage. Standard errors are clustered at the county level.

(a) Effect of Insurer Insolvency



(b) Effect of Insurance Insolvency with Control

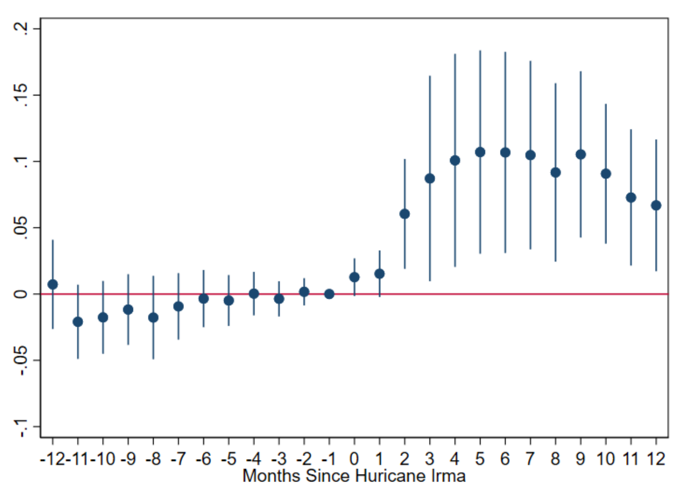


Table A.1: AM Best Rating Replication Model

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

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.