Adaptation, Insurance Prices, and Government Policy*

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Abstract

We study the impact of tropical cyclone events on property insurance prices in Florida following the 2004 cyclone season. Motivated by models of a state-run insurer that acts to maximize insured assets and two types of private firms that differ with regard to their choice of capital reserves and their share of coverage offered in different markets, we show that substitution and government policy following cyclone events dampens the insurance price response. In particular, we characterize the insurance market as consisting of three types of insurers: large, small, and state-owned (Citizens). Small insurers have the lowest prices. Citizens offers lower prices than large insurers and socializes the risk by raising prices across both coastal and inland areas. Hence, we show that following the 2004-5 cyclone season, transacted private prices rose only about 5.8% in counties that experienced category 1 (cat 1+) or higher winds and did not rise significantly in counties with less than cat 1+ winds. This is because a large number of property owners substituted from large to small insurers following the increase in posted prices by large firms. Citizens' prices rose by about 26.5% in counties with cat 1+ winds, but about 30.6% in counties with less than cat 1+ winds. We conclude by discussing the policy tradeoff of creating a competitive market with a state-owned insurer and small insurers with low prices, which increases insurance take-up, but dampens the price signal to reduce development in risky areas.

Keywords: property insurance, hurricanes, natural disasters, adaptation, state-owned enterprises

JEL Codes: Q54, Q58, G22, G28

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1 Introduction

Adaptation is an important strategy in limiting the effects of climate change. Economic actors implicitly or explicitly rely on markets to provide signals of where adaptation strategies are most beneficial relative to the cost (Fisher-Vanden, Wing, Lanzi, and Popp, 2013). For example, high property insurance prices in coastal areas vulnerable to natural disasters, storm surge, and flooding discourage coastal development, thereby reducing future coastal climate change impacts.

State insurance regulators seeking to encourage adaptation face difficult trade-offs following a natural disaster that increases risk perceptions. Insurance companies often desire to increase insurance rates following a natural disaster to reflect the increase in risk perceptions (either higher damages per event or a change in the likelihood of an event). Regulators may prevent insurance prices from rising too quickly, because higher prices may cause existing property owners to drop insurance, exposing constituents to potentially large losses.[1] The issue of affordability threatens the role that insurance premiums can play in making disaster risk tangible to households.

By limiting price increases, state regulators encourage households to keep purchasing insurance, an important adaptation tool. But if insurance prices rise too slowly, coastal development may continue, increasing capital at risk and ultimately making residents more vulnerable. Conte and Kelly (2018) find that the fat-tailed nature of the aggregate damage distribution for tropical cyclones making landfall in the United States could stem from the fat-tailed distribution of coastal city size. Given the challenge that fat-tailed distributions pose to insurers, preventing the over-aggregation of at-risk assets in densely-populated areas via reduced development offers another adaptation strategy. Insurance price increases effectively cause long-run substitution from one adaptation strategy (insurance) to another (reduced coastal development). However, reducing coastal development is not an option in the short run, so large short-run price changes may result in fewer households with insurance and reduced ability to adapt.

Property insurance is a highly regulated industry, and state insurance regulators desiring to limit price increases operate a number of policy levers. These include denying price rate increases (price increases require regulatory approval in most states) and lowering standards to increase competition. In Florida, state insurance regulators have another lever available, given the existence of the state-owned insurer, Citizens Property Insurance Corporation (Citizens). Here, the insurance regulators can attempt to mitigate the potential for reduced insurance coverage by requiring Citizens to charge below market prices and/or socialize risk geographically.

We are interested in studying the impact of natural disasters on insurance prices, accounting for potential differences in response by large and small private firms and state-owned insurers. Here, we study the response of the Florida insurance market to the 2004-5 hurricane seasons. This period saw 5 hurricane-

[1] Grace, Klein, and Kleindorfer (2004) finds that demand for catastrophic property insurance is elastic.

strength storms make landfall in FL, whereas previously the most in any two year period was 3 (40 years previously). In turn, such an apparently large change in risk perceptions induced a desire for property insurers to increase prices.

We divide the property insurance market into three types of insurers: large private, small private, and the state-owned Citizens. We use difference-in-difference and event-study specifications and contrast the change in insurance prices in counties that experienced high winds from the hurricanes versus counties that did not. We find that private insurer transaction prices rose by about 5.8% in coastal counties that experienced category 1 or higher (cat 1+) maximum winds, subsequent to the 2004 hurricane events. Counties that experienced less than cat 1+ winds saw an insignificant 3.1% increase.

Our data observes transaction prices and not posted prices. We show that policies in force (PIF) by large insurers fell from about 1.6 million to about 1.2 million in the 3 years following the 2004-5 season whereas new entrants went from 0 to 0.6 million policies and Citizens increased from about 0.4 million to about 0.45 million. Further, entrants and Citizens had much lower transaction prices both before the 2004-5 season. Although all three types increased prices after the 2004-5 season, entrant prices were still well below incumbents and Citizens. We therefore conclude that although posted private prices increased, private transaction prices increased only modestly since many property owners switched to less expensive alternatives.

We next show that Citizens increased transaction prices by about 26.5% in cat 1+ counties and by about 30.5% in counties with less than cat 1+ winds. Thus, Citizens increased prices more in unaffected counties, whereas private insurers increased prices more in affected counties. This result provides some evidence that Citizens was socializing the risk. Citizens limited the price increase in risky areas to encourage property owners to buy insurance and increased prices in less risky areas to keep premium revenue high enough to limit state-wide expected losses.

2 Literature

Our study of the reaction of insurance prices to natural disasters which increase risk perceptions is ultimately motivated by adaptation. Without the first step of an increase in insurance prices, it is unlikely that adaptations such as reduced development in risky areas will occur. Fisher-Vanden, Wing, Lanzi, and Popp (2013) provide an important framework for thinking about adaptation and price changes. They characterize Type I adaptations as general equilibrium responses to relative price changes. They note that Computable General Equilibrium (CGE) models are capable of accounting for such general equilibrium effects. Our results provide an important caveat that price increases predicted by competitive CGE may not account for policy responses that limit price increases, such as state-owned insurers.

A recent literature (e.g. Gollier, 2003; Ericson and Sydnor, 2018; Rampini and Viswanathan, 2016; Bauer,

Phillips, and Zanjani, 2013) focuses on the role of liquidity constraints in generating additional demand for insurance to help with consumption smoothing when traditional financial savings/borrowing instruments are unavailable. Unlike models without liquidity constraints, where households fully insure if and only if insurance is actuarially fair (e.g. Arrow, 1963; Mossin, 1968), these models generate positive, but less than full insurance, when premiums exceed actuarially fair levels. Further, an increase in risk perceptions generates an increase in insurance demand even though prices also rise with risk and insurance is more expensive than actuarially fair. Their idea that insurance helps smooth consumption provides an additional motivation for policy makers to limit price increases in our context. Further, our empirical results support this idea in that we show policies in force increase after the increase in risk perceptions, despite the increase in prices.

Many papers empirically estimate insurance demand following natural disasters. For example, Gallagher (2014) shows that flood insurance demand increases after flood events, but the increase in demand eventually fades. Grace, Klein, and Kleindorfer (2004) estimate the price elasticity for catastrophe insurance in Florida, using insurers predicted expected losses in rate filings as a proxy for insurance demand. They find catastrophic insurance demand is elastic. This evidence supports our idea that insurance regulators might limit price increases due to concerns that price increases would result in a loss of coverage.

A large literature estimates the change in property values following natural disasters such as hurricane (Bin and Polasky, 2004; Hallstrom and Smith, 2005; Bin and Landry, 2013; Gibson and Mullins, 2020; Ortega and Taşpınar, 2018; Davlasheridze and Fan, 2019, e.g.). This literature shows that affected property values decline after hurricanes or sea level rise. The decline aggregates uninsured risks (e.g. job loss) and higher insurance costs for insurable risks.[2] This literature makes an important contribution in showing that property markets respond to hurricane and sea level rise risks. Our results show that government policies also matter: the change in property values resulting from a change in insurance prices depends on government policies such as the price charged for state-owned insurance. Indeed, Eastman, Kim, and Zhou (2024) instrument for insurance prices using a change in the Florida law in 2008 that required companies that offered auto insurance to also offer property insurance, if they offer property insurance in other states. They show a 10% increase in insurance prices decreased property values by 1.4%.

Regulatory impediments to price increases are important for our results. Grace and Klein (2009) provide a thorough description of the regulatory environment during the period of study. Oh, Sen, and Tenekedjieva (2022) uses state regulatory rules as an instrument in regression discontinuity framework across state borders. They show that rates do not respond to changes in risk in highly regulated states and insurance companies instead raise rates in less regulated states. Our results *within* the state of Florida show a related but distinct result: state-owned Citizens increases rates by less in risky areas, and compensates by increasing rates more in less risky areas. However, private insurers increase rates more in risky areas, despite higher

[2] Several papers more specifically estimate the effect of flood insurance premiums on property transaction prices (Nyce, Dumm, Sirmans, and Smersh, 2015; Georgic and Klaiber, 2022, see, for example,).

prices leading to a loss of policies.

Our work relates to literature covering insurance and other natural disasters. For example, Boomhower, Fowlie, Gellman, and Plantinga (2024) studies the California property insurance market following the recent wildfires. They show that less informed insurers charge higher prices than more informed insurers in high risk areas to mitigate the adverse selection problem.

Losses from many natural disasters, including hurricanes, have fat tailed distributions (e.g. Conte and Kelly, 2018; Coronese, Lamperti, Keller, Chiaromonte, and Roventini, 2019; Conte and Kelly, 2021). Fat tailed losses complicate insurance pricing. Diversification is more difficult as positive correlations exist between damages in different locations (Kousky and Cooke, 2009) and the cost of holding reserves can drive insurance prices above actuarially fair levels (Born and Viscusi, 2006; Kousky and Cooke, 2012), which in turn reduces the quantity of insurance purchased by property owners.

Keys and Mulder (2024) infer property level insurance costs from mortgage payments less principle, interest, and taxes. They show that premiums per property rose by about 20% from 2021-2024 in inflation adjusted dollars. They find that higher reinsurance costs, greater correlation between disaster risk and insurance prices, and higher home values all contributed to the increase in prices. They also show that Florida, which relies more heavily on smaller insurers that make extensive use of reinsurance, experienced higher prices than adjacent counties in Georgia, where insurers rely less on reinsurance. Our results in a different time period and controlling for exposure show generally smaller price increases, but nonetheless provide supporting evidence in that the market share of entrants, which rely more on reinsurance, grew substantially.

3 Data and Regulations

3.1 Wind Speed

We use maximum-sustained wind speed during each of the storms in our dataset recorded at points on a 6 kilometer grid recorded by NOAA and maintained by the company RMS. Figures 1-**??** provide county-level maps of the maximum sustained wind speed experienced within each of Florida's 67 counties during the quarters (quarter 3 in 2004, 2005, and 2008 and quarter 4 in 2005) in our sample period (2003-2016) in which a tropical cyclone made landfall in Florida.[3]

Figure 1 shows the results for tropical storm Bonnie and the four hurricanes (Charley, Frances, Ivan, and Jeanne) that made landfall in quarter 3 of 2004. The figure shows the maximum wind speed among all storms that impacted a given county in the quarter. Bonnie made landfall near the FL Panhandle, Charley on the west coast near Tampa, Frances on the east coast near West Palm Beach, Ivan in the Panhandle, and Jeanne

[3] Note the scale used for the colors is different in each figure.

also near West Palm Beach. The last hurricane that made land fall before 2004 was in 1995, and multiple hurricanes had not made landfall in Florida in the same season since 1950. Hence the 2004 hurricane season is an unprecedented event that makes for an interesting test of the reaction of property owners, insurers, and policy makers.

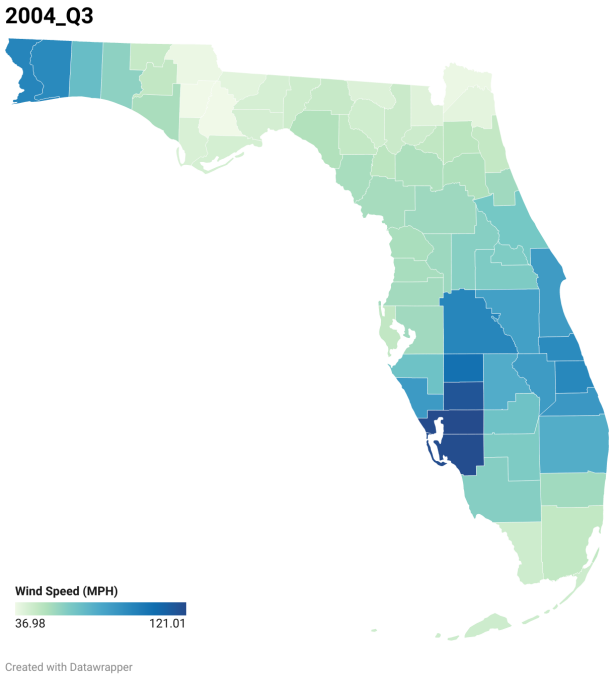


Figure 1: Maximum wind speed in each county, geographically and over tropical cyclones Bonnie, Charley, Frances, Ivan, and Jeanne, quarter 3, 2004.

3.2 Insurance Regulations

The regulatory system for Florida property insurance is complex and multi-faceted. Here we provide a summary of the most relevant regulations. See Grace and Klein (2009) and the references therein for a more comprehensive discussion.

Florida requires that residential property insurance companies offer coverage for hurricanes as designated by the National Hurricane Center (of Insurance Regulation, 2004). Although property insurers must offer policies covering hurricanes, they also may offer policies that do not. Hence, policies are either all-peril which cover hurricanes and other perils, wind-only which covers wind related perils including hurricanes, tropical storms, tornadoes, hailstorms, and thunderstorms, and ex-wind which cover perils other than wind. Wind only policies are attractive to owners of rental properties, who care about the structure but not the contents. In addition, some property owners may wish to purchase an ex-wind and a wind policy separately for cost reasons. Policies often contain a larger deductible for hurricane damages and a lower deductible for non-hurricane wind damage (Kaminski, 2006).

The Florida Citizens Property Insurance Corporation (Citizens) was created in 2002 by the state legislature as an insurer of last resort for those who cannot find property coverage in the private insurance market. Rates are required to be actuarially sound, meaning that they reflect all costs associated with the transfer of risk. The Florida Hurricane Catastrophe Fund (FHCF) was created in 1993 after Hurricane Andrew to provide reinsurance to private insurers in the state to cover the catastrophic losses associated with tropical cyclone damages.

The popularity of Citizens has been cited by critics as evidence that the state encourages continued development in high-risk areas (Kaminski, 2006). As a result, legislative changes were enacted to reduce Citizens' role in property insurance. In 2006 legislation was passed to prohibit coverage of properties with structure and contents replacement values exceeding $1 million and vacation or second homes of any value, effective July 1, 2008.

Property insurance is a highly regulated industry. Prices do not adjust immediately with supply and demand. Instead, property insurers follow a regulated process which has changed over time. Here we summarize the 2004 rules given by FLOIR (2024).

1. Each insurer makes a "base rate filing" every 12 months for each line of business. The actual rate offered to property owners varies from the base rate based on individual risk factors.

2. Insurers are required in the rate filing to "demonstrate that the rates filed are not excessive, inadequate, or unfairly discriminatory." To do this:

   (a) Insurers are required to submit actuarial data justifying the rate increase.[4] The data include past premium and loss trends, reinsurance cost data, and hurricane loss projection models.

   (b) A public hearing is required if the rate increase is 25% or more.

3. After consideration of the above data, FLOIR may approve the rate increase or not.

4. FLOIR may revoke a previously approved rate increase as being "excessive," but not within one year "unless the office finds that a material misrepresentation or material error was made by the insurer or was contained in the filing."

Price increases are thus likely to evolve slowly following a change in risk perceptions. Base rates change only annually at the insurer level, and even then insurers must wait until previous annual insurance contracts expire to raise rates. Insurers may further prefer a series of small rate increases rather than a single large increase which triggers a public hearing.

Citizens follows a similar process for approval of rate increases. However, some special rules apply to Citizens:

[4] Even if no rate increase is proposed, the data and justification are required.

1. The legislature designed Citizens such that rates are not supposed to be competitive with private insurers. Citizens is designed to be an insurer of last resort.

2. The legislature sometimes imposes maximum rate increases by statute. The maximum rate increase changes over time, but was 20% in 2003 and 2004.

3. Citizens is exempt from the state corporate income tax.

Although the rules are strict, FLOIR may incur political pressure to respond to price increases in the private market. For example, FLOIR sometimes lets new entrants into the market with the understanding that the entrants will achieve a specific number of policies, which requires low prices (see Klein, 2007, for an excellent discussion). The presence of new entrants is an econometric challenge since the object of interest, the price changes resulting from a change in risk perceptions, is confounded with the price change resulting from new entrants.

3.3 Insurance Price Data

The insurance data are provided by the Florida Office of Insurance REgulation. The period of study is from quarter 1 of 2003 to quarter 4 of 2007 and FL has 67 counties. Table 1 shows the non-commercial lines of business recognized by FLOIR, along with the number of observations of each line. Policies are separated into lines based on the characteristics of the insured (tenant, homeowner association, owner) and the type of property being insured (apartment, condo, mobile home, farm, homeowner, or dwelling). The data includes a heterogeneous mix of residential lines such as houses, apartments, and condos, but no strictly commercial buildings such as warehouses or office buildings. The vast majority of type observations cover all perils, but a significant minority cover only wind damage.[5]

[5]Note that Table 1 refers to an observation as a county/quarter/firm/line of business with at least some policies. It does not refer to the line of business policies in force by the firm within the county/quarter.

Insurance Policy Type	Observations
All perils	
Apartment Buildings	9,052
Condominium Association	4,246
Dwelling, Fire and Allied Lines	33,378
Homeowners Association	1,528
Farmowners	2,055
Condominium Unit Owners	30,210
Homeowners (Excl. Tenant and Condo)	59,623
Mobile Homeowners	19,238
Tenants	25,967
Wind Peril Only	
Wind-Only Apartment Buildings	468
Wind-Only Condominimum Association	673
Wind-Only Dwellings	547
Wind-Only Homeowners Association	245
Wind-Only Condominimum Unit Owners	565
Wind-Only Mobile Homeowners	287
Wind-Only Tenants	429
Total Observations	188,511

Table 1: Observations by policy type for non-commercial properties from quarter 1 of 2003 to quarter 4 of 2007. 'Homeowner' refers to policies which insure a single family home plus detached structures such as garages. 'Dwelling' refers to policies that insure just the livable area. Ex-wind policies are not included.

The data are disaggregated by firm (i), quarter (t), county (c), and type of property insurance (line of business, l). Let D_{iclt} the total "structure exposure" (hereafter "exposure") in dollars for policies in force which include wind coverage, for a particular firm/county/line of business/quarter. Total structure exposure includes the total dollar coverage amount for structure, appurtenant structures contents and loss of use. Total structure exposure is gross of deductibles. Let M_{iclt} be total direct premiums written for policies which include wind coverage. Our primary dependent variable is the average premium per dollar of coverage, which we denote as the price, P_{iclt}:[6]

$$P_{iclt} = \frac{D_{iclt}}{M_{iclt}}. \tag{1}$$

Table 2 gives the summary statistics for the price data in the period prior to treatment (2004Q2). The mean price across all insurers is approximately 0.75 cents per dollar of coverage. Rates in coastal counties are higher than inland, as expected, since coastal properties are generally more risky. The data exhibit significant variation, with Citizens offering a 17% lower average price than private insurers and 2004 entrants offering an approximately 46% lower price than private insurers (both incumbents and entrants). The price data are much more variable for private insurers, which could indicate either that private insurers insure

[6] Grace and Klein (2009) provide summary trends for both premiums per dollar of coverage and premiums per policy. Price increases for premiums per policy are generally larger. Premiums per policy increase both because of higher risk perceptions and because of increases in the replacement/construction costs during this period. Premiums per dollar of coverage focuses directly on price of the risk. If property owners choose higher deductibles after a storm for affordability reasons, then the price will underestimate the true cost of insurance, as premiums decline with a larger deductible, but exposure does not. Effectively, an unobserved decrease in quality occurs. This problem is also present when using premiums per policy in force.

properties with more variable risks or that private insurers use a more variable pricing strategy across similar properties. The price data are also significantly skewed for private insurers, indicating similarly either that private insurers are insuring more high-risk properties or that private insurers have a pricing strategy where prices are more strongly increasing in risk. For private insurers the maximum price is substantially greater than one and 0.14% of all price observations are greater than one. The existence of prices above unity poses a conundrum in that any policy holder would presumably prefer a lottery in which \$1 is lost with probability less than one versus a certain loss of more than \$1. A total of 0.6% of observations have prices greater than \$0.2 per dollar of coverage, which also seems incompatible with any realistic level of risk aversion. The analysis removes these outliers.

			All Insurers			
		2004Q2			2007Q4	
Price Statistic	All	Inland	Coastal	All	Inland	Coastal
Mean Price	0.75	0.68	0.82	0.70	0.64	0.76
Std Dev Price	1.05	0.87	1.20	0.86	0.78	0.93
Median Price	0.50	0.47	0.52	0.52	0.47	0.57
Min Price	1.56e-05	2.91e-04	1.56e-05	2.80e-03	7.98e-03	2.80e-03
Max Price	19.00	18.07	19.00	19.81	16.50	19.81
Total Observations	12,640	6,508	6,132	12,163	6,261	5,902
			Private Insurers			
Mean Price	0.75	0.68	0.83	0.69	0.63	0.76
Std Dev Price	1.06	0.87	1.23	0.87	0.78	0.95
Median Price	0.50	0.47	0.53	0.51	0.46	0.56
Min Price	1.56e-05	2.91e-04	1.56e-05	2.80e-03	7.98e-03	2.80e-03
Max Price	19.00	18.07	19.00	19.81	16.50	19.81
Total Observations	12,240	6,360	5,880	11,753	6,091	5,662
			Insurers with 04Q2 Exposure ≥ 10%			
Mean Price	0.71	0.73	0.69	0.73	0.68	0.801
Std Dev Price	1.06	1.03	1.11	0.92	0.86	0.98
Median Price	0.49	0.50	0.47	0.55	0.49	0.61
Min Price	3.42e-03	4.01e-03	3.42e-03	7.05e-03	7.98e-03	7.05e-03
Max Price	10.05	10.05	8.40	19.81	15.70	19.81
Total Observations	824	515	309	5,222	2,613	2,609
			Insurers with 04Q2 Exposure < 10%			
Mean Price	0.75	0.68	0.83	0.62	0.55	0.68
Std Dev Price	1.06	0.86	1.23	0.72	0.65	0.78
Median Price	0.50	0.47	0.53	0.44	0.40	0.50
Min Price	1.56e-05	2.91e-04	1.56e-05	3.87e-03	6.69e-03	3.87e-03
Max Price	19.00	11.87	19.00	19.00	8.06	10.23
Total Observations	11,416	5,845	5,571	4,542	2,254	2,288
			Citizens			
Mean Price	0.68	0.87	0.58	0.87	1.06	0.74
Std Dev Price	0.52	0.50	0.50	0.49	0.53	0.40
Median Price	0.48	0.71	0.41	0.74	0.86	0.64
Min Price	1.25e-01	1.64e-01	1.25e-01	2.06e-01	3.53e-01	2.06e-01
Max Price	3.00	2.16	3.00	2.96	2.96	2.37
Total Observations	400	148	252	410	170	240

Table 2: Summary statistics for price, which is the premium in cents per dollar of coverage, for all policies offering wind coverage. All statistics use only price data less than 20 cents per $ of coverage.

The data in the final treated quarter (2007Q4) shows a very different pattern of prices. The mean price for private insurers actually decreased from 0.75 to 0.69 cents/$ of coverage from 2004Q2 to 2007Q4. The standard deviation is also lower, indicating either a change in what types of properties are covered by private insurers or a change to a less variable pricing strategy. The average price for Citizens increased so much (from 0.68 to 0.87, a 28% increase) that the average price for Citizens was greater than that for private insurers in 2007Q4. Similarly, the mean price for 2004 entrants increased from 0.49 to 0.65, a 33% increase. However, the mean price for the 2004 entrants was still below both the average of all private insurers and Citizens in 2007Q4.

The data consists of transaction prices and not posted prices. For example, private insurers may have increased posted prices across all counties and lines of business, yet still see a decrease in mean transaction prices if the increase in posted prices resulted in property owners with relatively high prices substituting to Citizens, less expensive incumbent insurers, or 2004 entrants, or dropping insurance entirely. Similarly, if substitution from private insurers to lower priced entrants occurred in relatively high priced counties/lines of business, the mean transaction price of entrants would increase consistent with Table 2.

Table 3 gives the top 10 insurers in terms of policies in force in quarter 2 of 2004. Citizens is by far the largest insurer in terms of policies with wind coverage, which along with its 17% lower average price in Table 2, indicates the rule that Citizens be an insurer of last resort may not be enforced in practice.

All Policies		Policies with Wind Coverage	
Insurer	Policies in Force	Insurer	Policies in Force
State Farm Florida Insurance Company	1,025,653	Citizens Property Insurance Corporation	458,617
Citizens Property Insurance Corporation	776,669	State Farm Florida Insurance Company	279,519
Allstate Floridian Insurance Company	589,190	Allstate Floridian Insurance Company	138,518
Nationwide Insurance Company of Florida	279,701	Nationwide Insurance Company of Florida	77,041
United Services Automobile Association	167,699	Cypress Property & Casualty Insurance Company	69,408
American Strategic Insurance Corporation	132,306	United Services Automobile Association	66,402
Liberty American Select Insurance Company	131,685	Liberty American Select Insurance Company	52,617
Clarendon Select Insurance Company	127,406	Allstate Floridian Indemnity Company	42,596
Allstate Floridian Indemnity Company	111,722	Florida Family Insurance Company	41,041
Atlantic Preferred Insurance Company, Inc.	104,623	USAA Casualty Insurance Company	39,382
Others	2,333,362		742,406
Total	5,780,016		2,007,547

Table 3: The ten insurers, including Citizens, with the highest total policies in force in Quarter 2 of 2004.

Table 3 shows the top 10 insurers have significant market presence. The Herfindahl–Hirschman index for the top 10 wind insurers is 0.21, indicating moderate competition. However, many county/quarter/lines of business may have relatively few competitors as insurers sometimes specialize in particular markets. In a fully competitive market, prices for identical products are identical across firms. The moderate competition and dispersed prices in Table 2 indicates that insurers have some pricing power. This may result from informational reasons. In particular, property owners sometimes use the insurer recommended by their mortgage provider and are not aware that they can shop around. We will argue in the results that insurers pricing power is limited, however, and large price increases result in property owners switching insurers.

Table 3 shows that about two million policies with wind coverage exist of the five million total, and so

approximately three million policies are ex-wind. This implies at least one million insured have no wind coverage. Given that some types of the insured such as landlords tend to purchase only wind insurance, the number of properties with no wind coverage is likely greater than one million. The large number of properties without wind coverage motivates insurance regulators to consider the effect of regulatory decisions on insurance take up.

Figure 2 shows the evolution of policies in force which include wind coverage over time. Policies in force for insurers whose policies represent at least 10% of exposure in a particular policy type by county market generally increased over time in both coastal and inland counties, with the increase particularly notable in the wake of the hurricanes that hit the state in the third quarter of 2004. On the other hand, firms whose policies represented smaller shares of total exposure in their respective markets saw different changes in their policies in force across coastal and inland counties. In inland counties, these firms saw an increase in policies in force following the 2004 storms that nearly disappeared by the end of the study period. In coastal counties, these firms saw a significant reduction in policies in force after the 2004 season. One explanation for this pattern is that these smaller firms were ill-equipped for the losses that they incurred during the tail-event storms of the 2004 hurricane season, because they underestimated the probability of such tail events, held insufficient capital reserves to cover their losses following the storm, or both. Interestingly, Citizens seemed to initially experience an increase in policies in coastal counties that eventually disappeared, while there was a moderate, though steady, increase in Citizens policies in inland counties following the 2004 hurricane season.

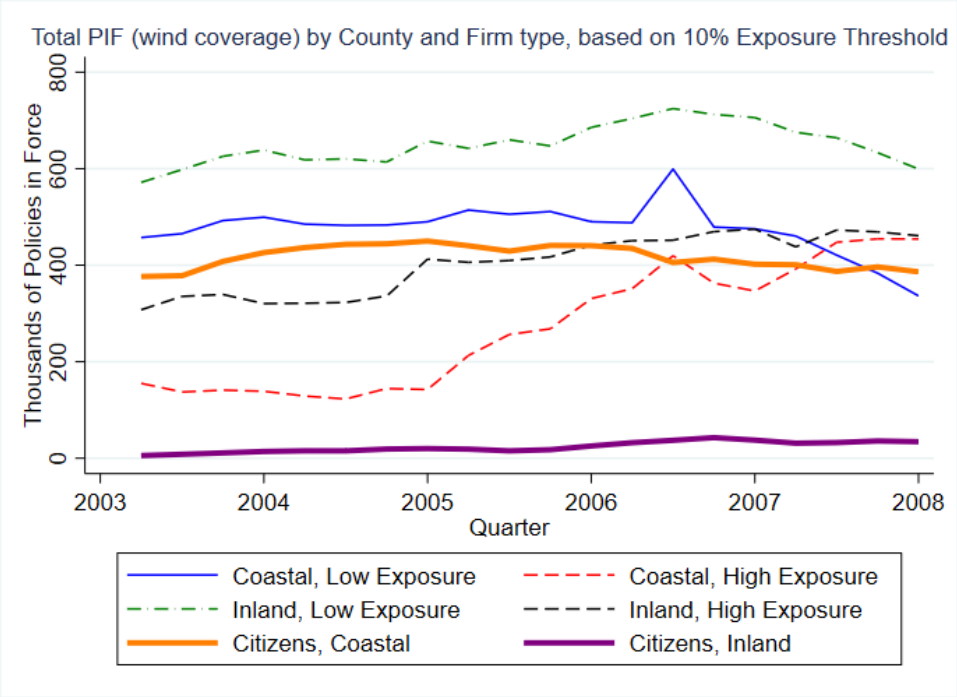


Figure 2: Total policies in force offering wind coverage for all private insurers, split by percentage of total exposure within policy-type by county markets, and Citizens.

4 Models of Behavior for State-Run and Private Insurers

Consider a market with N private firms indexed by $i = 1, ..., N$ and one state-run insurer, denoted by G. Consider two regions in the state that differ with regard to the risk of hurricane damages: coastal areas with hurricane probability θ_H and population M_H and inland areas with hurricane probability θ_L and population M_L, with $\theta_L < \theta_H$. Furthermore, let there be two types of private insurers that differ in the percentage of total exposure that they cover and the capital reserves that they elect to maintain. We consider operating decisions of the various firms in two time periods $t = 0, 1$, with firms making decisions based on the probability of a tail-event storm in period $t = 0$ and then firms revising their decisions following a tail-event storm in period $t = 1$.

4.1 State-run Insurer

Let the state-run insurer, G, operate with a goal of maximizing insured assets in the state, which is consistent with a focus on protecting total wealth, enabling economic recovery, and maintaining property values post-disaster. In this case, the firm's objective function is given by:

$$\max_{P_G^H, P_G^L} E_G = N_G^H(P_G^H) \cdot \bar{C}_H + N_G^L(P_G^L) \cdot \bar{C}_L \tag{2}$$

where: $N_G^r(P_G^r)$ is the number of policies in region $r \in \{H, L\}$ at price P_G^r and $\bar{C}_r$ is the average coverage amount per policy in region r

The state insurer must bring in as much money through premiums as it pays out in claims, or limit this deficit to an acceptable level, D, representing the taxpayer subsidy to the firm:

$$P_G^H \cdot N_G^H + P_G^L \cdot N_G^L \geq \theta_H L \cdot N_G^H + \theta_L L \cdot N_G^L + C_{\text{admin}} - D \tag{3}$$

where, θ_r is the probability of loss in region r, L is the loss per dollar of coverage, and C_{admin} represents administrative costs.

Let the demand for coverage in each region be given by:

$$N_G^r(P_G^r) = M_r \cdot \left(1 - \beta_r P_G^r\right) \quad \text{for } r \in \{H, L\} \tag{4}$$

where: M_r is the total potential market (population of homeowners) and β_r represents the price sensitivity in region r. Let high-risk demand be more price elastic due to high baseline costs, so that $\beta_H > \beta_L$.

In this case, the state-run insurer sets its pricing in the high- and low-risk regions by maximizing the following Lagrangian:

$$\mathscr{L} = N_G^H \cdot \bar{C}_H + N_G^L \cdot \bar{C}_L + \mu \left[P_G^H N_G^H + P_G^L N_G^L - \theta_H L \bar{C}_H N_G^H - \theta_L L \bar{C}_L N_G^L - C_{\text{admin}} + D\right] \tag{5}$$

The first-order condition for the optimal high-risk price is given by:

$$\frac{\partial \mathscr{L}}{\partial P_G^H} = \bar{C}_H \frac{\partial N_G^H}{\partial P_G^H} + \mu \left[N_G^H + P_G^H \frac{\partial N_G^H}{\partial P_G^H} - \theta_H L \bar{C}_H \frac{\partial N_G^H}{\partial P_G^H} \right] = 0 \tag{6}$$

With linear demand, $\frac{\partial N_G^H}{\partial P_G^H} = -M_H \beta_H$, equation 6 becomes:

$$-\bar{C}_H M_H \beta_H + \mu \left[N_G^H - (P_G^H - \theta_H L \bar{C}_H) M_H \beta_H\right] = 0 \tag{7}$$

Rearranging:

$$P_G^H - \theta_H L \bar{C}_H = \frac{N_G^H}{\mu M_H \beta_H} - \frac{\bar{C}_H}{\mu} \tag{8}$$

We derive a similar relationship for the low-risk region:

$$P_G^L - \theta_L L \bar{C}_L = \frac{N_G^L}{\mu M_L \beta_L} - \frac{\bar{C}_L}{\mu} \tag{9}$$

The resulting first-order conditions depicted in equations 8 and 9 can be rearranged to show that the state-run insurer's aim to maximize the assets insured leads to the condition that the marginal cost of pro-

viding an additional dollar worth of coverage is equalized across the high- and low-risk areas. This condition is found by solving for μ in the two first-order conditions.

We can find optimal pricing formulas in each risk region by recalling that: $N_G^r = M_r(1-\beta_r P_G^r)$, meaning that we can rewrite equation 8 as:

$$P_G^H = \theta_H L\bar{C}_H + \frac{1-\beta_H P_G^H}{\mu\beta_H} - \frac{\bar{C}_H}{\mu} \tag{10}$$

Solving for P_G^H and simplifying yields:

$$P_G^H = \frac{\mu\beta_H\theta_H L\bar{C}_H + 1 - \beta_H\bar{C}_H}{\mu\beta_H + 1} \tag{11}$$

We can derive a similar expression for P_G^L:

$$P_G^L = \frac{\mu\beta_L\theta_L L\bar{C}_L + 1 - \beta_L\bar{C}_L}{\mu\beta_L + 1} \tag{12}$$

For a subsidy to be offered in the high-risk region,$P_H < \theta_H L\bar{C}_H$, it must be that $\bar{C}_H > \frac{1}{\theta_H L+\beta_H}$. So, then we will expect $P_G^H < \theta_H L\bar{C}_H$ if there are many assets at risk, namely there are high expected losses, and there is elastic demand for coverage, namely reducing the price will significantly increase policy uptake. If we let σ represent the subsidy offered in high-risk areas by the state-run insurer, then we see that $\sigma = \frac{1-\beta_H P_G^H}{\mu\beta_H} - \frac{\bar{C}}{\mu}$. We can rewrite equation 10 as $P_G^H = \theta_H L - \sigma$. Given this pricing in the high-risk area, a surcharge must be levied in the low-risk region to meet the budget constraint. We see that:

$$P_G^L = \theta_L L\bar{C}_L + \frac{(\theta_H L - P_G^H)N_G^H + C_{\text{admin}} - D}{N_G^L} \tag{13}$$

If $P_G^H < \theta_H L\bar{C}_H$, then it must be that $P_G^L > \theta_L L\bar{C}_L$ to maintain budget balance. So, we can rewrite the equation for the price offered by the state-run insurer in the low-risk region as $P_G^L = \theta_L L + \tau$, where $\tau = \frac{1-\beta_L P_G^L}{\mu\beta_L} - \frac{\bar{C}}{\mu}$.

The aggregate damages from tropical cyclones have been shown to be consistent with a fat-tailed distribution (Conte and Kelly, 2018). In the case of a fat-tailed distribution, it is possible for beliefs about storm risk to update dramatically following a single tail event. Assume that the state-run insurer updates expected losses directly based on observed damages: $E[L]^{t+1} = \lambda \cdot L_t^{observed} + (1-\lambda)\cdot E[L]^t$, where $\lambda \in [0,1]$ is the weight given to recent experience. Then, because previous experience need not be a good predictor of future tail events, expected losses could increase substantially in the wake of tail-event storms, leading to large changes in prices affected by these storms. Given that subsidization is a result of the state-run insurer's objective of maximizing covered assets, this model predicts that tail-event storms will lead to larger price increases in low-risk areas than in high-risk areas for policies offered by the state-run insurer.

Define the subsidy required following the extreme event:

$$\sigma_H^{(1)} = P_H^{\text{fair},(1)} - P_G^{H,(1)} \tag{14}$$

Substituting:

$$\sigma_H^{(1)} = \theta_H^{(1)} L\bar{C}_H - P_{\max}^H(1-\rho^{\text{target}}) \tag{15}$$

We can express the change in the subsidy following the tail event as:

$$\Delta\sigma_H = \sigma_H^{(1)} - \sigma_H^{(0)} \tag{16}$$

$$= [\theta_H^{(1)} - \theta_H^{(0)}] L\bar{C}_H \tag{17}$$

$$= \lambda(1-\theta_H^{(0)}) L\bar{C}_H \tag{18}$$

We see that the subsidy increase depends on the weight on the tail event in belief updating, λ; the pre-event underestimated probability, $\theta_H^{(0)}$; the loss severity, L; and the average coverage in the high-risk region, $\bar{C}_H$. Furthermore, we note that the change in the subsidy is increasing in λ, L, and $\bar{C}_H$, while it is decreasing in $\theta_H^{(0)}$.

Putting more weight on the tail event in updating our beliefs leads to a larger subsidy increase. Larger realized losses lead to a larger subsidy increase. With the average coverage involving more valuable properties, there will be a larger subsidy increase. Finally, if there is less underestimation regarding the tail-event probability, there will be a smaller subsidy increase.

Now, consider the surcharge in the low-risk areas, which is dictated by the budget constraint facing the state-run insurer following the tail-event storm:

$$\sigma_H^{(1)} N_G^{H,(1)} = \tau_L^{(1)} N_G^{L,(1)} + D^{(1)} \tag{19}$$

Solving for the optimal surcharge yields:

$$\tau_L^{(1)} = \frac{\sigma_H^{(1)} N_G^{H,(1)} - D^{(1)}}{N_G^{L,(1)}} \tag{20}$$

If we assume constant policies and deficits, namely that $N_G^{H,(1)} \approx N_G^{H,(0)} = N_G^H$ and $N_G^{L,(1)} \approx N_G^{L,(0)} = N_G^L$ and $D^{(1)} = D^{(0)} = D$, and substitute the optimal change in the price subsidy in the high-risk areas, then we can express the change in the surcharge in low-risk areas following the tail-event storm as:

$$\Delta\tau_L = \frac{\lambda(1-\theta_H^{(0)}) L\bar{C}_H \cdot N_G^H}{N_G^L} \tag{21}$$

The surcharge increases in proportion to the change in the optimal subsidy:

$$\Delta\tau_L = \Delta\sigma_H \times \frac{N_G^H}{N_G^L} \tag{22}$$

and we see that the surcharge increase is the subsidy increase scaled by the ratio of high-risk to low-risk policies. The size of the surcharge increase is increasing in λ, L, and N_G^H, while it is decreasing in $\theta_H^{(0)}$ and N_G^L.

4.2 Private Insurers

The possibility of catastrophic tropical-cyclone events has led states to require minimum capital reserves in order to service their policyholders in the case of tail events. Florida has several statutes delineating minimum reserve amounts for a variety of firm types operating in the state. The need to hold these reserves increases the prices charged by these firms above actuarially-fair levels. Given our interest in the impact of extreme events on the behavior of insurers, we will model firms as attempting to maximize their profits with costs that account for the maintenance of adequate capital reserves.

We consider two types of private insurers. First, we have firms that cover a large percentage of total exposure for a policy type within a county, denoted as type L firms. Then, we have firms that cover a small fraction of total exposure for a policy type within a county, denoted as type S firms. There are several pathways that could explain why certain firms cover a significant percentage of exposure, and we are going to proceed under the assumption that, in this case, these firms have access to large capital reserves and can withstand severe losses associated with a tail-event storm.

We proceed by first considering the pricing behavior of large-exposure firms prior to the tail-event storms and then explore how they update prices following the storms based on their capital reserves. We then turn to small-exposure firms.

4.2.1 Large-Exposure Firms

Large firms attempt to maximize their profits, π_L from the policies offered and the prices at which they are offered. Let $\pi_L = (P_L - MC_L) \cdot N_L - r \cdot K_L$. Further, let the marginal cost function be given by:

$$MC_L = \gamma + \theta_H L_0 (1 + \delta s_L) \bar{C}_H \tag{23}$$

The marginal cost function is derived from the total cost function for type L firms, given by $C_L(q_L, \theta) = c_0 + (\gamma + \theta L_L) q_L$, where c_0 represent base underwriting costs, θL_L depict expected hurricane losses, and γq_L reflect administrative costs. $\theta \in [0,1]$ is the probability of a hurricane event, $L_L > 0$ is the loss per unit of coverage for type L firms conditional on a hurricane, and $\gamma > 0$ represents marginal administrative costs.

The term δ captures the loss rate per dollar of coverage offered by an insurer. If it were the case that high-exposure firms tended to offer coverage in high-risk areas, then we might expect $\delta > 0$. Other conditions that could lead to positive values for δ include firm specialization in certain kinds of policy types, so that damage rates are higher for high-exposure firms; ability of small firms to target low-risk policyholders; management of broad portfolio of policies could lead large firms to invest less in monitoring. s_L denotes the exposure share for large firms in a policy-type by county market.

So, with the capital requirement $K_L = \kappa_L \ell N_L$, where ℓ denotes the expected loss per policy ($\theta_H L_0(1 + \delta s_L)\bar{C}_H$), and flow cost rK_L per period, the firm's pricing problem is:

$$\max_{P_L} \pi_L = (P_L - MC_L)N_L(P_L) - r\kappa_L \ell N_L(P_L) \tag{24}$$

From the first-order condition, we are left with the following expression for the optimal price:

$$P_L^* = MC_L^{\text{eff}} + \mu_L = \gamma + (1 + r\kappa_L)\theta_H L_0(1 + \delta s_L)\bar{C}_H + \mu_L \tag{25}$$

where the effective marginal cost includes capital-holding costs and μ_L, the equilibrium markup as a result of market power, is endogenously determined by the firm's capital choice and resulting competitive position and satisfies the standard markup condition based on demand elasticity.

For large firms, it is optimal to hold capital reserves in excess of regulatory minimums, where $K_L = \kappa_L \theta_H^{(0)} L_0()1+\delta s_L) N_L \bar{C}_H > \kappa_{min}$. These higher reserves reduce the probability of bankruptcy during tail-event storms, leading to higher expected future profits. The additional reserves might also help them achieve ratings agency requirements that can offer access to reinsurance and capital markets at better rates. Finally, these higher reserves can improve reputation or brand loyalty, facilitating a quality premium, μ_L, on their transaction prices.

Given the expression for the optimal price in equation 25, we can see how a tail-event storm leads to a change in the optimal price. Tail-event storms lead to a change in the expected probability of a hurricane, which is a critical determinant of the price charged by large insurers. The change in the price of coverage for policies offered by large firms, ΔP, is given by:

$$\Delta P_L = (1 + r\kappa_L)\Delta\theta_H \cdot L_0(1 + \delta s_L)\bar{C}_H \tag{26}$$

The capital cost multiplier amplifies the price increase. But the large-exposure firm's decision to hold more than the minimum required captial reserves means that prices prior to the tail-event storm are already inflated. So, the percentage change in optimal price following a tail-event storm will be moderate.

4.2.2 Small-Exposure Firms

Small firms have the same objective of maximizing profits from the policies in force and the prices at which they are offered as large firms. Small firms have similar expressions of profit and marginal cost as large firms:

$$\pi_S = (P_S - MC_S) \cdot N_S - r \cdot K_S \tag{27}$$

$$MC_S = \gamma + \theta_H L_0 (1 + \delta s_S) \bar{C}_H \tag{28}$$

with the key difference being that small firms choose to hold the minimum capital reserve that meets the regulatory requirement, namely $\kappa_S = \kappa_{min}$. With this in mind, the optimal price of coverage from small firms in the high risk area prior to the tail-event storm is given by:

$$P_S^* = MC_S^{\text{eff}} + \mu_S = \gamma + (1 + r\kappa_{min})\theta_H L_0 (1 + \delta s_S) \bar{C}_H + \mu_S \tag{29}$$

Because small firms do not hold adequate capital reserves, a tail-event storm leads to a capital shortfall for these firms. The shortfall represents the gap between the realized losses ($L_0(1+\delta s_S)N_S\bar{C}_H$), and the capital reserves held in the pre-tail-event period, $K_S^{(0)}$. The shortfall is given by: $[1-\kappa_{min}\theta_H^{(0)}]L_0(1+\delta s_S)N_S\bar{C}_H$. In addition to the shortfall caused by the inadequate initial capital reserves, the tail-event storm also increases the capital requirements in the post-event period, meaning that the small firms have a total financing need of:

$$[1 + \kappa_S^{req}\theta_H^{(1)} - 2\kappa_{min}\theta_H^{(0)}]L_0(1 + \delta s_S)N_S\bar{C}_H \tag{30}$$

where $\theta_H^{(1)}$ represents the updated probability of a tail-event storm following the recent experience and κ_S^{req} represents the updated capital requirement following the tail-event storm, which revealed underestimated risk.

These additional capital requirements, stemming from the initial shortfall as well as the updated regulatory requirements impact the post-event price charged by small firms. The new price in high-risk areas following the tail-event storm is given by:

$$P_S^{(1)} = \underbrace{\gamma + (1 + r\kappa_S^{\text{req}})\theta_H^{(1)} L_0 (1 + \delta s_S)\bar{C}_H + \mu_S}_{\text{Ongoing actuarial costs}} + \underbrace{\frac{r[\theta_H^{\text{true}} + \kappa_S^{\text{req}}\theta_H^{(1)} - 2\kappa_{\min}\theta_H^{(0)}]L_0(1 + \delta s_S)\bar{C}_H}{T}}_{\text{Amortized capital rebuilding}} \tag{31}$$

where T represents the amortization period for rebuilding the capital reserves.

With this expression for the post-event price charged by small firms, we can see how prices change for these firms as a result of the tail-event storm, with the change in the price of coverage for policies offered by

small firms,ΔP_S, given by:

$$\Delta P_S = \Delta\theta_H \cdot L_0(1+\delta s_S)\bar{C}_H + r[\kappa_S^{\text{req}}\theta_H^{(1)} - \kappa_{\min}\theta_H^{(0)}]L_0(1+\delta s_S)\bar{C}_H + R \tag{32}$$

where R captures the amortized capital rebuilding term, the second term on the right-hand side of equation 31.

The additional capital needs facing firms with small exposure in policy type by county markets suggest that these firms would be expected to require significant price increases following tail-event storms, which customers might not be willing to bear given the presence of the state-run insurer and that large firms. As a result, we might expect to see small firms moving out of markets in the wake of tail-event storms.

Overall, these models generate predictions for firm behavior that we will explore in the empirical analysis. First, assuming that Citizens aims to maximize insured assets across the state, we expect to see price increases for its policies statewide, with price increases that are mitigated in coastal counties that are at higher risk from tail-event tropical cyclone damages and price increases that are magnified in inland counties that face lower risk from these extreme events. Next, we expect to see substantial price increases among private insurers whose policies represent a substantial portion of exposure in various markets, although we expect this affect to be attenuated when we consider samples that only include firms that maintained solvency following the tail events of 2004, as would be the case in econometric models with firm-level fixed effects. While small firms with relatively limited capital reserves prior to the extreme events would be expected to have the largest price increases in order to make up their inadequate capital reserves prior to the storms, these firms are not likely to stay in operation, so we might actually see relatively modest price increases amongst smaller firms that are able to stay in operation following the tail-event storms of the 2004 hurricane season.

5 Econometric Models

We rely on two standard identification strategies to explore our focal hypotheses about how home insurance premiums responded to the storm events that affected Florida in the third quarter of 2004. First, we conduct several regressions based on difference-in-difference (DID) models reliant on the two-way fixed-effects structure to explore how premiums offered by private insurers and Citizens separately respond to these events. Then, we turn to event-study analyses to explore dynamic treatment effects.

The first set of DID models is used to explore the hypothesis that the average price offered by a single insurer for a particular policy type that is taken up by a customer will increase more in the treated counties following the 2004 hurricanes in Florida than the prices offered by that insurer for that policy type in an untreated county. Our econometric strategy relies on the hypothesis that risk perceptions likely increased

most in counties that were most affected by the 2004 hurricane season. We observe transaction prices, not posted prices. By measuring the change in policy prices after the 2004 season relative to less affected counties, we find the causal effect of the change in risk perceptions induced by the hurricanes on insurance prices, under the standard SUTVA and parallel-trend assumptions. We select quarter 3 of 2004 as the start of the treatment, since insurers could increase at least some prices immediately after the first hurricane which made landfall on August 13, 2004, about halfway into the third quarter.

In our models using data from private insurers, we include insurer and policy-type fixed effects as well as particular insurer and policy-type time trends, allowing us to identify a conditional causal effect. The inclusion of these various fixed effects reduces concerns about potential SUTVA violations, namely that exposure to high winds in one county A does affect insurance prices in other counties. For our models based on data from Citizens, these models include policy type fixed effects and unique policy-type time trends. In the models for private insurers standard errors are clustered by county and insurer, while standard errors are clustered by county for the Citizens models.

Several challenges to our econometric strategy exist. First, counties are large and heterogeneous. A single statistic for hurricane strength is unlikely to correctly measure changes in risk perceptions which likely vary in different regions of a particular county. We considered several measures of hurricane strength, including average wind speed in the county, logged wind speed, and various binning strategies (for example, bins if average wind speed was tropical storm, category 1, etc.). A simple 2-bin indicator function where $HURR_c = 1$ if county c has an average wind speed of a category one hurricane or higher and zero otherwise proved the most robust. For results using other measures to distinguish treated and control counties, see tables **??** to **??** in the Appendix. Equation 33 presents the specification used for models using data from the private insurers.

$$\log P_{iclt} = \alpha_i + \beta_l + \gamma_{it} + \delta_{lt} + \theta HURR_c + \lambda HURR_c \cdot POST_t + \epsilon_{iclt} \tag{33}$$

Here P_{iclt} is the average transaction price (in cents) per dollar of coverage for insurer (i), quarter (t), county (c), and policy type (line of business), (l), as defined by equation (1). Further, α_i, β_c, γ_l, and δ_t are a battery of fixed effects coefficients, $HURR_c$ is a measure of the strength of the 2004 hurricanes in county c defined below, and $POST_t$ is an indicator which equals one if the quarter is after the second quarter of 2004. Model (33) allows the firm and line of business fixed effects to vary by quarter, which controls for price trends that might not be related to the 2004 season.

We next run a set of DID models that exclude time trends but include POST, an indicator variable denoting whether the data comes from a quarter during or after the 2004 storm events (this variable equals

1 for all quarters after the third quarter of 2004, inclusive). These models allow us to explore whether the storm events had an overall impact on prices across the state of Florida in addition to the observed price effects within the treated counties. Such an aggregate post-treatment price change might be driven by several different mechanisms. Not all of them relate to violations of the SUTVA lack of interference assumption. A significant coefficient on the POST variable could be evidence of a common information shock, with firms understanding that the paths taken by the storms in these events are realizations drawn from a distribution of potential storm paths that could take the storms over different sets of counties during future events, meaning that some impact on beliefs about storm exposure could be observed across all counties in the state. Other aggregate shocks are possible, including increased reinsurance costs affecting markets worldwide and regulatory changes in Florida affecting all insurers. Next, it is possible that insurers might be concerned about the price elasticity of demand for their policies. If firms thought that demand for their policies was highly price elastic, then they might attempt to mitigate price increases in treated counties by simultaneously increasing prices elsewhere, which would violate the SUTVA interference assumption. This socialization of price increases might be of particular appeal to Citizens, the state-backed provider of insurance that may be particularly sensitive to the issue of insurance affordability, as the uptake of insurance at below actuarially-fair rates might be preferred to having uninsured residents suffer damages from tropical cyclones. Model (34) limits the fixed effects coefficients so that the post effect can be estimated clearly.

$$\log P_{iclt} = \alpha_i + \beta_l + \theta HURR_c + \eta POST_t + \lambda HURR_c \cdot POST_t + \epsilon_{iclt} \tag{34}$$

There are a number of reasons why we might expect dynamic effects of the 2004 hurricane season on homeowners' insurance policies in Florida. First, as explained earlier, property insurers follow a regulated process to change prices that has changed over time, with proposed rate changes needing to be approved by FLOIR before they can be presented to consumers. Next, while premium and loss data is required to support proposed price changes, it can take several months to a year for insurance firms to fully understand the claims that they face in the wake of tropical cyclones. As a result, we also consider an event-study design to better understand the dynamics of the policy price response to the 2004 hurricane season.

$$\log P_{iclt} = = \sum_{\tau \neq -1} \theta_\tau \text{Period}_{\tau,iclt} + \alpha_i + \beta_l + \gamma_{it} + \delta_{lt} + \varepsilon_{iclt} \tag{35}$$

Our dataset comprises an unbalanced panel, in which firms drop and offer policy types and enter and exit counties (and the state of Florida) over time, changing the market composition from quarter to quarter across counties. With our firm fixed effects, we are comparing prices within firms, including those offered by

the same firms across treated and control counties, though we also get identification from cross-sectional and time-series comparisons. With these fixed effects included, we are measuring the direct effect of the hurricanes on market prices offered by existing firms for existing policies. The composition effect could be found by subtracting this direct effect from the total effect estimated via a model without the firm and policy-type fixed effects.

The inclusion of firm- and policy type-specific time trends in the event-study analyses presents a potentially impactful variance-bias tradeoff regarding our estimated dynamic treatment effects and their statistical significance. These time trends allow for cleaner identification of our focal treatment effects of interest by reducing potential confounding from firm repositioning, market-wide repricing in particular policy types, and other aggregate shocks that might correlated with wind exposure. But, the potential exists for the standard errors to increase sufficiently with addition of these additional fixed effects that we might fail to detect real effects. See figures 9 through 11 in the appendix for results from event-study models that do not include these firm- and policy-type-specific time trends.

The event-study setup also allows us to explore the validity of the parallel-trends assumption that is critical for identification of the true causal effect of treatment in this model. We follow the imputation approach of Borusyak, Jaravel, and Spiess (2024) to test the parallel-trend and no-anticipation assumptions. This approach has attractive power properties and avoids the problem of inference after pre-testing described in Roth (2022) by using only clean control variation for counterfactuals. The method can handle heterogeneous treatment effects and is robust to changes in sample composition that might be at play in our context. Figure 12 in the appendix shows that our reported results are not affected by application of this method, while also demonstrating support for the validity of the parallel trends assumption in our event-study analyses.

We first explore these dynamic effects across all private insurers. Next, we consider these effects on subsets of the data, allowing the price changes implemented by insurers with larger market shares to have more of an impact, reflecting the fact that these insurers will be more reflective of the conditions facing property owners. We do this by restricting the sample to insurers with a threshold fraction of certain policy types across a county within a given quarter.

6 Results

6.1 Results by policy type

Table 4 gives the results for all private insurers using all fixed effects. Column two shows that counties that experienced category one or higher wind speeds saw a significant price increase of about 3.5% relative to unaffected counties, after 2004Q2. Columns 4 and 6 indicate the relative price increases were largest in coastal counties. This might indicate that coastal counties received a different “treatment” versus inland

counties. That is, whether or not a county experiences category one winds or higher might not adequately measure the true exposure. For example, if a hurricane made landfall in a part of a coastal county near a population center, but then traveled inland with category one winds but not over a population center, then the coastal county might show a larger increase in risk perceptions, even though in the regression both counties would be counted as treated. Finally, the results which include ex-wind policies are generally smaller in magnitude, as expected, since theoretically ex-wind policies should not increase in price following a change in wind risk perceptions.

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price
Counties with Category 1 wind speed	-0.00456	0.0145	-0.0183	-0.00137	0.00887	0.0351
	(0.0405)	(0.0309)	(0.0507)	(0.0483)	(0.0555)	(0.0375)
Post '04 periods in counties with Cat1+ winds	0.0299**	0.0350**	0.0238*	0.0273**	0.0269**	0.0360**
	(0.0116)	(0.0135)	(0.0129)	(0.0122)	(0.0116)	(0.0150)
Constant	-0.723***	-0.737***	-0.708***	-0.727***	-0.501***	-0.642***
	(0.0307)	(0.0228)	(0.0313)	(0.0234)	(0.0803)	(0.0463)
Observations	334229	244480	135316	127839	198652	116367

Results for all private insurers. The data cover the period from 2003Q1 through 2007Q4. Standard errors clustered by county and insurer in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Binary treatment based on Category 1 hurricane wind threshold for all private insurers.
Insurer, policy, insurer-by-quarter, and policy-by-quarter fixed effects included.

Table 5 gives the results for all private insurers, using the model with more limited fixed effects coefficients and includes the post coefficient. Unaffected counties show insignificant price increases post 2004Q2. This indicates no clear effect of the 2004 season on average transaction prices for private insurers in unaffected counties. However, private insurers may have increased posted prices in unaffected counties after 2004Q2, but consumers may have responded by switching to lower priced policies or dropping insurance, resulting in more limited transaction price increases. Regardless, the price increase in affected counties is significantly higher vs unaffected counties, with the price difference being of a similar magnitude as the model which includes the full fixed effects specification.

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price
Counties with Category 1 wind speed	0.00144	0.0200	-0.0143	0.00408	0.0173	0.0434
	(0.0391)	(0.0285)	(0.0502)	(0.0462)	(0.0534)	(0.0344)
Periods during and after 2004 Storms	0.0149	0.0310	0.000497	0.0118	0.0287	0.0547
	(0.0333)	(0.0423)	(0.0272)	(0.0278)	(0.0381)	(0.0592)
Post '04 periods in counties with Cat1+ winds	0.0223***	0.0272***	0.0223***	0.0229***	0.0142*	0.0191**
	(0.00608)	(0.00521)	(0.00233)	(0.00285)	(0.00801)	(0.00807)
Constant	-0.613***	-0.709***	-0.709***	-0.735***	-0.538***	-0.674***
	(0.0410)	(0.0383)	(0.0381)	(0.0326)	(0.0507)	(0.0503)
Observations	334441	244685	135517	128036	198918	116643

Results for all private insurers. The data cover the period from 2003Q1 through 2007Q4. Standard errors clustered by county and insurer in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Binary treatment based on Category 1 hurricane wind threshold for all private insurers. Insurer and policy fixed effects included.

Table 6 shows the results for Citizens are different than private insurers. In particular, column 2 shows that average prices in affected counties rose by about 6.6% *less* than in unaffected counties (compare with the increase by more in the private market), and the result is highly significant. Further, column 6 shows the result is concentrated in coastal counties. This is consistent with the idea that Citizens was socializing some of the risk by keeping prices relatively low in affected counties to encourage property owners to increase or maintain coverage, at the expense of providing incorrect risk signals. However, another possibility is that Citizens raised posted prices in affected counties by more than unaffected counties, and then saw relatively high-priced policy owners in affected counties switch from Citizens to relatively low-cost entrants, lowering transaction prices.

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price
Counties with Category 1 wind speed	0.0173	0.0740	-0.0803	-0.0560	0.0434	0.120
	(0.0539)	(0.0687)	(0.0578)	(0.0552)	(0.0645)	(0.0944)
Post '04 periods in counties with Cat1+ winds	-0.0446**	-0.0611***	-0.0388*	-0.0330	-0.0354	-0.0541**
	(0.0194)	(0.0198)	(0.0227)	(0.0229)	(0.0219)	(0.0231)
Constant	-0.441***	-0.555***	-0.137***	-0.167***	-0.319***	-0.657***
	(0.0472)	(0.0354)	(0.0441)	(0.0315)	(0.0766)	(0.108)
Observations	11449	7986	3280	2994	8138	4961

Results for Citizens. The data cover the period from 2003Q1 through 2007Q4. Standard errors clustered by county in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Binary treatment based on Category 1 hurricane wind threshold for Citizens. Policy and policy-by-quarter fixed effects included.

Table 7 gives the results for Citizens with more limited fixed effects. Column 2 shows that average transaction prices increased 30.6% across all counties after 2004Q2. This increase is very large, although from Table 2, Citizen's prices were 17% lower than private insurers prior to treatment and Citizens was the largest insurer in 2004. The increase in prices might therefore reflect that the price of Citizens insurance was too low relative to the risk and especially the idea of Citizens wanted to return to its mandate as an insurer of last resort. The interaction term in column two is marginally insignificant (but significant inland and marginally significant in coastal counties), but the coefficient is of a similar magnitude as in the model with the full set of fixed effects.

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price
Counties with Category 1 wind speed	0.0147	0.0576	-0.0618	-0.0379	0.0443	0.112
	(0.0518)	(0.0669)	(0.0625)	(0.0648)	(0.0628)	(0.0914)
Periods during and after 2004 Storms	0.276***	0.306***	0.264***	0.254***	0.283***	0.343***
	(0.0113)	(0.0142)	(0.0235)	(0.0175)	(0.0129)	(0.0178)
Post '04 periods in counties with Cat1+ winds	-0.0410*	-0.0410	-0.0594**	-0.0523**	-0.0370	-0.0454*
	(0.0214)	(0.0247)	(0.0257)	(0.0229)	(0.0237)	(0.0243)
Constant	-0.635***	-0.766***	-0.343***	-0.364***	-0.520***	-0.892***
	(0.0442)	(0.0395)	(0.0369)	(0.0353)	(0.0744)	(0.111)
Observations	11449	7986	3311	3025	8138	4961

Results for Citizens. The data cover the period from 2003Q1 through 2007Q4. Standard errors clustered by county in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Binary treatment based on Category 1 hurricane wind threshold for Citizens. Policy fixed effects included.

Figure 3 depicts the rolling estimates of the post treatment coefficient as the treatment window lengthens. Citizens prices are increasing across the board over time. This is expected as Citizens, like other insurers, can only increase prices slowly as previous contracts expire and rate increases are approved.

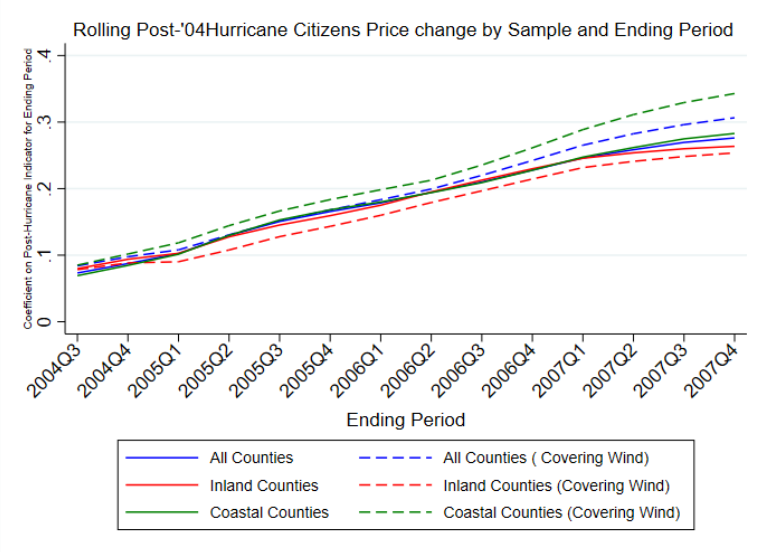


Figure 3: Price changes post '04 hurricanes for Citizens policies by sample and ending of post-treatment period.

Figure 4 depicts the rolling estimates of the interaction coefficient as the treatment window lengthens. The difference between treated and untreated prices becomes larger in magnitude over time, consistent with the idea that consumers become aware of price differences and switch out of high-priced policies slowly over time.

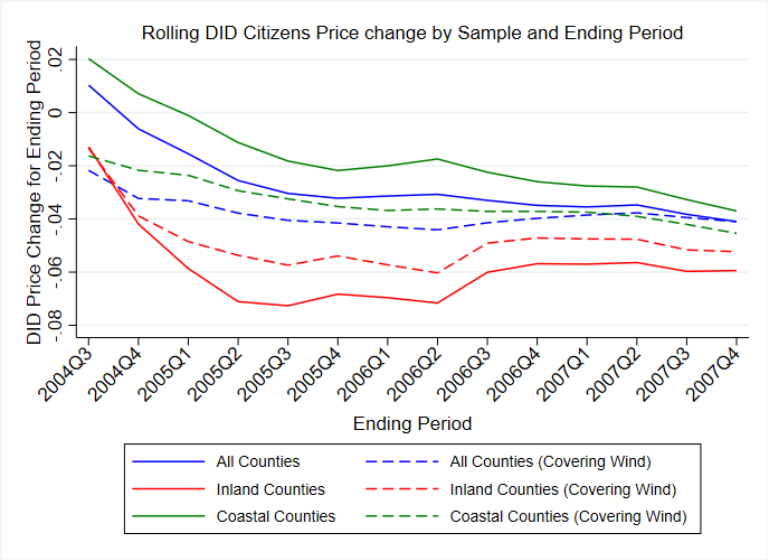


Figure 4: DID Price changes for Citizens policies by sample and ending of post-treatment period.

The analyses exploring how transaction prices responded to the named storms of 2004 show different responses across private insurers and Citizens in both inland and coastal counties. While it is difficult to infer how posted prices varied across Citizens and private insurers in response to these storm events, the statistics displayed in table 2 show that Citizens had lower mean and median prices than all private insurers (across incumbents and 2004 entrants) prior to the hurricanes that made landfall in the third quarter of 2004. This suggests that even though Citizens had much larger percentage increases in transaction prices in response to the storms, coverage from the state-run insurer might have seemed attractive to households with relatively highly-priced premiums on their policies from private insurers. To explore this point, we run a version of the model presented in equation 7 with the number of policies in force for Citizens as the dependent variable. The results are presented in table 8.

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	PIF	PIF	PIF	PIF	PIF	PIF
Counties with Category 1 wind speed	-140.2	-7.292	18.90	-9.940	-466.3	-156.6
	(791.7)	(645.9)	(68.45)	(47.86)	(1053.0)	(935.0)
Periods during and after 2004 Storms	488.5***	42.95	153.0***	99.59***	664.9***	10.68
	(153.8)	(41.98)	(35.62)	(21.01)	(225.3)	(61.37)
Post '04 periods in counties with Cat1+ winds	62.31	114.9	166.3	127.7*	-56.33	117.3
	(184.1)	(88.26)	(134.5)	(69.83)	(262.8)	(133.5)
Constant	1305.9**	1052.4**	60.68**	65.83**	1909.0**	1698.6**
	(599.1)	(400.0)	(29.16)	(27.23)	(866.6)	(662.6)
Observations	11449	7986	3311	3025	8138	4961

Results for Citizens. The data cover the period from 2003Q1 through 2007Q4. Standard errors clustered by county in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Binary treatment based on Category 1 hurricane wind threshold for Citizens. Policy and policy-by-quarter fixed effects included.

We see that there was a statistically-significant uptake of policies offered by Citizens beginning in the third quarter of 2004 across the state. The increase in the number of policies in force was driven by policies excluding wind coverage, although there was a statistically significant increase in the number of Citizens policies in force across all inland counties for policies offering wind coverage. While there was a general increase in uptake of Citizens policies, this was largely driven by counties that did not experience at least category 1 wind speeds in the third quarter of 2004. Only inland counties that experienced these hurricane-force winds saw an increase in Citizens policies in force for policies offering wind coverage after the storms (column 4).

6.2 Event Studies

Figure 5 is an event study plot corresponding to the results in column 2 of Table 4. Figure 5 shows no obvious trend prior to the 2004 quarter 3 hurricanes. In the first quarter post treatment, average transaction prices for private insurers in treated counties increase by almost 4% more than untreated counties. After 2006Q2, the average transaction prices increase about 5-6% more than unaffected counties. Note that one additional hurricane occurred in 2005Q3 and 2005Q4. These periods do no show any obvious differences, indicating that the main change in risk perceptions occurred in 2004Q3. A loss of significance occurs relative to Table 4, as the event study consists of smaller datasets corresponding to each individual quarter.

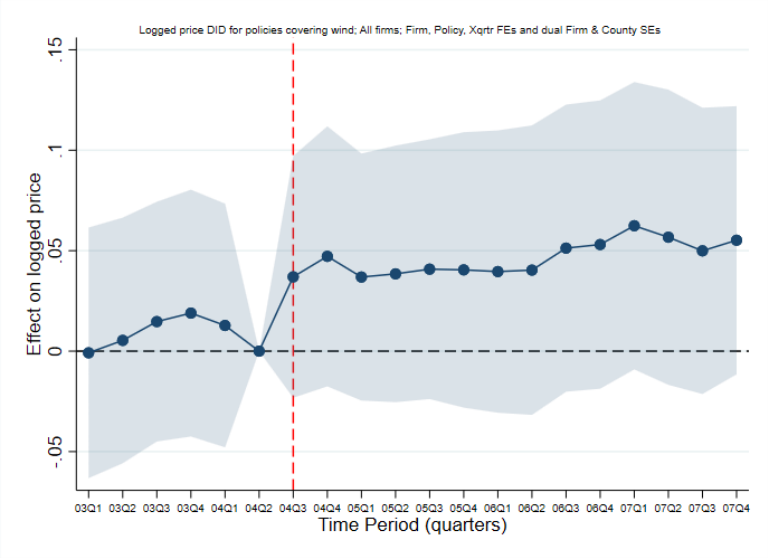


Figure 5: Event study for all private insurers and all policies covering wind. Uses the full fixed effects specification and dual clustered standard errors. The shaded regions are the 95% confidence intervals.

Since the dependent variable is the log of the premium per dollar of coverage, the total price for a property owner also increases by about 5-6%. Thus a typical property owner with a $5,000 per year premium would face a price increase of $250-$300 per year. Although economically meaningful, the price increase is modest given the unprecedented hurricane events of 2004. One possible issue is that our econometric specification weights each insurer/county/time/line of business observation equally. If insurers with larger market share, as defined by exposure covered, increased prices by more than insurers with small market share, then our estimate might not reflect the price increases faced by most property owners.

Figure 6 is the same as Figure 5, but excludes any insurer that has less than 10% of the total exposure of all firms in the county/quarter/line market. Figure 6 shows that excluding insurers with smaller than 10% market share by exposure further increases the coefficient estimates. Prices are about 9% higher than unaffected areas starting in 2006Q4. The results are statistically significant after 2006Q2.

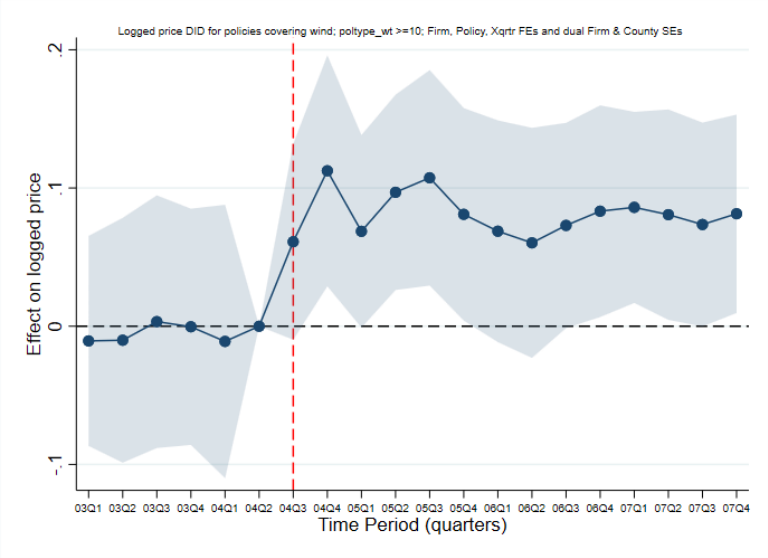


Figure 6: Event study for all private insurers with greater than 10% of the total exposure in a county/quarter/line of business and all policies covering wind. Uses the full fixed effects specification and dual clustered standard errors. The shaded regions are the 95% confidence intervals.

The results depicted in figure 6 stem from a model that includes firm and firm-by-quarter fixed effects. While controlling for time-invariant firm characteristics and allowing for firm-specific time trends is important to isolate the causal effect of the 2004 hurricanes, doing so prevents us from considering how the composition effects of these storms might have affected policy premiums.

	Post x Cat 1+ Interaction	
Firm Type	0	1
	All Policies	
All Private Insurers	18.70	15.16
Private Firms with≥ 10% Exposure	10.05	15.16
Private Firms with < 10% Exposure	8.65	0
	Wind Policies	
All Private Insurers	13.29	9.60
Private Firms with ≥ 10% Exposure	7.48	9.60
Private Firms with < 10% Exposure	5.81	0

Table 9: Average count of firms operating in policy-type by county markets based on value of treatment by post treatment interaction term.

Table 9 presents counts of firm types in operation based on the value of our binary treatment-post interaction term in equation 33. For the column in which this variable takes on a value of zero, we are taking the average count of firms operating in a certain policy-type market within a county in a given quarter, across

all counties before 2004Q3 and all counties that did not experience cat 1+ winds during that quarter. For the column when this variable is 1, we are taking the average count of firms in operation during in a certain policy-type market within a county in a given quarter or after 2004Q3 only in counties that did experience these hurricane-force winds. Table 9 shows that we saw market exit on average among private insurers in operation after the 2004 storm events across counties that experienced hurricane-force winds. It also shows that while the average number of private insurers fell after the 2004 storms in counties that experienced hurricane-force winds, the number of firms whose policies represented at least 10% of exposure in a given market saw increases in the average number of active firms. Of significant note is that firms with low levels of exposure in their policies in force disappeared following these storms in affected counties. On the other hand, we did see firm counts increase when considering only the largest firms by the percentage of total exposure.

This substantial attrition of low-exposure firms could explain why the observed price increases in this subset of private insurers are smaller than predicted by the model of firm behavior. While firms in this category that continued operation following the tail-event storms would have needed to charge significantly higher premiums for coverage, the observed prices could have diverged from these large changes due to solvency issues and competition from larger firms.

On the other hand, the increase in the average number of large-exposure firms following the storms could also offer an explanation for the somewhat muted price responses among this group of private insurers, as increased competition, perhaps by firms with different reliance on reinsurance that could keep costs and prices down, may have mitigated transaction-price increases.

7 Discussion

The hurricanes that made landfall in Florida in 2004 imposed at least $45 billion dollars worth of damages in the state, making it the worst hurricane season in the state's history. Given the unprecedented nature of these impacts, it is possible to expect that insurers would have significantly increased their beliefs about the risk associated with homeowner policies in parts of the state. We observe transaction prices as opposed to posted prices and offer several possible explanations for the more muted response that we observe in transaction prices following the 2004 hurricanes.

One explanation is that transaction prices for firms that entered markets following the 2004 storms were significantly lower than incumbent private insurers. Thus, incumbent insurers may have actually increased posted prices much more than 9%, but property owners switched their insurance to new entrants with lower prices.[7] Another possibility is that insurers weighed the unprecedented 2004-5 season against the 100+ years

[7] New entrants are included in some of the private insurance regressions. However, a switch from a high-priced private incumbent to a lower-priced entrant still reduces the average price for all private insurers post 2004Q3, reducing the coefficient estimates.

of hurricane data and made only small increases in risk perceptions. From 1850-2003, either one or zero hurricanes made landfall in Florida in any given year, except for 1950, when two hurricanes made landfall. So the insurers could have interpreted the 2004-5 season as a one-off that was unlikely to repeat (indeed, after 2005 no hurricanes made landfall in Florida until 2017 and only in 2024 did more than one hurricane make landfall).

To resolve these competing explanations, we can look at the policies in force by incumbents, new entrants, and Citizens post 2004Q3. Table 3 and Figure 2 show that policies in force by incumbents fell from about 1,600K in 2004Q3 to about 1,200K in 2007Q4. Further, 2004 entrants increased policies in force from zero at entry in 2004 to about 600K in 2008 and Citizens policies in force increased from 458,617 in 2004Q3 to xxx in 2007Q4. Apparently, significant switching occurred which limited the average price increase post 2004Q3 of private insurers, especially relative to Citizens. Table 8 shows that the 2004 hurricanes caused policies in force to increase for Citizens, despite the large transaction-price increases following the storms, likely made possible by the fact that Citizens had lower initial prices relative to private insurers.

The Florida Office of Insurance Regulation faces a difficult tradeoff with respect to adaptation. Allowing prices to increase significantly deters development in high risk areas, a kind of adaptation. However, for existing property owners in high risk areas, significant price increases causes at least some property owners to drop insurance coverage all together, reducing insurance, a different type of adaptation. Overall, FLOIR seems to have opted to maintain high levels of coverage, choosing to keep coverage levels high at the expense of more coastal development. Indeed, the total policies in force across all firm types (Citizens, entrants, and incumbents) increased over the post period.

There are also risk tradeoffs. Since Citizens relies on taxpayer backing and reinsurance and new entrants rely on reinsurance (and effectively taxpayers pay claims if entrants default anyway), the increase in PIF by new entrants and Citizens exposes the state to hurricane risk and also the risk of price increases by reinsurers.

8 Conclusion

Development in at-risk areas and the frequency and intensity of natural disasters like tropical cyclones and wildfires have continued since our study period, magnifying the tradeoffs facing state insurance regulators in the wake of these potentially catastrophic events. Our results of relatively modest increases in transaction prices following the unprecedented 2004 hurricans season suggest that homeowners rely on access to alternative insurers to mitigate the increased premiums that they face when insurers adjust their pricing in response to disasters that increase risk perceptions. This switching behavior emphasizes the importance of affordability in insurance markets, which mitigates the role that insurance can play in conveying disaster

risk to households.

The observed price dispersion prior to the 2004 storms across large and small private firms and Citizens could represent differences in risk perceptions, market power, or differences in business models. While we modeled small firms as holding inadequate capital reserves, it is also the case that these firms, particularly those that might be new entrants to the Florida market, use more reinsurance. This approach is cheaper, but price swings or quantity limits in reinsurance could result in rapid price increases or restrictions on market share. That we observe transaction price increases for small firms that are substantially larger when we allow for composition effects from the tail-event storms of the 2004 hurricane season relative to when we consider behavior only by firms that maintained solvency following these events is consistent with either differences in risk perceptions or business models. Market power of firms with large shares of total exposure could explain the result that we observe the largest increases in transaction prices when considering the firms with the largest market share in a particular policy type by county market. Of the 75 private insurers with at least 10% of this market share, only 10 were Florida-based, while a number were blue chip, national or international firms. If the largest firms were increasing prices to effectively quit the market without triggering penalties for failing to offer coverage, then our results could point to a fundamental market failure in catastrophic risk insurance that might require more direct market intervention to avoid further development in at-risk areas (e.g., managed retreat) or the application of capital market solutions like catastrophe or resilience bonds to facilitate increased adaptation to the state of the world.

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Appendix

Wind speed maps

Figure 7 shows the maximum wind speed across each county for hurricane Dennis, which made landfall in the Florida Panhandle in the third quarter of 2005.

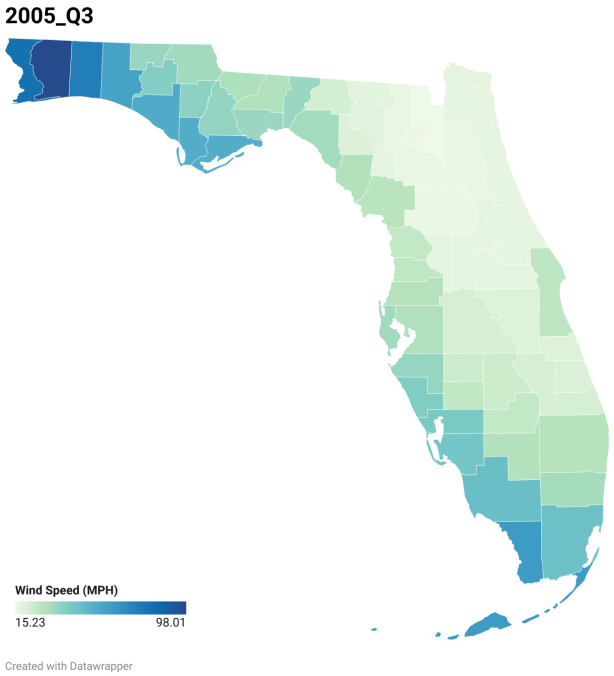


Figure 7: Maximum wind speed across each county for hurricane Dennis, quarter 3, 2005.

Figure 8 shows the maximum wind speed across each county for hurricane Wilma, which made landfall on the west coast south of Tampa in the fourth quarter of 2005. Together, Figures 7 and 8 show that two additional "treatments" occurred in 2005.

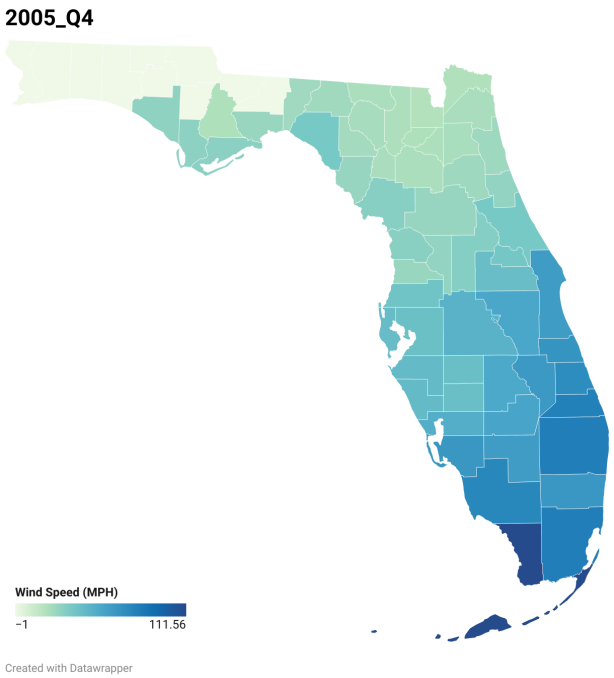


Figure 8: Maximum wind speed across each county for hurricane Wilma, quarter 4, 2005.

TWFE results for alternative treatment effects

Continuous treatment, using raw maximum wind speed

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price
Max '04 Wind	0.000208	0.000340	-0.00103	-0.000283	-0.0000158	0.000634
	(0.000852)	(0.000560)	(0.00112)	(0.000842)	(0.00113)	(0.000694)
Periods after 2004 Storms	-0.0132	-0.00307	-0.0370	-0.0281	0.0111	0.0339
	(0.0385)	(0.0430)	(0.0263)	(0.0274)	(0.0454)	(0.0611)
Post '04 periods by max wind speed (cont)	0.000504***	0.000631***	0.000703***	0.000740***	0.000290*	0.000331**
	(0.000122)	(0.000102)	(0.000108)	(0.0000915)	(0.000153)	(0.000122)
Constant	-0.617***	-0.722***	-0.648***	-0.716***	-0.531***	-0.704***
	(0.0727)	(0.0471)	(0.0793)	(0.0549)	(0.103)	(0.0650)
Observations	316163	231389	128239	121322	187919	110062

Results for all private insurers. The data cover the period from 2003Q2 through 2007Q4. Standard errors clustered by county and insurer in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Continuous treatment based on raw maximum wind speed

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price
Max '04 Wind	0.0000513	0.000184	-0.00225	-0.00140	0.0000865	0.000973
	(0.00125)	(0.00137)	(0.00143)	(0.00134)	(0.00168)	(0.00202)
Periods after 2004 Storms	0.305***	0.310***	0.319***	0.280***	0.314***	0.361***
	(0.0347)	(0.0368)	(0.0625)	(0.0446)	(0.0361)	(0.0426)
Post '04 periods by max wind speed (cont)	-0.000865*	-0.000399	-0.00129	-0.000773	-0.000822	-0.000600
	(0.000490)	(0.000499)	(0.000786)	(0.000597)	(0.000504)	(0.000515)
Constant	-0.474***	-0.690***	-0.213**	-0.279***	-0.532***	-0.942***
	(0.0926)	(0.105)	(0.0941)	(0.0869)	(0.131)	(0.165)
Observations	10943	7604	3181	2900	7762	4704

Results for Citizens. The data cover the period from 2003Q2 through 2007Q4. Standard errors clustered by county in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Continuous treatment based on raw maximum wind speed

Semi-continuous treatment, based on Cat1 wind speed threshold

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price
Max Wind over Cat1	0.000336	0.000377	-0.0000270	0.000190	0.000139	0.000445
	(0.000468)	(0.000334)	(0.000521)	(0.000479)	(0.000528)	(0.000361)
Periods after 2004 Storms	0.0181	0.0372	0.0173	0.0267	0.0201	0.0523
	(0.0339)	(0.0447)	(0.0315)	(0.0333)	(0.0356)	(0.0584)
Post '04 periods by Cat1+ winds	0.0000864	0.000143***	0.000117***	0.000112***	0.0000497	0.0000789
	(0.0000579)	(0.0000445)	(0.00000269)	(0.0000116)	(0.0000790)	(0.0000794)
Constant	-0.617***	-0.714***	-0.714***	-0.740***	-0.541***	-0.684***
	(0.0367)	(0.0314)	(0.0350)	(0.0294)	(0.0465)	(0.0401)
Observations	134227	97056	54198	51020	80024	46030

Results for all private insurers. The data cover the period from 2003Q2 through 2007Q4. Standard errors clustered by county and insurer in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Semi-continuous treatment based on Category 1 hurricane wind threshold

	All Counties		Inland		Coastal	
	All policies	Wind coverage	All policies	Wind coverage	All policies	Wind coverage
	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price	Logged Price
Max Wind over Cat1	0.000353	0.000629	-0.000866	-0.000633	0.000346	0.00106
	(0.000652)	(0.000681)	(0.000520)	(0.000508)	(0.000768)	(0.000947)
Periods after 2004 Storms	0.118***	0.124***	0.109***	0.0898***	0.125***	0.150***
	(0.0101)	(0.0101)	(0.0216)	(0.0152)	(0.0100)	(0.0107)
Post '04 periods by Cat1+ winds	-0.000275*	-0.000286	-0.000628*	-0.000444	-0.000196	-0.000303**
	(0.000163)	(0.000173)	(0.000325)	(0.000289)	(0.000157)	(0.000139)
Constant	-0.466***	-0.681***	-0.303***	-0.324***	-0.522***	-0.896***
	(0.0377)	(0.0419)	(0.0348)	(0.0319)	(0.0501)	(0.0668)
Observations	4484	3165	1253	1183	3231	1982

Results for Citizens. The data cover the period from 2003Q2 through 2007Q4. Standard errors clustered by county in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Semi-continuous treatment based on Category 1 hurricane wind threshold

Event-study models without firm- and policy-type-specific time trends

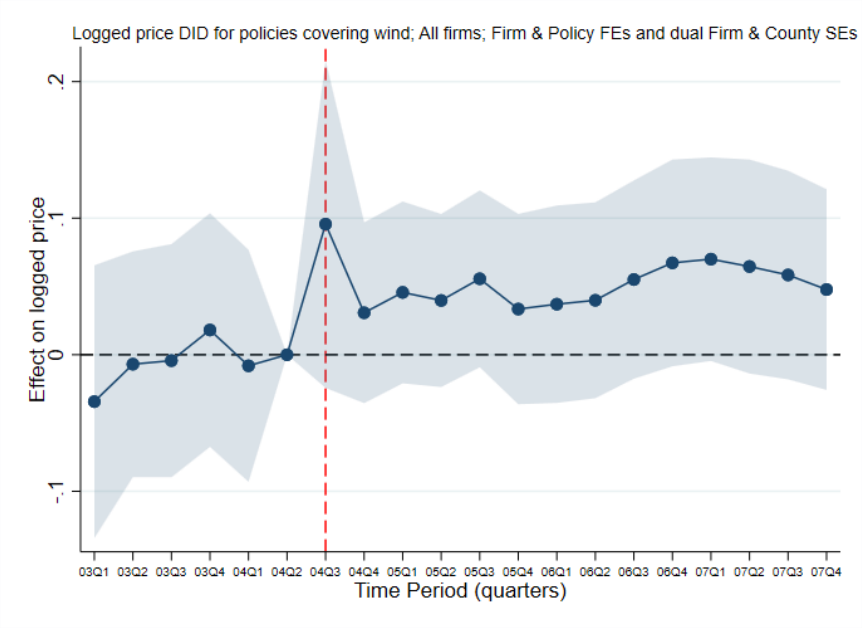


Figure 9: Results for all private insurers.

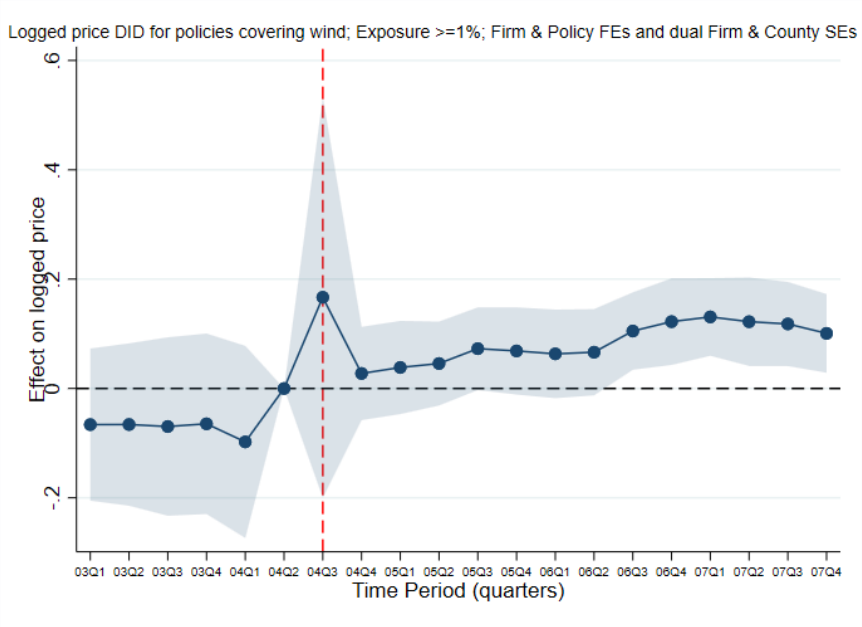


Figure 10: Results for private insurers whose exposure by county-policy type-quarter is at least 1%.

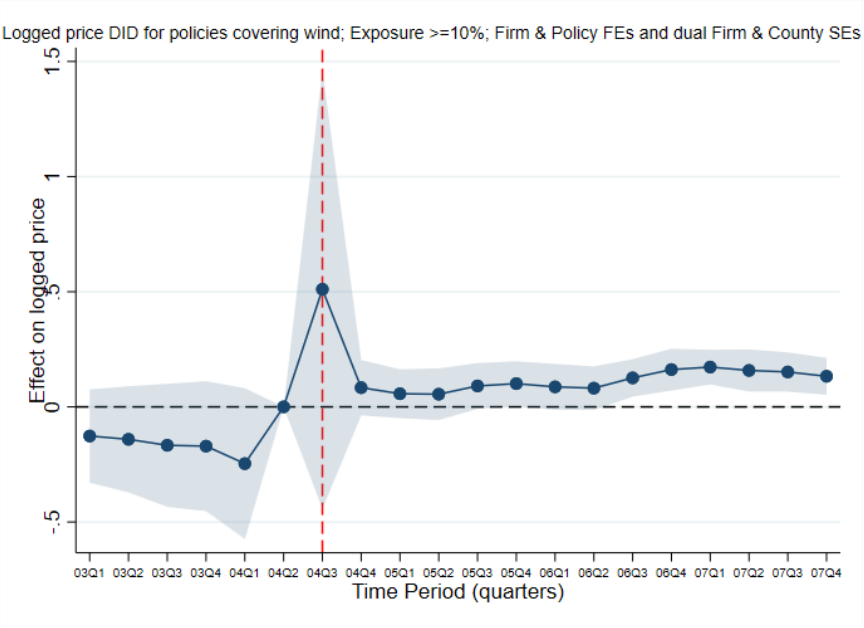


Figure 11: Results for private insurers whose exposure by county-policy type-quarter is at least 10%.

Borusyak et al. (2024) Imputation-based Event-study results – All firms

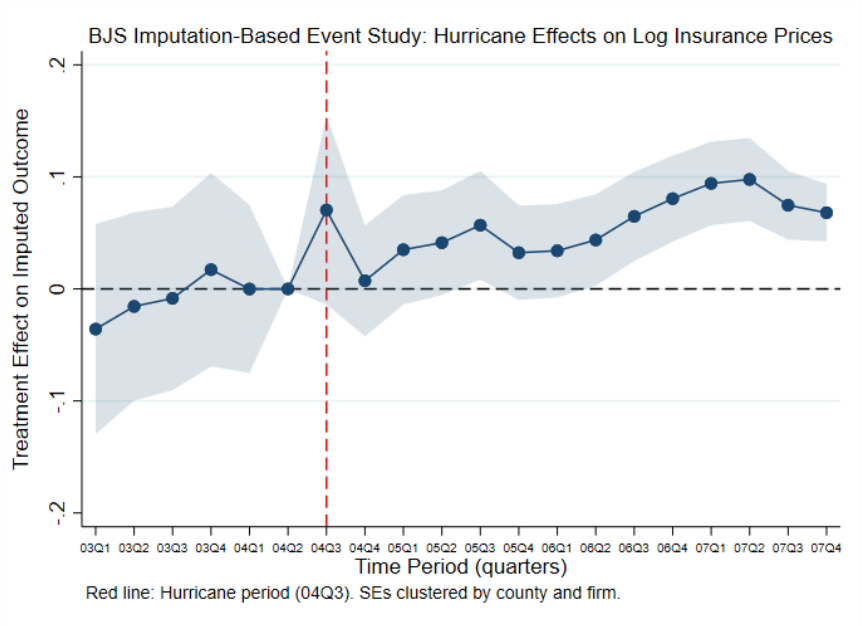


Figure 12

Derivation of optimal capital reserves

Here, we derive the optimal level of capital reserves held by a large-exposure firm. Capital cost appears explicitly in the per-period profit formulation. Express objective regarding choice of capital reserves as:

$$V(\kappa_L) = \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \left[\mu_L N_L - r\kappa_L \theta_H L_0 (1+\delta s_L) N_L \bar{C}_H\right] \cdot \mathbb{1}[\text{Survive}]\right] \tag{36}$$

Let $\ell = \theta_H L_0 (1+\delta s_L)\bar{C}_H$ be the expected loss per policy. Then:

$$V(\kappa_L) = \sum_{t=0}^{\infty} \beta^t [S(\kappa_L)]^t \left[\mu_L N_L - r\kappa_L \ell N_L\right] \tag{37}$$

$$V(\kappa_L) = \frac{N_L[\mu_L - r\kappa_L \ell]}{1 - \beta S(\kappa_L)} \tag{38}$$

In the previous equation, $S(\kappa_L)$ represents the probability of firm L survival. It is based on the idea that the firm will survive to the next period if the capital reserves exceed the realized losses.

$$\Pr(\text{Survive to } t+1) = \Pr(K_L > \tilde{L}_L^{(t)}) \tag{39}$$

where $\tilde{L}_L^{(t)}$ is the realized loss in period t. Given the definition of the realized loss and capital reserves,

we have that:

First-order condition:

$$\frac{dV}{d\kappa_L} = \frac{-r\ell N_L}{1-\beta S(\kappa_L)} + \frac{N_L[\mu_L - r\kappa_L\ell]\cdot\beta S'(\kappa_L)}{[1-\beta S(\kappa_L)]^2} = 0 \tag{40}$$

Multiplying by $\frac{[1-\beta S(\kappa_L)]^2}{N_L}$:

$$-r\ell[1-\beta S(\kappa_L)] + [\mu_L - r\kappa_L\ell]\cdot\beta S'(\kappa_L) = 0 \tag{41}$$

Rearranging terms yields:

$$r\ell[1-\beta S(\kappa_L)] = [\mu_L - r\kappa_L\ell]\cdot\beta S'(\kappa_L) \tag{42}$$

In equation 42, the left-hand side represents the marginal cost of holding an additional unit of capital reserves, which captures the opportunity cost of reserves, r multiplied by the expected loss per policy, ℓ, weighted by the survival-adjusted discount factor. The right-hand side represents the marginal benefit of capital reserves, namely the future profit stream that is realized due to an increased survival probability for the firm.

Further rearrangement and simplification of the first-order condition yields the optimal level of capital reserves for the large-exposure firm:

$$\kappa_L^* = \frac{\mu_L}{r\ell} - \frac{1-\beta S(\kappa_L^*)}{\beta S'(\kappa_L^*)} \tag{43}$$