When Insurance Markets Fail:
Catastrophe-Risk Frictions and Public Reinsurance

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Natural-catastrophe risk has emerged as a major driver of insurance unaffordability and unavailability. I study a novel Australian policy response: government-provided, mandatory, cost-neutral reinsurance for cyclone damage in home insurance. I find that public reinsurance reduces home insurance premiums by 23 percent, and increases the probability of insurance being offered by 12 percent. Theoretically and empirically, I show that the cost of holding capital against correlated or ambiguous risks drives private insurance prices up, and consequently that the fiscally-balanced public reinsurance decreases prices by substituting in cheaper public capital that doesn't require a correlation, ambiguity or risk premium.

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1. Introduction

Climate change is increasing the frequency and severity of natural disasters worldwide, posing significant challenges for the insurance industry and the households it protects. Insurers around the world[1] have responded to extreme weather shocks that cause concentrated damage - cyclones, floods, and wildfires - by dramatically increasing premiums and, in some cases, withdrawing from the market altogether, leaving homeowners struggling to find affordable coverage, or any coverage at all. Recent US-focused work has emphasized both the idiosyncratic regulatory frictions that arise from state-based insurance regulations - particularly their fragmented system of rate approval - and the possibility that US disaster risk is unusually difficult to diversify, given that it constitutes the largest share of global natural catastrophe exposure.[2] However, similar market dysfunction is occurring across a wide variety of geographies and risks, suggesting that the key constraint is upstream: the high shadow price of bearing and sharing catastrophe tail risk in global reinsurance (insurance for insurers) and capital markets.

To isolate the role of global tail-risk sharing from local retail frictions, I study a context with similar problems but a completely different policy landscape: the cyclone-exposed regions of Australia. From the perspective of global risk pooling, Australian cyclone exposure should be an attractive risk. It is largely uncorrelated with other major sources of natural catastrophe risk around the world, such as North Atlantic hurricanes or European winter storms (e.g., Swiss Re Institute 2022), making it ideal for diversification in global reinsurance portfolios. Furthermore, losses from Australian cyclones are uncorrelated with the returns of both Australian and global capital markets (Froot 1999; Cummins 2008a), suggesting that capital market instruments such as catastrophe bonds should efficiently absorb this risk. Yet both reinsurance and capital markets charge large markups - approximately 70 percent and 200 percent over expected losses, respectively. The difficulty of either mechanism to efficiently bear this supposedly diversifiable risk is therefore puzzling.

This paper makes three contributions. First, I empirically document the shortcomings of private risk-sharing in a setting where it ought to be relatively successful: risks that are largely uncorrelated with global catastrophe losses and capital market returns. Second, I identify the frictions responsible for the wedge between expected losses and the cost of bearing catastrophe tail risk. Third, I use the introduction of the Cyclone Reinsurance Pool (CRP) - a mandatory, actuarially priced, public reinsurance program - as a quasi-experimental shock that relaxes these constraints and tests to what extent upstream tail-risk frictions are a cause of downstream insurance-market outcomes.

I find that public reinsurance reduced premiums by up to 23 percent in the highest-cyclone-risk

[1] Recent coverage of collapsing insurance markets spans five continents, including Florida Journal (2021), the United Kingdom Independent (2021), Canada News (2020), Australia Australian Competition and Consumer Commission (2020a), India Times (2021), and South Africa Bloomberg (2021).

[2] See, for example: (Keys and Mulder 2024a; Sastry, Sen, and Tenekedjieva 2024; Leverty and Grace 2011; Oh and Sen 2023; Grace and Klein 2013; Friedman, Mukherjee, and Sridhar 2021).

zipcodes (and 14 percent on average across all treated insurers), and increased the probability of a home insurance quote being offered by 12 percent (5 percent on average). This effect operates entirely through the most constrained insurers: local Australian insurers who previously purchased reinsurance on the open market, rather than vertically integrated Australian subsidiaries of global reinsurers. Prior to the CRP, hazards that were spatially correlated and ambiguous were expensive to insure relative to expected damage. The CRP cuts the correlation premium by roughly two-thirds and shifts the ambiguity-premium relationship significantly downward. These price reductions are not driven by a subsidy. The CRP is fiscally balanced overall, and the effects I find are in fact larger after accounting for the CRP's built-in spatial cross-subsidy between low- and high-risk locations. Instead, the gains come from substituting cheaper public capital for more expensive private capital in tail-risk markets. The result is large insurance price declines and expanded availability at no net cost to the taxpayer. These findings are particularly timely given that a similar public reinsurance program is being actively considered in the U.S. Senate (U.S. Senate 2025).

By providing the first comprehensive evaluation of public reinsurance - socialising the natural catastrophe tail risk - this paper offers a path forward distinct from previous interventions. Governments have experimented with three broad approaches to rising insurance prices, each with significant drawbacks: direct public provision (e.g., US flood and crop insurance), which has typically devolved into subsidy schemes with consequent moral hazard; public insurers of last resort (e.g., Florida Citizens, California Earthquake Authority), which have decoupled risk from prices and cannibalised the private market; and rate regulation, which has caused insurer exit and solvency strain.[3] These interventions all operate downstream by regulating or providing consumer-facing primary insurance, rather than addressing the upstream constraint: the high price of bearing catastrophe tail risk in reinsurance and capital markets. These mixed results motivate a different approach: address the tail-risk constraint at its source rather than subsidising or capping retail premiums.

To understand how public risk-sharing might improve market function, as a first step I give an overview of the primary private mechanisms through which insurers can presently offload tail risk: reinsurance and catastrophe bonds (Section 2). I document that both markets are characterized by high prices: the markup relative to expected risk is about 70 percent (reinsurance) and up to 200 percent (catastrophe bonds). These large markups foreshadow why a public reinsurance program priced at expected risk can deliver large insurance price decreases without any net cost to the taxpayer.

My empirical setting (Section 3.1) is the market for homeowners insurance in Northern Australia. Northern Australia experiences multiple cyclone-force storms each year. Cyclone exposure has caused problems in the homeowners insurance market: premiums rose 122 percent from 2007

[3] Direct public provision: Michel-Kerjan, Raschky, and Kunreuther (2017); Babcock (2015); Klosin and Solomon (2024); Kousky (2018); Michel-Kerjan (2010); Ostriker and Russo (2024); Gruber and Solomon (2026). Insurers of last resort: Friedman, Mukherjee, and Sridhar (2021); Newman and Christopherson (2009); Ben-Shahar and Logue (2011). Rate regulation: Leverty and Grace (2011); Oh and Sen (2023); Grace and Klein (2013).

to 2019 (compared to 52 percent in the rest of the country), and many insurers have withdrawn from the market altogether, with some regions served by only one or two insurers (Australian Competition and Consumer Commission 2020a). This is largely driven by costs associated with tail risks. It is not due to regulatory frictions idiosyncratic to the US: the homeowners insurance market in Australia does not have any price controls, and insurers can change prices or discontinue coverage at will.

I study the Cyclone Reinsurance Pool (CRP), a mandatory public reinsurance scheme run by the Australian federal government (Section 3.2). The CRP takes on only the cyclone risk from homeowners insurance policies. Operationally, once the meteorological bureau declares a cyclone, all losses (from wind, flood, etc.) incurred during and 48 hours after the cyclone event are covered by the pool. In exchange, the insurers pay a premium to the CRP for each policy. The premiums are set to cover expected costs by statute[4], and are calculated using three state-of-the-art catastrophe models as well as all of the historical data on pricing, reinsurance costs, and claims collected from the insurers. The premiums are location- and house-specific and incorporate incentives for risk-reducing behaviors such as building to higher cyclone resilience standards, retrofitting older homes, and implementing community-level mitigation measures[5]. The pool features some spatial cross-subsidies that I account for in my analysis. The pool was announced in July 2022. All insurers had to join the pool by the end of 2023, but could (and did) join earlier. I utilize the staggered entry of insurers in one of my identification strategies.

My data (Section 3.3) come from two sources. First, I use data from Australian Securities and Investments Commission (ASIC), a government-run comparison website that collects quotes from eleven different insurers. In each zipcode, quotes are collected for three addresses (that are fixed across time) for various policy and structure configurations. Crucially, all quotes are collected *as if* the house has fixed structural characteristics, regardless of the actual house at that address. As such, the variation in insurance prices and offerings is driven solely by differences in geographic risk across addresses, not by differences in the type of home or policy. Moreover, these addresses are sampled from all in the zipcode and do not necessarily have insurance. This removes any concern about observing prices only from homes that have bought insurance. Second, I hand-collected premiums for a randomly chosen address (again, fixed over time) in each zipcode, for a subset of the original insurers. In my analysis I use all the data for power, but the results are robust to using either in isolation. All of the insurance policies quoted cover damage from cyclones, storms, and floods.

I use two complementary empirical strategies to causally assess the impact of the reinsurance pool. They both yield economically identical results.

First, I exploit differential exposure to cyclones across areas (Section 3.5.1). Using a cyclone catastrophe model created by Geoscience Australia (2018), I compute cyclone risk in each zipcode. I

[4] Australian Government (2022)

[5] Australian Competition and Consumer Commission (2022)

estimate a continuous treatment specification that allows for outcomes (prices and offerings) to depend differentially on cyclone risk in each period. Prior to the pool, low- and high-cyclone-risk areas are on parallel trends. The localities with no cyclone risk implicitly control for any location-independent time-series variation.

Second, I leverage the staggered entry of insurers into the pool (Section 3.5.2). Of the eleven insurers in my analysis sample, three entered in January 2023, seven in July, and one in November 2023. Entry timing was primarily determined by the expiration of existing reinsurance treaties that were in place prior to the CRP. I estimate a difference-in-differences specification, in which the not (yet) treated insurers act as controls for the insurers who have entered the pool. I check for robustness to the now standard set of issues that arise with staggered entry and potentially heterogeneous treatment effects.

The reinsurance pool increased insurance availability and reduced premiums substantially (Section 4). Using the differential-exposure strategy, once all insurers had entered the pool, the premium in the highest cyclone-risk zipcodes fell by 23 percent more than in the lowest-risk zipcodes, and the probability of a home insurance quote being offered rose by 12 percentage points. Using the staggered-entry strategy, once an insurer joins the pool, its premiums decline by 14 percent on average and it is 5 percent more likely to offer an insurance product at all. These effects are substantial. The pre-treatment average premiums in high-cyclone-risk areas are $3,409, and the probability of insurance being offered is 0.56. A 23 percent premium decrease translates into approximately $784, roughly 0.8 percent of national average individual income in 2023 ($98,812, per Australian Bureau of Statistics (2023)). A 12 percentage point increase in insurance being offered is equivalent to approximately 21 percent of the baseline.

To understand the mechanisms by which the CRP causes premium reductions and availability increases, I write down a model of insurance pricing under catastrophe risk (Section 5). Insurers compete in quantities to maximize profit subject to a solvency constraint: they must hold enough capital to withstand a shock that causes many losses at once. I derive four comparative static results that guide subsequent empirical analyses: the price of insurance is increasing in the risk correlation, in the ambiguity of risk, in the insurer's capital cost, and in the degree of imperfect competition. Because the CRP prices at expected risk, with no factor due to correlation, ambiguity, capital costs or competition, the observed headline price declines are plausibly due to any of these pre-CRP markups being reduced. I test each of these empirically.

First, I provide evidence ruling out an implicit subsidy (Section 6). I exploit the fact that several Australian insurers are subsidiaries of global reinsurance groups. These vertically-integrated international subsidiaries can access reinsurance within their corporate group and are less exposed to the open-market reinsurance frictions that bind domestic insurers. If the CRP were a simple subsidy, both groups should benefit. Instead, I find the premium reductions are driven entirely by domestic insurers. For foreign subsidiaries, the CRP had a zero, or even slightly positive, effect on prices. This heterogeneity demonstrates that the CRP worked by providing risk-priced reinsurance to those who previously lacked it, not by universally mispricing risk.

Second, I show that the primary driver of pre-CRP frictions and post-CRP savings came from the high cost of insuring spatially correlated risk (Section 7). To test how the pool addresses correlation, I use a cyclone-simulation model to measure local risk in each zipcode and its correlation with other locations. Before the pool, this correlation carried a substantial penalty: holding local risk constant, a zipcode whose risk was perfectly correlated with other areas faced 125 percent higher premiums and was 12 percentage points less likely to be offered insurance than an uncorrelated zipcode. The introduction of the pool cut this premium penalty by roughly two-thirds (from 125 percent to 45 percent) and eliminated the availability gap entirely. This shows that the CRP's core effect operates by reducing the cost of insuring correlated risk, over and above expected risk.

Third, I quantify the extent to which the ambiguity of cyclone risk contributes to high prices and depressed availability, and whether these frictions are reduced by the CRP (Section 8). Natural disaster risk is inherently ambiguous, at best approximated by uncertain models. This 'model risk', in which an incorrect model shocks an insurer's entire portfolio at once, has been posited as a reason for increased costs or insurer withdrawal.[6] I proxy for ambiguity with the uncertainty in the estimated average risk across different bootstrapped draws from the cyclone-simulation model. This measures hazard-model uncertainty as a pure function of the catastrophe model, independent of premium levels or insurance market structure. The CRP's introduction shifts the ambiguity-price relationship significantly downward, consistent with the pool absorbing some of the uncertainty premium that insurers were pricing in.

Fourth, I exhibit evidence consistent with the CRP lowering prices by indirectly inducing competition (Section 9). The pool's introduction enabled new insurers to enter high-risk markets they previously avoided. The price declines observed in the headline results are strongest in the zipcodes in which new insurers entered. Descriptively, between 11 percent and 38 percent of the insurance price decline is associated with the additional competition; the remainder is the direct effect of cheaper reinsurance.

These findings point to a diagnosis of strained home insurance markets in catastrophe-exposed regions: high prices and a lack of availability at the downstream retail level are largely due to expensive tail-risk sharing upstream. When capital-constrained domestic insurers lack access to fairly priced reinsurance - whether due to the spatial correlation of their exposures, the inherent ambiguity in modeling natural catastrophe risk, or concentration and bargaining power in the reinsurance market - they face prohibitive costs for insuring concentrated risks. By providing reinsurance at expected cost, the CRP addresses the tail-risk cost - limited risk-bearing capacity in private reinsurance markets - without resorting to subsidies or price controls. This prognosis of the source of the problem, and a working solution to it, suggests targeted interventions to restore market function in other catastrophe-exposed insurance markets.

[6] See, for example, Kunreuther et al. (1995); Eeckhoudt and Gollier (1995); Harrison and Swarthout (2014); Kunreuther, Pauly, and McMorrow (2013)

Literature Review

First, my paper relates to a literature on frictions in insurance markets that can lead to high prices or low availability, often (but not exclusively) related to natural catastrophes. Since insurance is premised on the diversification of risk, concentrated or correlated risk is theorized to cause increased premiums and decreased insurance availability (e.g., Ibragimov, Jaffee, and Walden (2009); Kousky and Cooke (2012); Kunreuther and Michel-Kerjan (2009)). These are exacerbated by capital market imperfections (including reinsurance and catastrophe bonds), which prevent insurers or reinsurers from diversifying across time (e.g., Froot (2001); Jaffee and Russell (1997); Cummins (2008b); Michel-Kerjan, Raschky, and Kunreuther (2006); Dieckmann (2011); Collier et al. (2026)). Analogous problems[7] exist for aggregate consumption risk in other financial markets. Frictions that can lead to insurance market dysfunction include adverse selection (e.g., Einav, Finkelstein, and Cullen (2010); Hendren (2013); Solomon (2024)), informational frictions and an associated winner's curse on the supply side (e.g., Boomhower et al. (2024)), moral hazard (e.g., Ehrlich and Becker (1972); Shavell (1979)), and behavioral factors such as ambiguity aversion, myopia, and limited attention on both the demand and supply sides (e.g., Kunreuther, Pauly, and McMorrow (2013); Meyer and Kunreuther (2016); Browne, Knoller, and Richter (2015); Solomon (2023)). Related work by Keys and Mulder (2024b) shows that rising US home insurance prices correlate with increasing reinsurance costs. I provide causal evidence for this linkage, clarify the mechanisms and drivers of high reinsurance costs, and show that public reinsurance can nullify their impact on premiums.

Second, my paper contributes to the literature on the government regulation of insurance markets. Interventions such as publicly provided insurance, subsidies, and mandatory coverage have been implemented to address market frictions and increase access to coverage. Public insurance programs such as the NFIP have increased access to flood insurance (Browne and Hoyt 2000; Wagner 2021b; Kousky 2018), but have distorted risk signals and risk mitigation behavior (Wagner 2021a; Ostriker and Russo 2024). Similarly, government-provided crop insurance provides risk protection value to farmers, but distorts cropping and production decisions (e.g., Babcock (2015); Yu and Smith (2019); Klosin and Solomon (2024)). Attempts to control price increases have usually backfired, leading to insurer exit and/or cross-subsidies (e.g., Oh and Sen (2023); Kelly, Kleffner, and Li (2013)). Some US states have public 'insurers-of-last-resort', which have cannibalized the private markets they were designed to supplement (see, e.g., Froot (2001) and Grace, Klein, and Kleindorfer (2004)). The most relevant studies on public reinsurance are government reports (Flood Re 2022) on UK Flood Re (a reinsurer of last resort run by the UK government) and the CRP (Australian Reinsurance Pool Corporation 2023a). Consistent with my causal estimates, they find, in the time series, that public reinsurance decreases home insurance costs and increases availability. Relative to this literature, my contribution is to study a novel policy solution - fiscally balanced public reinsurance - in which the government bears only tail risk, thereby reducing the expected cost of the program

[7] See, for example, Caballero and Krishnamurthy (2008); Subramanian and Wang (2021); Chien and Lustig (2009).

relative to one in which it serves as the insurer for all risks.

2. The Market for Catastrophe Risk

2.1. Insurance and Tail Risk

Insurance is premised on diversification. Pooling a large number of independent risks allows insurers to make aggregate losses predictable. The ideal insurance production function therefore takes risks that are 'positive β' (marginal utility is high when risks are realized) and transforms them into diversified, predictable cash flows uncorrelated with individual or market swings.

In practice, however, the assumption of independence is frequently violated. This is particularly true in property insurance markets, where insurers often exhibit significant geographic concentration rather than holding diversified portfolios. Empirically, many insurers pursue specialization strategies, focusing on regions where they possess a comparative advantage in underwriting or distribution, despite the apparent costs of non-diversification (Cummins and Nini 2002). This tendency can be reinforced by regulatory frameworks, such as the state-based system in the U.S., which may implicitly favor a regional focus (Grace, Klein, and Phillips 2007). The direct consequence of this geographic concentration is a heightened vulnerability to spatially correlated perils, where a single event like a cyclone can generate catastrophic losses across a large segment of an insurer's portfolio.

This exposure to correlated tail risk fundamentally alters an insurer's cost structure. To ensure solvency and maintain the ability to pay claims following a major disaster, insurers must hold substantial and costly capital reserves as a buffer against catastrophic losses. As I discuss in the next section, evidence from the reinsurance market suggests that the price of catastrophe coverage is a significant multiple of its actuarial expected loss; Cummins, Lalonde, and Phillips (2004) confirm that the marginal cost of capital for U.S. property-liability insurers is substantially higher for high-risk, catastrophe-exposed lines than for more diversifiable lines of business. When these capital costs become prohibitively high, insurers may be forced to restrict coverage or withdraw from the market entirely (Jaffee and Russell 1997).

2.2. Reinsurance and Catastrophe Bonds

To manage the high cost of holding capital against correlated perils, primary insurers turn to global risk-transfer markets. The two primary mechanisms are reinsurance and catastrophe (cat) bonds. Reinsurance allows a primary insurer to cede its tail risk to a global reinsurer, who diversifies it within a larger portfolio of uncorrelated geographic perils. Cat bonds transfer the risk directly to capital markets, where investors are compensated for bearing catastrophe risk that is largely uncorrelated with traditional financial asset returns (Froot 1999; Cummins 2008a).

The Reinsurance Market

Reinsurance allows primary insurers to spread some of their risk to other entities. Reinsurers provide value by assembling a portfolio that is diversified, geographically and in terms of the types of risk exposure. The transfer can be structured in two primary ways. Under a quota share treaty, the reinsurer assumes a fixed percentage of the primary insurer's book of business, receiving that same percentage of premiums and paying the corresponding share of all losses. Alternatively, under an excess-of-loss contract, the reinsurer covers losses only above a specified attachment point, insulating the primary insurer from high-severity events. While both arrangements provide capital relief, excess-of-loss reinsurance is the principal tool used by insurers to manage catastrophic tail risk (Morrison 2012). The layered structure of reinsurance - primary insurers retain lower layers and cede excess layers to reinsurers - has a natural industrial-organization rationale: primary insurers have a comparative advantage in underwriting and claims-handling individual risks, while reinsurers have a comparative advantage in raising capital against very large losses, so cost minimization assigns each layer to the entity with the lowest marginal cost at that loss level (Boyer and Nyce 2013a).

This tail-risk protection is expensive. The price of catastrophe reinsurance is often a significant multiple of its actuarially fair value. Froot (2001) documents reinsurance prices that are between 2x and 7x expected losses over the period 1989 to 1998. Recent work confirms that these markups remain large, indicating persistent frictions in the market (Kim and Li 2025; Texas Windstorm Insurance Association 2024). In Appendix A.1 I study reinsurance flows for Australian insurers using balance sheet data. I find that Australian insurers pay similarly high reinsurance markups - up to 70 percent - prior to the introduction of the CRP.

The high cost of reinsurance has been hypothesized to stem from several market frictions. First, the global reinsurance market is highly concentrated; a small number of large firms have substantial market share, and the barriers to entry are extreme (Keys and Mulder 2024b; Dyson 2025). Second, reinsurers themselves face high capital costs to back correlated tail risk, which are passed through in their pricing (Froot 2004; Boyer and Nyce 2013a). Third, reinsurers face adverse selection, as primary insurers have an incentive to cede their worst-understood or highest-risk policies, and moral hazard, as a reinsured primary may have diminished incentives for prudent underwriting and claims management (Wen, Chen, and Wu 2015). Moreover, model and basis risk loads (Irina Demirag 2017), collateral and rating-agency requirements, and post-event capital scarcity (Froot and O'Connell 1999; AM Best 2024) have all been associated with higher reinsurance prices.

Catastrophe Bonds

Catastrophe (cat) bonds represent an alternative mechanism for transferring natural catastrophe risk directly to capital markets. Mechanically, a sponsor (an insurer or reinsurer) pays a premium to a Special Purpose Vehicle (SPV), which in turn issues interest-bearing bonds to investors. The bond principal is held as collateral and is forfeited to pay the sponsor's claims if a pre-defined catastrophic event - the 'trigger' - occurs. Triggers are heterogeneous, but are typically structured based on the sponsor's actual losses (indemnity), an industry-wide loss index, or the physical parameters of the event itself (parametric), such as wind speed or earthquake magnitude (Artemis.bm 2024). Notably, this structure means the bonds are fully collateralized, eliminating counterparty credit risk for the sponsor.

Cat bonds tap into the deep global capital markets, and because catastrophic risk is largely uncorrelated with financial market returns, they offer powerful diversification benefits to investors (Polacek 2018). Australian cyclone risk, which is also largely uncorrelated with other major global natural catastrophes (Elsner and Kocher 2000), represents a particularly attractive hedge risk for capital market investors.

Despite this theoretical appeal, the market for cat bonds has not eliminated the high cost of catastrophe risk. As I demonstrate empirically in Appendix A.1, and in line with Tomunen (2025), catastrophe bonds trade at a spread over twice as high as the bonds' expected loss. Several frictions may explain this puzzle. High transaction costs can make issuance prohibitively expensive, particularly for smaller insurers or more specialized risks, thus limiting market access (Bouriaux and Scott 2008). Moreover, Tomunen (2025) shows that the market is dominated by a small number of specialized fund managers who face frictions in raising outside capital. Until recently, retail investors could not easily participate in this market, further limiting capital availability.

2.3. Implications

Descriptively, both traditional reinsurance and catastrophe bonds trade at large multiples of expected loss. I do not want to make strong normative statements about the private reinsurance and cat bond markets; simply, though, current prices are higher than actuarially fair. This wedge explains why a public reinsurer that prices close to expected loss can generate savings on the order of 20 percent or more. In Sections 6, 7, and 8 I study the mechanisms by which public reinsurance decreases prices and, by implication, why costs for private reinsurance and catastrophe bonds were high.

A second implication is conceptual: most models treat insurers as risk-neutral entities who are insensitive to the types of risk they hold. In practice, capital is costly and solvency constraints bind, so insurers behave as if they are risk averse. Ignoring this convex capital cost means standard welfare calculations might understate the gains from shifting tail risk to a low-cost public balance sheet. Additionally, optimal insurance design needs to account for the as-if insurer risk aversion generated by the cost of tail risk.

3. Setting, Policy Change, Data and Empirical Strategy

3.1. Cyclone Risk in Australia

Each year, typically between November and April, approximately 10.8 cyclones form in the Australian region. In comparison, there are on average 12.1 cyclones in the North Atlantic, 16.6 in the Northeast Pacific, 26.0 in the Northwest Pacific, 4.8 in the North Indian Ocean, 9.3 in the Southwest Indian Ocean, and 7.1 in the Southwest Pacific.[8] Appendix Figure A3 maps the global distribution of tropical cyclones. Because of data availability[9], this study focuses on the North Queensland region. The state of Queensland occupies the north-eastern portion of Australia, and North Queensland is approximately the area of the state north of the Tropic of Capricorn. In North Queensland, cyclones regularly cause damage in excess of 1 billion Australian dollars (AUD) (Insurance Council of Australia 2023), against an estimated combined Gross Regional Product of approximately 68 billion AUD and population of approximately 740,000.[10]

3.1.1. Home Insurance in Australia

Insurance for damage to residential property is called 'Home Insurance' or 'Home and Contents Insurance' in Australia, and is provided by general insurers. Home insurance policies cover losses due to theft, vandalism, fire, and accidents, as well as damage due to climatic events such as cyclones, storms, and floods.[11] The Australian general insurance industry is quite concentrated, with the largest two companies accounting for 56 percent of market share, and the largest six for 87 percent (Senate Economics References Committee 2017).

General insurance is regulated at the national level by the APRA, Australian Securities and Investments Commission (ASIC) and the Australian Competition & Consumer Commission (ACCC). Unlike the U.S., there is no state-by-state regulation. Crucially, *insurers can set any prices* they wish, and do not need regulatory approval for a price change. Regulation focuses more narrowly on capital adequacy for systemic stability, prudential standards, and competition[12]

The affordability of home insurance, especially in areas with high natural disaster risk, has at-

[8]See, respectively: Australian Bureau of Meteorology (2023), National Hurricane Center, NOAA (2023a), National Hurricane Center, NOAA (2023b), Japan Meteorological Agency (2023), India Meteorological Department (2023), Météo-France La Réunion (2023), Australian Bureau of Meteorology and New Zealand MetService (2023).

[9]The primary data source - Australian Securities and Investments Commission (ASIC) - collates quotes only from North Queensland.

[10]Aggregated across the Queensland Government's three statistical regions north of the Tropic of Capricorn: Far North Queensland (Queensland Government 2024a), North Queensland (Queensland Government 2024c), and Greater Whitsunday (Queensland Government 2024b).

[11]Full details of the coverage of the policies in the dataset are discussed in section 3.3.

[12]The two key prudential regulations are GPS 116 (Australian Prudential Regulation Authority APRA) and GPS 114 (Australian Prudential Regulation Authority APRA). The former requires that insurers hold capital and reinsurance sufficient to cover a 1-in-200-year loss. The latter specifies the capital charges to be held against various assets, in particular against reinsurance receivables.

tracted public policy interest in recent years. From 2007 until 2019, home insurance premiums rose 122 percent in Northern Australia (Australian Competition and Consumer Commission 2020a), compared to 52 percent for the rest of Australia. This difference was attributed largely to rising reinsurance expenses: the reinsurance expense per dollar of earned premium for the entire general insurance industry rose from 18c to 30c between 2010 and 2023 (Australian Prudential Regulation Authority 2023). This includes many lines of insurance (for example, auto insurance, which has not experienced large changes in reinsurance costs) and so likely understates the effects on home insurance. This led to a public inquiry in 2020 (Senate Economics References Committee 2017), which recommended what became the Cyclone Reinsurance Pool that this paper studies.

3.2. Policy Change - Cyclone Reinsurance Pool

The Cyclone Reinsurance Pool was introduced by the Australian Government in July 2022. The pool is mandatory: all home insurance policies in Australia must be enrolled by their insurers. Policyholders never interact directly with the CRP. Claims and premiums are still paid by the policyholder to the insurer, and the CRP, as with all reinsurance, deals only with the insurer. The CRP calculates and charges a premium to insurers on each policy to cover the cyclone risk. In exchange, the CRP commits to pay all claims incurred due to a cyclone. Operationally, the beginning and end of a cyclone event are declared by the Bureau of Meteorology (the public weather agency), and any claims incurred due to damage during the cyclone event, or in the 48 hours afterwards, are covered by the CRP. This includes any damage due to flood, wind, rain, storm surge, and any other cyclone-related damage within the defined window. The CRP is guaranteed by the Australian Government.

Insurers had to join the CRP by the end of 2023, but could do so earlier. Of the eleven insurers in my analysis sample, three joined in January 2023, seven in July 2023, and one in November 2023. The staggered entry will be the basis for one of my two identification strategies. The timing of insurer entry was primarily determined by the expiration month of each insurer's prior reinsurance contracts together with operational constraints of the ARPC onboarding process; both forces were fixed before any insurer could have responded to its own Northern Australia cyclone premium dynamics. Appendix Table A6 catalogues the evidence for each insurer's entry date, sourced from audited annual reports, directors' reports, ASX releases, and ARPC press announcements (Commonwealth of Australia 2022).

The CRP is statutorily required to be budget neutral (Commonwealth of Australia 2023; Australian Reinsurance Pool Corporation 2023d). To calculate the reinsurance premiums charged to insurers for each policy, the CRP combined catastrophe exposure datasets received from all insurers with the latest generation catastrophe models (Lee and Musulin 2022). The analysis was reviewed by Aon (a risk-management consultancy) and the Australian Government Actuary (Australian Reinsurance Pool Corporation 2022a).

The CRP is backed by an annually reinstated A$10 billion Commonwealth guarantee, sized to absorb a catastrophic single-event tail loss. For calibration, the pool's expected annual loss is approximately A$776 million (Lee and Musulin 2022), while Cyclone Tracy (1974) - the largest historical Australian cyclone - would, normalised to 2023 dollars, cause approximately A$7.4 billion in insured losses (Insurance Council of Australia 2023). By statutory design the CRP charges no margin for profit or return on capital. This distinguishes it from standard commercial reinsurance. Were the CRP to require the use of the A$10 billion government guarantee, no interest would be payable. As of 2025, reserves have been sufficient to meet claims and the guarantee has not been used, including after the March 2025 Tropical Cyclone Alfred event (Australian Reinsurance Pool Corporation 2025).

When designing the CRP, particular attention was paid to ensuring that risk mitigation by homeowners was incentivized. Operationally, premiums depend on: the building type, construction type, roof type, construction year, number of storeys, elevation, and more. Reinsurance premiums have transparent discount schedules built in based on these mitigation choices.

3.3. Data

3.3.1. Insurance Prices

Insurance price data primarily come from a government-run home insurance price comparison site (Australian Securities and Investments Commission ASIC). This website allows individuals to compare home insurance prices in their zipcode across different insurers. I do not see the raw quotations for all addresses. Instead, I see quotes for three addresses within each zipcode: the addresses at the 10th, 50th, and 90th percentiles of cyclone risk according to an underlying risk model. These addresses are constant over time.

Each address is quoted *as if* the house being insured had fixed characteristics, regardless of the type of home that is actually at that address. For example, quotes are obtained for each address as if the insured home was worth $750,000, was constructed between 1980 and 2009, and had brick veneer walls and a tiled roof. The actual home at that address might not have these characteristics. Fixing the characteristics of homes, over time and space, is useful for my analysis. It removes any selection effect whereby homes in high-risk areas might systematically differ in material or value from homes in low-risk areas. It isolates the effect of cyclone risk due to geography on insurance offering and premiums.

For each of these addresses, a quote is obtained from eleven insurers for a variety of different policy options (coverage levels, deductibles, etc.). Collectively these insurers cover 95 percent of the home insurance market (Australian Reinsurance Pool Corporation 2023c). Appendix Table A12 details which risks are covered by each insurer's intermediate policy. All policies cover damage from cyclones, storms, and associated flood. These policy inclusions and exclusions do not change over time. Throughout, "zipcode" refers to the four-digit Australian postcode and "suburb" to the smaller Australian administrative locality nested within a postcode; each postcode in the analysis sample typically contains several suburbs.

The NQHI-portal data are insurer-supplied quotes for a representative house rather than transacted prices. To assess whether these quotes are informative about the prices households would actually face, I hand-collected actionable prices for randomly chosen real addresses in each zipcode from the websites of three of the eleven analysis insurers (Allianz, RACQ, and Sure), holding the policy contract terms and modelled house characteristics fixed across snapshots. Comparing the hand-collected buyable premium to each NQHI-portal quote, the buyable premium sits approximately at the median of the quoted distribution: on average about 12 percent above the low quote, 3 percent below the median, and 30 percent below the high. The pattern is broadly stable across cyclone-risk terciles and across the three insurers, consistent with the quoted panel spanning the realised-price level without systematic bias toward one tail. Appendix A.2 reports the full within-cell validation (Table A5).

Search frictions are high in this market. My data allow for a comparison of multiple insurers at once because the quotes are for a representative house, and the regulator compelled the insurers to provide such quotes. For a homeowner to actually get eleven quotes, they would need to go through eleven separate insurer processes that generally ask for different information. The leading comparison site only compares a handful of small insurers (Compare the Market Pty Ltd 2025). There are two implications. First, price dispersion persists in this market through a combination of differentiated products and search frictions. Second, because there is no sharp Bertrand-style competition, even once one insurer enters the CRP, the others do not quickly adjust their pricing. This is shown clearly in the time series and event study graphs in Appendix A.8.

3.3.2. Cyclone Risk Data

Data on cyclone risk come from the National Tropical Cyclone Hazard Assessment Data (CHAD), a catastrophe model created by Geoscience Australia (2018), an agency of the Australian government. The CHAD uses data on past tropical cyclones to simulate possible cyclones. For each simulated cyclone, maximum wind speeds at each geographic location are recorded.

The CHAD summarizes risk by expected maximum wind speeds over different time horizons. For each zipcode, I use the expected maximum wind speed over a 25-year period as my primary measure of cyclone risk. In Appendix A.10 I show results are robust to using a 2-, 5-, or 100-year period. The area of study, North Queensland, is approximately defined as the portion of Australia above the Tropic of Capricorn (a latitude of 23 degrees south) and east of the 140-degree meridian.

3.4. Summary Statistics

Summary statistics are in Table 1. Table 1 shows the mean and standard deviation of the quoted premiums and probability of quotation. I compute these separately by zipcode-level cyclone risk and by riskiness of address within the zipcode. I define low-risk zipcodes as those in the bottom decile of cyclone risk (25-year maximum wind speed), high-risk zipcodes as those above the median, and medium-risk zipcodes as the remainder in the middle. Additionally, I divide the sample into insurer-time periods pre- and post-treatment.

Table 1 about here

In the pre-treatment period, premiums are higher and less insurance is offered in high-risk zipcodes. After treatment, there is little change in premiums in low-risk zipcodes, whereas there is a notable decrease in high-risk zipcodes. Moreover, the standard deviation decreases by markedly more in the high-risk zipcodes than in the low, suggesting that the very high-risk addresses are particularly affected. Similarly, the probability of insurance being offered increases by more in high-risk zipcodes than in the low.

To understand the dynamics, Appendix Figure A2 plots the time series of premiums and whether insurance is quoted or not. Specifically, I estimate regressions with insurer-by-policy fixed effects as well as dummy variables indicating the time period of observation, and plot the latter. A complementary view organised by entry cohort rather than by cyclone-risk category is provided in Appendix Figure A1, which shows mean annual premiums separately for each of the three CRP entry cohorts and for the balanced subset of address-policy-insurer units quoted in every snapshot.

The time series offers further suggestive evidence that the CRP closed the gap in prices and availability between high- and low-cyclone-risk locations. The pre-treatment difference in availability between high and low risk was approximately 5 percent, which was entirely closed once all insurers had entered the pool; the pre-treatment difference in prices was approximately \$900, which fell to \$500.

3.5. Empirical Strategies

3.5.1. Differential Cyclone Exposure

My first empirical strategy compares locations that are differentially affected by cyclones and which are differentially exposed to the effects of the reinsurance pool. Implicitly, low-cyclone-risk zipcodes act as controls for the high-risk zipcodes. Any market-wide time-varying changes are felt by the low-risk zipcodes, allowing me to isolate the effect of the reinsurance pool on the zipcodes exposed to high cyclone risk.

The data are defined at the level of address a, calendar time t, insurer i, zipcode z, and policy type p. The outcomes, at the a, t, i, z, p level, are: whether or not an insurer quoted for a particular address and the (log of the) premium if it does. I label the binary outcomes for whether a price is quoted by $Quoted_{a,t,i,z,p}$, and the (natural) log of the premium quoted if it exists by $Log(Premium)_{a,t,i,z,p}$.

Cyclone risk is measured at the zipcode z level. The measure of risk is the maximum expected wind speed over a 25-year period from the 2018 National Tropical Cyclone Hazard Assessment Data (Geoscience Australia 2018). In Appendix A.10 I show that these results are robust to alternative measures of cyclone risk. For interpretability, I normalize this measure of cyclone risk to be between zero and one. The lowest windspeed-risk zipcode in my data is coded as zero; the highest is coded as one. Standard errors are clustered at the zipcode level.

$$Quoted_{a,t,i,z,p} = \gamma_t + \alpha_i + \beta \times \text{Cyclone Risk}_z + \tau_t \times \mathbb{1}\,[time = t] \times \text{Cyclone Risk}_z + \epsilon, \tag{1}$$

$$Log(Premium)_{a,t,i,z,p} = \gamma_t + \alpha_i + \beta \times \text{Cyclone Risk}_z + \tau_t \times \mathbb{1}\,[time = t] \times \text{Cyclone Risk}_z + \epsilon. \tag{2}$$

The coefficients of interest are τ_t, the differential impact of cyclone risk in periods before and after insurers enter the reinsurance pool. This is after controlling for the baseline impact of cyclone risk on prices and insurance availability, as estimated by β. The event study plots show τ_t for all t, but the final estimates I tabulate use $\tau_{Jan,2024}$, the period in which all insurers have entered the pool.

After normalizing cyclone risk to between 0 and 1, I interpret $\tau_{Jan,2024}$ as the impact of the reinsurance pool on the highest-risk zipcode relative to the lowest-risk zipcode.

3.5.2. Staggered Insurer Entry

My second empirical strategy identifies the effects of the reinsurance pool by exploiting the staggered entry into the pool by different insurers. Three insurers joined in January 2023, seven in July 2023, and one in November 2023. Entry timing was driven primarily by the expiration dates of insurers' pre-existing private reinsurance treaties, together with operational constraints of the ARPC onboarding process. Neither is plausibly correlated with an individual insurer's Northern Australia cyclone premium dynamics. Appendix A.3 catalogues the per-insurer evidence drawn from audited annual reports, directors' reports, ASX releases, and ARPC announcements.

For nine of the eleven insurers in the analysis sample, the entry date either coincides with or is operationally forced by a pre-existing treaty anniversary. The two exceptions are Sure Insurance, whose managing director publicly described CRP entry as a voluntary decision taken "earlier than required" in light of the hard reinsurance market, and Youi Pty Ltd, which announced CRP entry simultaneously with non-renewing its aggregate natural-perils reinsurance treaty and cited hard-market pricing. As a robustness check, Appendix A.14 re-estimates the headline price and quote regressions on the nine-insurer sample that excludes these two; all results persist and in fact strengthen in sign and significance. Appendix Figure A1 visualises mean annual premiums separately for each cohort.

The insurers who joined in January 2023 did not make their insurance price and offering changes instantaneously. In particular, changes to insurance offering occurred in March-April 2023. As such, while I code treatment to insurance prices as occurring in January 2023, I code treatment to insurance offering as only occurring in April. This is discussed and analyzed in more detail in

Appendix A.12 and robustness checks to this coding are in Appendix A.13. An advantage of the other empirical strategy - differential cyclone exposure - is that it does not suffer from this ambiguity.

An additional concern is that not-yet-treated insurers might nevertheless respond to price and availability changes made by early-treated insurers due to competition. This would, if anything, bias this empirical strategy downward (i.e., be adversarial to my results). In any case, as Appendix Figure A2 demonstrates, the effects of the CRP were not instantaneous; rather, they compounded over time as more and more insurers entered the pool, with the sharpest changes due to the last tranche of treated insurers in November 2023. The primary reason for the lack of Bertrand-style price competition and adjustment is likely search frictions. There is no price comparison tool available for consumers for their actual homes. My data are quoted as if the same home stands in each geography. This is helpful for cleanly identifying the effects of geography, i.e., differential cyclone risk, but not for a household who wants to efficiently gather buyable quotes for their actual home.

The data are defined at the level of address a, calendar time t, insurer i, zipcode z, and policy type p. The outcomes, at the a, t, i, z, p level, are: whether or not an insurer quoted for the 10th/50th/90th percentile address and the premium if it does. I label the binary outcomes for whether a price is quoted by $Quoted_{a,t,i,z,p}$, and, if so, the log of the premium quoted by $Log(Premium)_{a,t,i,z,p}$.

I estimate a difference-in-differences model. The primary specifications I estimate are:

$$Quoted_{a,t,i,z,p} = \gamma_t + \alpha_i + \tau \times \text{Insurer } i \text{ in the pool at time } t_{i,t} + \epsilon, \tag{3}$$

$$Log(Premium)_{a,t,i,z,p} = \gamma_t + \alpha_i + \tau \times \text{Insurer } i \text{ in the pool at time } t_{i,t} + \epsilon. \tag{4}$$

I include calendar time fixed effects γ_t. Because treatment is at the insurer level, in the primary specifications I include insurer fixed effects α_i. However, I also show that the results are robust to including more granular fixed effects at the insurer-by-policy-parameter level. The treatment effect of interest is τ, the estimate of the effect of an insurer i being enrolled in the pool at time t. Standard errors are clustered at the insurer level. In Appendix A.9, I show that the results persist when I use the Callaway and Sant'Anna (2021) correction for TWFE specifications. To check robustness to concerns regarding cluster-robust standard errors with only 11 clusters (insurers), in all specifications I additionally report wild cluster robust p-values.

4. Effects of the CRP

4.1. Premium Reductions

Did the reinsurance pool reduce insurance premiums? To study this, I estimate equations (2) and (4). The results are in Table 2. The equivalent event studies are in Appendix A.8. Recall that the tabulated coefficient for specification (2) is $\tau_{Jan,2024}$, the effect after all insurers have entered the reinsurance pool.

Table 2 about here

Table 2 compares the treatment effects estimated from the staggered entry empirical strategy (columns (3) and (4)) with the differential exposure (columns (1) and (2)). Focusing on the insurer-fixed-effect specifications in columns (2) and (4): once an insurer enters the pool its premiums drop by approximately 14 percent on average (column (4)), and once all insurers have entered the pool the premium at the highest-cyclone-risk zipcode is approximately 23 percent lower than at the lowest-cyclone-risk zipcode (column (2)). These two estimates cohere: because the median zipcode-level cyclone-risk measure in the sample is approximately 0.7, the differential-exposure specification implies a premium reduction at the median-risk zipcode of approximately $0.7 \times 23\% \approx 16\%$, close to the staggered-treatment average of 14 percent. Applied to the pre-treatment average premium of $3,409 in high-cyclone-risk areas, a 16 percent reduction at the median-risk home translates to approximately $545 per year.

This is direct evidence that the reinsurance pool achieved its stated goal of reducing premiums. This is consistent with multiple mechanisms: the reinsurance pool might be an implicit subsidy, if premiums were incorrectly set to be better than actuarially fair; the policy might stimulate entry into markets, and the premium reductions are due to increased competition; or the re/insurance market might have priced well above expected loss, perhaps due to the correlation or ambiguity of risk. In Sections 6 to 9 I test all of these mechanisms. Additionally, in Appendix A.1 I demonstrate that the observed 20 percent price reductions are quantitatively consistent with easing of the pre-CRP markups if the CRP simply priced at cost without any subsidy. In Appendix A.9, I test the robustness of the results that leverage staggered insurer entry to the Callaway-Sant'Anna (Callaway and Sant'Anna 2021) group-time ATT estimator and find they are qualitatively similar, albeit slightly less precise. The square brackets in Table 2 report wild cluster robust p-values.

4.2. Expanded Insurance Offering

Did the reinsurance pool cause insurers to offer policies in locations where they previously did not? I estimate equations (1) and (3). The results are in Table 3. The equivalent event studies are in Appendix A.8.

Table 3 about here

Table 3 shows that insurers substantially expanded the zipcodes in which they offered insurance after entering the reinsurance pool. The increase, after all insurers have entered the pool, in the probability of insurance being offered is approximately 12 percentage points higher in the highest-cyclone-risk zipcodes than in the lowest-cyclone-risk zipcodes (column (2) of the table).

The staggered-entry specification estimates an average increase of 5 percentage points (column (4)), which is not statistically distinguishable from zero under the wild cluster bootstrap. The lack of precision on the staggered coefficient reflects clustering at the insurer level, of which there are only eleven in the analysis sample, and among whom availability decisions are highly correlated. I test for robustness to alternative staggered-treatment estimators in Appendix A.9. The full event-study coefficient paths for the quote outcome are plotted in Appendix A.8.

This is evidence for tail-risk-induced supply-side frictions in the home insurance market. Cheaper tail-risk reinsurance stimulated insurers to offer insurance where they refused, at any price, to sell before. In subsequent sections I explore the precise ways in which insurers are averse to tail risk and, therefore, the frictions implicitly eased by the CRP.

5. A Model of Insurer Pricing

To organise the mechanism tests that follow, I present a model of insurer pricing. The model has four primitives: correlation between risks, ambiguity over the loss distribution, the shadow cost of capital, and the degree of competition (i.e., the number of insurers). Each of these generates a comparative static prediction that I test empirically in the subsequent mechanisms sections. Proofs are in Appendix B.

5.1. Setup

There are M symmetric risks, indexed by $i = 1, \dots, M$. Each risk has loss indicator $X_i \in \{0, 1\}$, corresponding to a loss of unit size. Each risk has marginal loss probability p and pairwise correlation $\rho \in [0, 1]$. The probability p is itself uncertain: $p = p_H$ with probability $q \in (0, 1)$ and $p = p_L$ with probability $1 - q$, with $0 < p_L < p_H < 1$. Let $\mu := qp_H + (1 - q)p_L$ and $\sigma^2 := q(1 - q)(p_H - p_L)^2$ denote the unconditional mean and variance of p. The parameter ρ captures co-movement of realised losses conditional on the loss probability; σ captures ambiguity about the loss probability itself.

The market has N symmetric insurers competing in quantities. Insurer n writes fraction $k_n \in [0, 1]$ of the M risks, indexed by $\mathcal{I}_n \subseteq \{1, \dots, M\}$ with $|\mathcal{I}_n| = k_n M$.[13] Its aggregate portfolio loss is

$$L_n := \sum_{i \in \mathcal{I}_n} X_i.$$

Industry coverage $Q = \sum_n k_n$ clears the market through linear inverse demand $P = \bar{Q} - Q$. The choice variable k_n thus plays a dual role: it is both the quantity sold and (through $k_n M$) the degree of portfolio diversification.

The insurer holds capital $a_n \geq 0$ at shadow cost $\tau \in (0, 1)$ per dollar. It must satisfy the survival

[13] We treat k_n as continuous; equivalently, M is large.

constraint, interpreted as a reduced-form regulatory capital requirement[14]

$$\Pr\big(L_n > k_n MP + a_n\big) \le \alpha,$$

where α is an exogenous probability-of-default tolerance. This constraint says that premiums collected $k_n MP$ plus capital held a_n must cover total losses with probability $1-\alpha$. Equivalently, the insurer's probability of insolvency must be no higher than α.

Insurer n chooses (k_n, a_n) to maximise expected profit subject to the survival constraint and the market-clearing condition, taking all other insurer's choices as given:

$$\text{(5)} \quad \max_{k_n \in [0,1],\, a_n \ge 0} \quad \Pi_n = k_n M(P-\mu) - \tau a_n \quad \text{s.t.} \quad \Pr\big(L_n > k_n MP + a_n\big) \le \alpha, \quad P = \bar{Q} - \big(k_n + \textstyle\sum_{m \neq n} k_m\big).$$

5.2. Equilibrium and Comparative Statics

I solve for a symmetric Cournot equilibrium in which each insurer chooses its quantity and capital holdings subject to the survival constraint. The equilibrium condition and derivation are in Appendix B. The model yields three comparative statics.

PROPOSITION 1. *Under the large-portfolio normal approximation to portfolio losses, suppose the derived Cournot game has an interior symmetric equilibrium in which zero capital would violate the survival constraint.*[15] *Then:*

- *Greater correlation across realised losses raises the equilibrium price.*
- *Greater ambiguity about the loss probability raises the equilibrium price.*[16]
- *A higher shadow cost of capital raises the equilibrium price.*

This generates three sharp predictions: insurance is more expensive when the risks being insured are (a) more correlated; (b) more ambiguous or (c) the insurer has a higher cost of capital. Conversely, since the CRP did not price in any ambiguity, correlation or cost of capital, the price reductions the CRP induced should be highest for correlated and ambiguous risks and for capital-constrained insurers. I test these mechanisms in Sections 6, 7 and 8.

[14] This captures, in reduced form, a Value-at-Risk-based capital requirement. For example, Solvency II calibrates the Solvency Capital Requirement to a one-year 99.5 percent Value-at-Risk standard (European Parliament and Council of the European Union (2009)), and APRA's LAGIC framework calibrates a general insurer's Prescribed Capital Amount to a 99.5 percent probability of sufficiency over a one-year horizon (Australian Prudential Regulation Authority (APRA)).

[15] Formally, at the symmetric equilibrium k^*, this requires

$$k^* M(\bar{Q} - Nk^* - \mu) < z_\alpha \sqrt{k^* M\, V(k^* M)}.$$

Equivalently, the insurer must hold strictly positive capital.

[16] The ambiguity comparative static is a mean-preserving spread in the distribution of p: σ increases while μ is held fixed.

5.3. Competition Effects

Relatedly, as the number of insurers increases (i.e. there is more competition), there are two countervailing impacts on prices. As N rises, each insurer's equilibrium share k^* falls, so each insurer holds a smaller portfolio and marginal cost rises through reduced diversification. At the same time, the Cournot markup over marginal cost falls.

Whether the diversification or the markup channel dominates is an empirical question. In our setting, since the number of risks is very large and the number of insurers small, I expect the competition channel to be more important and, therefore, for competition to reduce prices. I study this in Section 9.

6. Mechanism I: Subsidy or Reducing Reinsurance Access Frictions?

The prior sections demonstrated that the CRP reduced prices. There are multiple potential explanations for this. First, the CRP might have accidentally subsidized reinsurance, which would have caused the insurance price declines. Second, the spatial cross-subsidy built into the CRP could have polluted my estimates of the price effects. Or, third, the CRP could have relaxed a friction derived in the model above. In this section, I show that the price effects observed are not due to a subsidy or cross-subsidy, and instead are caused by relaxing reinsurance access frictions.

To rule out a subsidy and speak to the reinsurance access friction I leverage heterogeneity in the insurers exposed to this policy. Of the eleven insurers, three are Australian affiliates of large global insurers - Allianz, Westpac, and Sure (a subsidiary of Liberty Mutual). These subsidiaries have internal reinsurance with their corporate parents.[17] The other eight insurers are domestic with no direct international affiliation and who must obtain reinsurance on the open market. Using this split I test whether the CRP mostly benefits firms that were previously reinsurance-constrained.

I estimate slight extensions of (2) and (4). I extend these specifications by interacting the coefficient of interest (cyclone risk or the insurer having entered the pool, respectively) with a dummy variable for the insurer being one of three foreign subsidiaries. The resulting coefficients τ measure treatment effects only for domestic insurers, while τ_F is the additional treatment effect for the foreign subsidiaries. The results are in Table 4.

Table 4 about here

The results in Table 4 demonstrate that the price reductions are entirely driven by domestic insurers without access to in-house reinsurance. Focusing on the insurer-fixed-effect columns (2) and (4): the domestic-insurer treatment effect is -0.313 in the differential-exposure specification and -0.290

[17] See, Allianz Re (2024) and the direct balance sheet evidence in Appendix A.1.

in the staggered specification, both highly significant, implying a ≈ 31% reduction in the highest-cyclone-risk zipcode and a ≈ 29% average reduction for domestic insurers. For subsidiaries of foreign insurers, in contrast, after adding together the coefficients in the first and second rows, the CRP has no statistically significant downward effect and in some specifications a modest upward movement. The absence of a price reduction for foreign subsidiaries is explained by these insurers already having inexpensive intra-group reinsurance prior to the CRP, so the mandatory CRP cession provided minimal marginal cost saving.

Because only reinsurance-constrained domestic insurers gain from the pool, the evidence is inconsistent with a blanket subsidy. If there were simply a universal subsidy, prices for foreign subsidiaries with access to in-house reinsurance would have decreased as well. Instead, the CRP appears to relax a friction in the private reinsurance market. Section 7 digs deeper into the structural origins of that friction. Appendix A.1 shows that the pre-CRP markups were of sufficient size to rationalize the price reductions observed here without the need for any subsidy.

Access Frictions - Pre-CRP Reinsurance Intensity. The foreign versus domestic split provides a clean, if coarse, test of whether pre-CRP reinsurance access drove the observed effects. I now exploit finer, continuous variation in reinsurance access across all insurers using regulatory balance sheet data from the Australian Prudential Regulation Authority (APRA).

Specifically, I construct each insurer's *ceding ratio* - the share of gross earned premium ceded to reinsurers - from APRA's quarterly insurer-level filings in the fiscal year immediately preceding the CRP's introduction. A higher ceding ratio indicates that an insurer already had access to attractively priced external reinsurance prior to treatment. A lower ceding ratio indicates that an insurer lacked such access, and was instead retaining tail risk on its own balance sheet. In the pre-treatment data, the ceding ratio ranges from 0.054 to 0.742.

I estimate slight extensions of (2) and (4), interacting the coefficient of interest - cyclone risk - with the insurer's pre-treatment ceding ratio. The results are in Table 5.

Table 5 about here

The results confirm the access friction mechanism. For the insurers with the lowest pre-treatment ceding ratios (approximately 0.054) - indicating essentially no prior reinsurance flowing to external reinsurers - the estimated premium reduction is the largest: approximately 38 percent under differential exposure and 26 percent under staggered entry (columns (2) and (4) of Table 5 multiplied by a ceding ratio of 0.054). In contrast, insurers that already had substantial reinsurance usage prior to the CRP were less affected by the policy change; their prices did not fall and in some cases even rose. The ceding ratio is a descriptive proxy for reinsurance usage rather than a clean measure of access frictions: a low ratio is consistent with a binding access constraint but also with an insurer's strategic decision to retain tail risk on its own balance sheet, so the heterogeneity documented here should be read as suggestive rather than as direct causal evidence for an access-friction channel.

This coheres with and confirms the general point. Insurers who had access to reinsurance prior to the CRP, measured directly or indirectly proxied for via the foreign vs domestic distinction, were barely affected by the policy. In contrast, the CRP's price reductions came entirely from removing frictions for insurers whose reinsurance access was previously constrained.

6.1. Testing for Cross-Subsidisation

The preceding evidence is consistent with the fact that, as designed, there was no overall subsidy in the CRP's pricing. However, there is the potential for a *spatial cross-subsidy*. The CRP, by construction, aimed to set reinsurance rates for low-risk properties that were similar to the (marked-up) private rates that prevailed before the CRP. That is, the CRP expects to make a profit on low-risk properties. In contrast, the CRP reinsurance rates for high-risk properties were designed to a) not have a direct markup, and b) be further lowered by incorporating any CRP profits from the low-risk property markups.

Although a cross-subsidy from low- to high-risk properties would complicate the interpretation of the differential exposure strategy, it does not threaten the staggered treatment. So while the core findings are robust, understanding the effect of any cross-subsidy is of independent interest.

To measure the magnitude of any cross-subsidy directly, I use the ARPC's own published cross-subsidy schedule. The ARPC actuary's Premium Determination Report (Finity Consulting Pty Ltd 2024) reports the premium-adequacy ratio (Cyclone Pool premium divided by modelled cost) at each risk tier: 1.36 for minimal-risk properties, 1.18 for low-risk properties, 0.90 for medium-risk and 0.46 for high-risk properties. Aggregating medium and high by property weight in cyclone-affected regions gives 0.84 for medium/high combined (the below-cost ratio reflecting the downward cross-subsidy from the former tiers). I use these published ratios to conduct two direct tests of the cross-subsidy channel.

First, I split the headline staggered treatment effect by ARPC-published risk class and check whether the treatment effect is larger (in magnitude) for the risk classes that receive the largest cross-subsidy. If cross-subsidisation were driving the headline effect, the medium/high-risk class would show a much larger treatment effect than the low-risk class. Table 6 reports the result: the low-risk treatment effect (-0.137) is in fact slightly larger in magnitude than the medium/high-risk effect (-0.104), with a pooled effect of -0.149 - the opposite of what cross-subsidisation would predict, ruling it out as driving the headline results.

Table 6 about here

Second, I divide post-treatment premiums by the ARPC's published premium-adequacy ratio (1.36 for minimal, 1.18 for low, 0.84 for medium/high), and re-run the staggered specification on the adjusted premium. This removes the proportional cross-subsidy built into the CRP's pricing and isolates the pure markup-reduction channel. Table 7 reports the adjusted staggered ATT of

−0.227, larger in magnitude than the unadjusted headline estimate of −0.149 (both significant under the wild cluster bootstrap). The headline effect is therefore conservative with respect to cross-subsidisation: correcting for the mechanical cross-subsidy built into the CRP's pricing makes the pure markup-reduction effect larger, not smaller.

Table 7 about here

Taken together, these two tests confirm that the headline price reduction documented in Section 4.1 is driven by the reduction in private-market reinsurance markups rather than by cross-subsidisation from low- to high-risk properties.

7. Mechanism II: The Cost of Insuring Correlated Risk

A primary difference between insuring cyclone risk and selling, for example, life insurance, is that the former risk can hit many people at once. As shown in the model in Section 5, insurers must hold more capital to stay solvent in these years of correlated losses. This adds to the cost of insurance and reinsurance. The CRP does not charge a correlation premium either explicitly or implicitly, since the CRP is not required to hold capital against tail scenarios. As a result, I test whether the CRP reduced prices because it substituted public capital with no capital cost for private capital that was expensive to hold against correlated shocks.

Data on Risk and Correlation. Data on risk in each zipcode and the correlation across zipcodes comes from the CHAD (Geoscience Australia 2018), as in Section 3.3. CHAD summarizes expected maximum wind speeds in each location over different time horizons ranging from 1 year to 10,000 years.

To compute the correlation in risk between zipcodes, I use 10,000 randomly sampled cyclones simulated by CHAD. For each cyclone, the maximum wind speed in each zipcode is recorded. I then compute the correlation between wind speed in each zipcode and the equally weighted aggregate of the remaining zipcodes. Conceptually, this is equivalent to an insurer having an equally weighted portfolio of policies in all but one zipcode and computing the correlation between the new zipcode and its existing portfolio. This is the measure of correlation used throughout.

Method. I study the impact of the spatial correlation in risk on premiums and insurance offered, controlling for local risk. To study how the reinsurance pool changed the impact of spatial correlation on premiums and insurance offerings, I restrict to data in the first time period (October 2022, when no insurers were in the pool) and the last time period (January 2024, when all insurers were in the pool). Using this data, I estimate models of the form:

$$
\begin{aligned}
(6) \qquad Premium_{a,t,i,z,p} &= \gamma_t + \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \kappa \times \text{Risk Correlation}_{z,-z} \\
&\quad + \kappa_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Correlation}_{z,-z} + \epsilon, \\
(7) \qquad Quoted_{a,t,i,z,p} &= \gamma_t + \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \kappa \times \text{Risk Correlation}_{z,-z} \\
&\quad + \kappa_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Correlation}_{z,-z} + \epsilon,
\end{aligned}
$$

The coefficients of interest are κ and κ_{Post}. κ measures the baseline difference in premium/probability of insurance offered between a zipcode z whose risk is uncorrelated with the remaining zipcodes $-z$, and a zipcode whose risk is perfectly correlated with the remaining. κ_{Post} measures the change in the impact of correlation due to the introduction of the reinsurance pool. In all cases, I control for risk in zipcode z, so that κ and κ_{Post} are interpreted as the impact of inter-zipcode correlation holding local risk constant. Although correlation coefficients in principle lie in $[-1, 1]$, in my sample the zipcode-to-rest-of-sample correlation is positive for every zipcode and ranges from near zero up to approximately one, reflecting the fact that all zipcodes in North Queensland are exposed to largely overlapping cyclone systems.

I run various specifications, with qualitatively identical results. Specifications (1) and (2) control for risk (maximum 25-year wind speed) in the same way as the core estimates of the treatment effects in Tables 2 and 3. Specifications (3) and (4) allow for insurer-time-specific pricing of risk. Specifications (5) and (6) include a richer set of risk measures[18] and allow for insurer-time-specific risk-pricing. For these three pairs of specifications, one includes insurer-time fixed effects, the other insurer-policy-time fixed effects. The results are in Table 8 below.

Table 8 about here

Table 8 shows that the spatial correlation of risk is a significant contributor to insurance prices and availability. Focusing on specification (6), a zipcode whose risk is perfectly correlated with all other zipcodes has a premium 125 percent (= $e^{0.813} - 1$) higher than a zipcode whose risk is uncorrelated. Similarly, the zipcode with perfectly correlated risk is approximately 12 percentage points less likely to be quoted insurance than the uncorrelated zipcode. The impact of spatial correlation of risk on insurance is dramatically reduced by the reinsurance pool. After the introduction of the pool, the perfectly correlated zipcode is only 45 percent (= $e^{0.813-0.439} - 1$) more expensive than the uncorrelated zipcode, and no less likely to be offered insurance.

Once the government reduces the cost (either directly or charged by a reinsurer) associated with the correlation of risk, insurance market function improves. Risk correlation no longer reduces the chance that insurance will be offered, and the impact of correlation on prices is reduced by 2/3 relative to the pre-pool level.

[18] In addition to expected maximum 25-year wind speed, I include expected maximum 2- and 200-year wind speed.

This demonstrates that private insurance and reinsurance markets are inhibited by correlated risk. To the extent the government is willing to hold that risk at expected cost, without charging for the correlation, the private market improves. This suggests that governments have a comparative advantage in holding correlated risk. They are less capital-constrained and cannot declare bankruptcy or be shielded by limited liability if a disaster strikes. This is consistent with the theoretical case for government entry as a reinsurer of last resort developed by Boyer and Nyce (2013b).

In Section A.7, I show that both the pre-CRP correlation premium and the post-CRP correlation-premium reduction are sharpest for domestic insurers relative to vertically integrated foreign subsidiaries. This is consistent with the costs of bearing tail risk being sharpest for smaller, domestic insurers who must purchase (relatively expensive) reinsurance on the open market. Correlation is a substantial source of this tail risk. The CRP, by reducing the costs of bearing tail risk, is most beneficial to such insurers.

8. Mechanism III: The Cost of Insuring Ambiguous Risk

Cyclone risk is difficult to estimate. As a result, as formalized in Section 5, when a model turns out to be incorrect, the pricing of an entire portfolio can be wrong at once. Thus, ambiguous risk functions as a correlated shock. The CRP, similarly to spatial correlation, does not charge an ambiguity premium. Hence, I test whether the price-reduction effects of the CRP are larger in the areas with more model ambiguity.

Measure of Risk Ambiguity. To proxy for hazard-model uncertainty in a way that does not get entangled with either the level of risk or the market structure of the private insurance market, I use the bootstrap standard deviation of the 25-year return-period wind speed at each zipcode, derived directly from Geoscience Australia's cyclone simulation model (the CHAD dataset described in Section 3.3). For each zipcode I draw 1,000 bootstrap resamples of simulated cyclones, compute the 25-year return-period wind speed in each resample, and take the standard deviation of these bootstrap estimates. This measure captures hazard-model uncertainty alone: it is a pure function of the catastrophe model.

The empirical proxy is the bootstrap analogue of the model's ambiguity parameter from Section 5, defined there as a mean-preserving spread on the loss probability. The proxy is conservative in two respects. First, it captures only hazard-model uncertainty and excludes loss-model and exposure-model uncertainty, which would compound it. Second, the bootstrap resamples within a single catastrophe model rather than across models, omitting between-model dispersion. Both restrictions push the empirical measure downward relative to the model's theoretical ambiguity parameter, so any ambiguity-related premium effect identified here is, loosely speaking, a lower bound.

Method. Analogously to Section 7, I study the impact of risk ambiguity on premiums and insurance offered, controlling for the level of local risk. I again restrict to data in the first and last time periods, before any insurers had entered the pool and after all insurers had entered, respectively. I estimate the following models:

$$\text{(8)} \qquad Premium_{a,t,i,z,p} = \gamma_t + \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \aleph \times \text{Risk Ambiguity}_z + \aleph_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Ambiguity}_z + \epsilon,$$

$$\text{(9)} \qquad Quoted_{a,t,i,z,p} = \gamma_t + \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \aleph \times \text{Risk Ambiguity}_z + \aleph_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Ambiguity}_z + \epsilon,$$

The coefficients of interest are $\aleph$ and $\aleph_{Post}$. $\aleph$ measures the baseline association between hazard-model uncertainty and the premium or probability that insurance is offered, per unit of bootstrap standard deviation in the 25-year return-period wind speed. $\aleph_{Post}$ measures the change in this impact of ambiguity due to the cyclone reinsurance pool. Throughout I control for the level of risk in multiple ways. The various specifications are analogous to those in Section 7. The odd-numbered specifications have insurer-time fixed effects, the even-numbered have insurer-policy-time fixed effects. Each pair of specifications controls for risk differently.

Table 9 about here

Table 9 shows a more nuanced picture for the ambiguity channel than for correlation. Pre-CRP hazard-model uncertainty has only a weak and statistically insignificant association with premium levels: specification (6) estimates a coefficient of +0.027 that is not distinguishable from zero. The CRP's introduction, however, significantly shifts the ambiguity-premium relationship downward: the post-CRP change is −0.162 log points per unit of bootstrap standard deviation, highly significant under the wild cluster bootstrap. After the CRP, more ambiguous zipcodes pay approximately 13.5 percent lower premiums per unit of hazard uncertainty than they would have under the pre-CRP pricing relationship.

This is consistent with the CRP absorbing the hazard-model uncertainty component of the pre-CRP reinsurance markup: if private reinsurance was implicitly charging a model-uncertainty load on top of the expected-loss component, the CRP's actuarially priced replacement removes that load, and the private retail pricing follows suit.

These effects are similar in direction but smaller in magnitude than the effects of correlation documented in the previous section. In Appendix A.16, I estimate the effects of correlation and ambiguity together and obtain even sharper estimates than in this and the prior section individually.

Similarly to the correlation analysis, in Section A.7, I show that both the post-CRP ambiguity-premium reduction are sharpest for domestic insurers relative to vertically integrated foreign subsidiaries. Since model risk driven by ambiguity functions as a tail shock - if the model is wrong, all liabilities can increase at once - the CRP plays the same role and benefits particularly the same insurers as for tail risk from correlation or any other source.

9. Mechanism IV: Competition Effects

The reinsurance pool induced insurers to offer insurance to locations they previously did not. The increased competition is a plausible additional channel through which the CRP affected retail prices.

To study this, I augment the specifications for both the differential exposure and staggered treatment with an interaction between the treatment variable of interest and a dummy $NewEntry_{z,-i,t}$ for entry by a different insurer $-i$ at time t into zipcode z. Hence, I estimate the treatment effect in zipcode-time period combinations in which there was no new insurer entry, and an additional effect for zipcode-time period combinations in which a new insurer entered. Note, I estimate the effects only on the set of insurers that was always present in the zipcode; there is no sample change. Because pre-treatment insurer presence is itself correlated with local risk and with the reinsurance-access frictions studied in Section 6, these estimates should not be interpreted causally.

Table 10 about here

Table 10 shows a strong association between CRP participation and new-entry dynamics: in both empirical strategies, the estimated treatment-associated price reduction is meaningfully larger in periods with new insurer entry than in periods without. The with-new-entry association is approximately 12 percent of the no-entry baseline in the differential-exposure column (-0.024 vs -0.200) and approximately 60 percent in the staggered column (-0.057 vs -0.094).

The discrepancy between the two columns reflects the different sources of identifying variation - cross-zipcode at a fixed time for differential exposure, and within-insurer across time for staggered treatment - rather than a tight point estimate of any single competition-channel parameter. These estimates are descriptive OLS associations consistent with induced competition being a quantitatively important secondary mechanism of the CRP; they are not causal point estimates of a direct/indirect decomposition. Read in that spirit, the evidence is consistent with frictions in the upstream reinsurance market having a compound effect downstream: prices were elevated both because reinsurance costs were high and because the cost of reinsurance deterred entry, and the CRP addresses the former directly while the latter follows from it.

10. Conclusion

Climate risk has emerged as a major driver of unaffordability and unavailability in catastrophe-exposed property insurance markets worldwide, reflecting frictions in the global reinsurance and capital markets that are supposed to absorb local tail risk. This paper studies a novel government response: public, risk-based reinsurance for cyclone risk in the Australian home insurance market. By assuming the tail risk, this government program reduced premiums by up to 23 percent in the highest-risk zipcodes (and by 14 percent on average across treated insurers) and increased the probability of a home insurance quote being offered by approximately 12 percentage points.

I show that these effects are primarily driven by a reduction in the reinsurance markup associated with the spatial correlation of cyclone risk, with additional contributions from the absorption of hazard-model uncertainty and from the induced entry of competing insurers into previously under-served zipcodes. Together, the evidence is consistent with the CRP reducing reinsurance prices by substituting lower-cost public capital for higher-cost private capital, which flows through to reduce prices and increase availability in home insurance markets.

Public reinsurance for natural-catastrophe risk is not unique to Australia. Florida's Hurricane Catastrophe Fund, the U.S. National Flood Insurance Program, Spain's Consorcio de Compensación de Seguros, Turkey's Catastrophe Insurance Pool, and the United Kingdom's Flood Re all share variants of the government-bears-tail-risk architecture studied here, though with substantial design differences in pricing, mandate, and budget-neutrality constraints (Solomon 2026). The Australian CRP is distinctive in its explicit actuarial-pricing mandate and its narrow (cyclone-only) scope, which together enable the causal identification this paper exploits. The findings here are therefore directly informative about proposals for comparable public reinsurance programs in other catastrophe-exposed retail markets.

This work suggests several avenues for future research. Does government reinsurance crowd out private reinsurance, or does it increase private risk appetite by socializing the risk from tail events? Moreover, it is important to quantify the extent to which public reinsurance alters insurer contract design incentives and possible mitigation choices by households. Public intervention may reduce incentives for new catastrophe models to be developed for or by the private market, an important long-term public good. Finally, the costs of tail risk demonstrate that insurers should not be modeled as risk neutral, and more work that fully explores the implications of this is needed.

Cyclone Risk		Pre-treatment Mean	Pre-treatment SD	Pre-treatment N	Post-treatment Mean	Post-treatment SD	Post-treatment N
Low Risk	Premium ($)	2452.94	2253.04	117876	2452.09	2237.35	69049
	Proportion of Insurers Quoting	0.58	0.49	202932	0.62	0.48	110814
Medium Risk	Premium ($)	2935.08	2601.92	454506	2882.05	2591.40	271694
	Proportion of Insurers Quoting	0.57	0.49	791298	0.63	0.48	431577
High Risk	Premium ($)	3305.20	2873.22	537355	3071.01	2646.79	329880
	Proportion of Insurers Quoting	0.54	0.50	992730	0.61	0.49	541458

TABLE 1. Summary statistics for building insurance premiums and proportion of insurers quoting, stratified by cyclone risk and divided into insurers pre- and post-entry into the reinsurance pool. Low zipcode cyclone risk is defined as the bottom decile, medium risk the second to fifth deciles, and high risk the upper half of the distribution. The table presents means, standard deviations, and sample sizes for each subgroup and treatment period

Empirical Strategy	Differential Exposure (1)	(2)	Staggered Treatment (3)	(4)
Effect Of CRP Participation On Log(Premium)	-0.178^{***}	-0.227^{***}	-0.140^{***}	-0.149^{**}
	(0.041)	(0.040)	(0.062)	(0.070)
			[0.009]	[0.026]
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	1 780 360	1 780 360	3 871 661	3 871 661
R^2	0.87	0.04	0.83	0.03

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2. Estimated effects of entering the reinsurance pool on quoted insurance premiums, using two empirical strategies: differential exposure (columns 1-2) and staggered treatment (columns 3-4). The coefficients tabulated are the average treatment effect in columns 3 and 4, and the treatment effect from the final period $\tau_{Jan2024}$ in columns 1 and 2. Standard errors, clustered at the zipcode or insurer level, are reported in parentheses. Wild cluster bootstrap p-values (Rademacher weights, exact enumeration) are reported in square brackets for insurer-clustered columns. Significance stars on insurer-clustered columns reflect bootstrap inference. Columns (1) and (3) include insurer x policy fixed effects, while (2) and (4) include only insurer fixed effects.

Empirical Strategy	Differential Exposure (1)	(2)	Staggered Treatment (3)	(4)
Effect Of CRP Participation On Whether Insurance Is Quoted	0.125***	0.123***	0.054	0.054
	(0.019)	(0.019)	(0.051)	(0.051)
			[0.396]	[0.371]
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	3 070 809	3 070 809	6 706 245	6 706 245
R^2	0.78	0.14	0.73	0.11

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 3. Estimated effects of entering the reinsurance pool on whether insurance was quoted, using two empirical strategies: differential exposure (columns 1-2) and staggered treatment (columns 3-4). The coefficients tabulated are the average treatment effect in columns 3 and 4, and the treatment effect from the final period $\tau_{Jan2024}$ in columns 1 and 2. Standard errors, clustered at the zipcode or insurer level, are reported in parentheses. Wild cluster bootstrap p-values (Rademacher weights, exact enumeration) are reported in square brackets for insurer-clustered columns. Significance stars on insurer-clustered columns reflect bootstrap inference. Columns (1) and (3) include insurer x policy fixed effects, while (2) and (4) include only insurer fixed effects.

Empirical Strategy	Differential Exposure		Staggered Treatment	
	(1)	(2)	(3)	(4)
Effect Of CRP Participation On Log(Premium) For Domestic Insurers	−0.250***	−0.313***	−0.266***	−0.290***
	(0.037)	(0.036)	(0.085)	(0.099)
			[0.000]	[0.000]
Additional Effect Of CRP Participation For Foreign Subsidiaries	0.406***	0.475***	0.398***	0.446***
	(0.019)	(0.021)	(0.086)	(0.101)
			[0.000]	[0.000]
Clustering	Suburb	Suburb	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	1 780 360	1 780 360	3 871 661	3 871 661
R^2	0.88	0.04	0.84	0.04

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE 4. Estimated effects of entering the reinsurance pool on insurance premiums for domestic and foreign subsidiary insurers, using two empirical strategies: differential exposure (columns 1-2) and staggered treatment (columns 3-4). The coefficients tabulated are the average treatment effect in columns 3 and 4, and the treatment effect from the final period $\tau_{Jan2024}$ in columns 1 and 2. The coefficient τ represents the treatment effect for domestic insurers, while τ_F captures the additional effect for foreign subsidiaries. Standard errors, clustered at the suburb or insurer level, are reported in parentheses. Wild cluster bootstrap p-values (Rademacher weights, exact enumeration) are reported in square brackets for insurer-clustered columns. Significance stars on insurer-clustered columns reflect bootstrap inference. Columns (1) and (3) include insurer x policy fixed effects, while columns (2) and (4) include only insurer fixed effects.

Empirical Strategy	Differential Exposure		Staggered Treatment	
	(1)	(2)	(3)	(4)
Estimate of τ	−0.375***	−0.427***	−0.283***	−0.286***
	(0.039)	(0.040)	(0.085)	(0.095)
			[0.000]	[0.000]
Estimate of $\tau\times$ Pre-CRP Ceding Ratio	0.805***	0.813***	0.541***	0.517*
	(0.035)	(0.032)	(0.250)	(0.271)
			[0.000]	[0.051]
Clustering	Suburb	Suburb	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	1 780 360	1 780 360	3 871 661	3 871 661
R^2	0.87	0.04	0.83	0.03

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE 5. Heterogeneity in the effect of CRP entry on log premiums by pre-treatment reinsurance ceding ratio (continuous). The ceding ratio is measured as the share of gross earned premium ceded to reinsurers in the fiscal year prior to CRP introduction, and ranges from 0.054 (Budget, Virgin) to 0.742 (NRMA). The coefficient τ captures the treatment effect for an insurer with a ceding ratio of zero, while $\tau\times$Ceding Ratio captures how this effect varies continuously with pre-treatment reinsurance access. Columns (1)–(2) report the differential exposure estimates $\tau_{Jan,2024}$; columns (3)–(4) report the average staggered treatment effect. Standard errors, clustered at the suburb or insurer level, are reported in parentheses. Wild cluster bootstrap p-values (Rademacher weights, exact enumeration) are reported in square brackets for insurer-clustered columns. Significance stars on insurer-clustered columns reflect bootstrap inference.

	FE: Insurer × Policy + Time			FE: Insurer + Time		
	Medium/High (1)	Low (2)	Full Sample (3)	Medium/High (4)	Low (5)	Full Sample (6)
Effect Of CRP Participation On Log(Premium)	−0.099** (0.047) [0.022]	−0.130*** (0.056) [0.008]	−0.140*** (0.062) [0.009]	−0.104*** (0.045) [0.000]	−0.137** (0.065) [0.028]	−0.149** (0.070) [0.026]
Clustering	Insurer	Insurer	Insurer	Insurer	Insurer	Insurer
N	1 256 378	2 529 332	3 871 661	1 256 378	2 529 332	3 871 661
R^2	0.90	0.83	0.83	0.03	0.04	0.03

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE 6. Staggered treatment effect by ARPC cyclone risk classification. Suburbs are classified as medium/high or low risk based on the ARPC's published risk map (Table 2.4 of the ARPC Premium Rate Assessment Report). If the CRP's built-in cross-subsidy drives the premium decline, medium/high-risk suburbs (which receive the largest subsidy) should show a larger treatment effect. Standard errors, clustered at the insurer level, in parentheses. Wild cluster bootstrap p-values (Rademacher weights, exact enumeration) in square brackets.

	Original		Cross-Subsidy Adjusted	
	(1)	(2)	(3)	(4)
Effect Of CRP Participation On Log(Premium)	−0.140***	−0.149**	−0.217***	−0.227***
	(0.062)	(0.070)	(0.077)	(0.087)
	[0.009]	[0.026]	[0.000]	[0.000]
Clustering	Insurer	Insurer	Insurer	Insurer
FE: Insurer × Policy	✓		✓	
FE: Insurer		✓		✓
FE: Time	✓	✓	✓	✓
N	3 871 661	3 871 661	3 871 661	3 871 661
R^2	0.83	0.03	0.81	0.03

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE 7. Staggered treatment effect with the cross-subsidy adjustment. Columns (1)–(2) report the baseline estimate. Columns (3)–(4) apply the cross-subsidy adjustment: post-treatment premiums are divided by the ARPC's premium adequacy ratio (1.36 for minimal, 1.18 for low, 0.84 for medium/high risk), removing the proportional cross-subsidy built into the ARPC's pricing schedule and isolating the pure markup-reduction channel. Standard errors, clustered at the insurer level, in parentheses. Wild cluster bootstrap p-values in square brackets.

Outcome: Log Premium	(1)	(2)	(3)	(4)	(5)	(6)
Pre-CRP Effect Of Risk	0.689***	0.680***	0.823***	0.813***	0.823***	0.813***
Correlation	(0.147)	(0.139)	(0.144)	(0.136)	(0.144)	(0.136)
Post-CRP Change In The	−0.134***	−0.150***	−0.242***	−0.255***	−0.435***	−0.439***
Effect Of Risk Correlation	(0.052)	(0.052)	(0.062)	(0.062)	(0.081)	(0.080)
Risk Controls:	Basic	Basic	Basic	Basic	Rich	Rich
Insurer x t Specific Risk Pricing			✓	✓	✓	✓
Clustering	Zip	Zip	Zip	Zip	Zip	Zip
FE:	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x t
N	471 278	471 278	471 278	471 278	471 278	471 278
R^2	0.90	0.06	0.90	0.06	0.90	0.06

Outcome: Insurance Offered	(1)	(2)	(3)	(4)	(5)	(6)
Pre-CRP Effect Of Risk	−0.112*	−0.112*	−0.123**	−0.123**	−0.123**	−0.123**
Correlation	(0.057)	(0.057)	(0.056)	(0.056)	(0.056)	(0.056)
Post-CRP Change In The	0.113***	0.112***	0.108***	0.108***	0.148***	0.148***
Effect Of Risk Correlation	(0.028)	(0.028)	(0.029)	(0.029)	(0.037)	(0.037)
Risk Controls:	Basic	Basic	Basic	Basic	Rich	Rich
Insurer x t Specific Risk Pricing			✓	✓	✓	✓
Clustering	Zip	Zip	Zip	Zip	Zip	Zip
FE:	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x t
N	782 118	782 118	782 118	782 118	782 118	782 118
R^2	0.86	0.16	0.86	0.16	0.86	0.16

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE 8. Estimated effects of the spatial correlation in risk on insurance premiums (top panel) and availability (bottom panel), before and after the introduction of the reinsurance pool. The estimating equations are (6 and 7). The coefficients in the first row represent the baseline difference in premiums or probability of being offered insurance between a zipcode with uncorrelated risk and one with perfectly correlated risk, holding local risk constant. The coefficients in the second row capture the change in this difference due to the reinsurance pool. Various specifications are presented, differing in the set of risk controls, the allowance for insurer-time specific risk pricing, and the fixed effects included. Standard errors, clustered at the zipcode level, are reported in parentheses.

Outcome: Log Premium	(1)	(2)	(3)	(4)	(5)	(6)
Pre-CRP Effect Of Risk	−0.104***	−0.078**	0.004	0.027	0.004	0.027
Ambiguity	(0.040)	(0.037)	(0.050)	(0.048)	(0.050)	(0.048)
Post-CRP Change In The	−0.054***	−0.060***	−0.154***	−0.156***	−0.160***	−0.162***
Effect Of Risk Ambiguity	(0.015)	(0.015)	(0.035)	(0.033)	(0.038)	(0.036)
Risk Controls:	Basic	Basic	Basic	Basic	Rich	Rich
Insurer x t Specific Risk Pricing			✓	✓	✓	✓
Clustering	Zip	Zip	Zip	Zip	Zip	Zip
FE:	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x *t*	Insurer x Policy x t	Insurer x t
N	471 299	471 299	471 299	471 299	471 299	471 299
R^2	0.89	0.05	0.89	0.05	0.90	0.06

Outcome: Insurance Offered	(1)	(2)	(3)	(4)	(5)	(6)
Pre-CRP Effect Of Risk	0.049***	0.049***	0.037***	0.037***	0.037***	0.037***
Ambiguity	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
Post-CRP Change In The	−0.005	−0.005	−0.004	−0.003	−0.007	−0.006
Effect Of Risk Ambiguity	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
Risk Controls:	Basic	Basic	Basic	Basic	Rich	Rich
Insurer x t Specific Risk Pricing			✓	✓	✓	✓
Clustering	Zip	Zip	Zip	Zip	Zip	Zip
FE:	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x *t*	Insurer x Policy x t	Insurer x t
N	782 139	782 139	782 139	782 139	782 139	782 139
R^2	0.86	0.16	0.86	0.16	0.86	0.16

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE 9. Estimated effects of hazard uncertainty on insurance premiums (top panel) and availability (bottom panel), before and after the introduction of the reinsurance pool. Hazard uncertainty is measured by the bootstrap standard deviation of the 25-year return-period wind speed at each postcode, derived from Geoscience Australia's cyclone simulation model. The coefficients in the first row represent the baseline association between hazard uncertainty and premiums or the probability of being offered insurance. The coefficients in the second row capture the change in this association due to the reinsurance pool. Various specifications are presented, differing in the set of risk controls, the allowance for insurer-time specific risk pricing, and the fixed effects included. Standard errors, clustered at the zipcode level, are reported in parentheses.

Empirical Strategy	Differential Exposure (1)	Staggered Treatment (2)
Association of CRP Participation with Log(Premium), No New Entry	−0.200***	−0.094**
	(0.019)	(0.032)
Additional Association of CRP Participation with Log(Premium), With New Entry	−0.024***	−0.057**
	(0.003)	(0.021)
Clustering	Suburb	Insurer
FE: Time	✓	✓
FE: Address × Insurer × Policy	✓	✓
N	1 566 708	3 403 253
R^2	0.87	0.87

* p < 0.1, ** p < 0.05, *** p < 0.01

TABLE 10. Descriptive associations between entering the cyclone reinsurance pool and insurance premiums, partitioned by whether new entry of insurers into the local (zipcode × product) cell occurs in the same period. Column (1) reports the differential-exposure specification with the tabulated coefficient being the treatment effect in the final period τ_{Jan2024}; column (2) reports the staggered-treatment specification with the average treatment effect. All specifications are OLS: no causal interpretation is claimed for the "with new entry" rows, which reflect associations between the CRP participation effect and contemporaneous changes in local insurer presence and are jointly determined with premiums. Standard errors, clustered at the suburb or insurer level, are reported in parentheses. For the insurer-clustered column wild cluster bootstrap p-values (Rademacher weights, exact enumeration) are reported in square brackets and significance stars reflect the bootstrap inference. All specifications include address × insurer × policy and time fixed effects. An earlier version of this table presented instrumental-variable estimates using the pre-treatment number of insurers quoting in a zipcode as the excluded instrument; that specification has been dropped after referee comments flagged the exclusion restriction as implausible.

References

Allianz Australia. 2023a. “Allianz joins the cyclone reinsurance pool.” Media release. Accessed: 2024-01-25.

Allianz Australia. 2023b. “Home insurance now available in new areas across Northern QLD and WA.” Media release. Accessed: 2024-01-25.

Allianz Re. 2024. “Allianz Re.” https://www.allianzre.com/en_GB.html.

Allianz SE. 2021. “Allianz completes transaction to purchase Westpac’s general insurance business.” Corporate press release. AUD 725m acquisition with 20-year distribution agreement; Westpac-branded general insurance is issued by Allianz Australia Insurance Ltd thereafter; accessed 2026-04-14.

Allianz SE. 2025. “Allianz Group Annual Report 2024.” Accessed 5 May 2025.

AM Best. 2024. “Significant Increase in Global Reinsurers’ ROE Due to Investment and Underwriting Results.” best’s special report, AM Best.

Artemis.bm. 2023a. “Suncorp reinsurance renewal on track but aggregates may be a challenge.” Trade press. Documents Suncorp’s 1 July catastrophe reinsurance anniversary; accessed 2026-04-14.

Artemis.bm. 2023b. “IAG secures FY24 whole-account quota share and aggregate cover.” Trade press. Documents IAG’s split reinsurance calendar: main $10bn cat tower renews 1 January, aggregate cover and Hannover Re 2.5% whole-account quota share renew 1 July; accessed 2026-04-14.

Artemis.bm. 2024. “Catastrophe bonds & ILS outstanding by trigger type.” https://www.artemis.bm/dashboard/cat-bonds-ils-by-trigger/.

Australian Bureau of Meteorology. 2023. “Southern Hemisphere Tropical Cyclone Climatology.” http://www.bom.gov.au/cyclone/climatology/. Accessed: 2023-05-24.

Australian Bureau of Meteorology and New Zealand MetService. 2023. “Southern Hemisphere Tropical Cyclone Climatology.” http://www.bom.gov.au/cyclone/climatology/. Accessed: 2023-05-24.

Australian Bureau of Statistics. 2023. “Average Weekly Earnings, Australia, May 2023.” https://www.abs.gov.au/statistics/labour/earnings-and-working-conditions/average-weekly-earnings-australia/latest-release. Accessed: 2023-06-11.

Australian Competition and Consumer Commission. 2020a. “Northern Australia Insurance Inquiry.”

Australian Competition and Consumer Commission. 2020b. “Northern Australia Insurance Inquiry: Final Report.”Technical report.

Australian Competition and Consumer Commission. 2022. “Northern Australia Insurance Inquiry.”Technical report, Australian Competition and Consumer Commission.

Australian Government. 2022. “Treasury Laws Amendment (Cyclone and Flood Damage Reinsurance Pool) Act 2022.” Available at: https://www.legislation.gov.au/Details/C2022A00035.

Australian Prudential Regulation Authority. 2023. “Quarterly General Insurance Statistics.” https://www.apra.gov.au/quarterly-general-insurance-statistics. Accessed: 2024-01-17.

Australian Prudential Regulation Authority (APRA). 2023a. “Prudential Standard GPS 110 Capital Adequacy.” The prescribed capital amount is calibrated so that an insurer holding a capital base equal to it can withstand losses at the 99.5 percent confidence level over a one-year period. Accessed: 12 May 2026.

Australian Prudential Regulation Authority (APRA). 2023b. “Prudential Standard GPS 116 Capital Adequacy: Insurance Concentration Risk Charge.” Accessed: 17 January 2024.

Australian Prudential Regulation Authority (APRA). 2023c. “Insurance (prudential standard) determination No. 4 of 2008 - Prudential Standard GPS 114 Capital Adequacy: Investment Risk Capital Charge.” Accessed: 17 January 2024.

Australian Reinsurance Pool Corporation. 2022a. “ARPC CRP Premium Rate Assessment Report.” Accessed: 2024-01-25.

Australian Reinsurance Pool Corporation. 2022b. “Cyclone Reinsurance Pool insurer onboarding specification, v2.01.” ARPC technical specification. Published downstream of IAG’s 2023 reinsurance programme placement window; accessed 2026-04-14.

Australian Reinsurance Pool Corporation. 2023a. “Cyclone Reinsurance Pool: Monitoring and Evaluation

Report."Technical report, Australian Reinsurance Pool Corporation.
Australian Reinsurance Pool Corporation. 2023b. "Opening Statement to Supplementary Budget Estimates, February 2023." Submission to the Senate Economics Legislation Committee. Names Allianz Australia and Sure Insurance as CRP participants effective 1 January 2023; accessed 2026-04-14.
Australian Reinsurance Pool Corporation. 2023c. "Update on the new financial year for the cyclone pool." Accessed: 2023-07-06.
Australian Reinsurance Pool Corporation. 2023d. "ARPC Annual Report 2022-23." Available online.
Australian Reinsurance Pool Corporation. 2024. "Cyclone Reinsurance Pool: 2023 Financial Outlook Report."Technical report, Australian Reinsurance Pool Corporation. Tables 1.4 and 6.1 give a premium-adequacy ratio of 104.5 % and a long-run target of 100 %.
Australian Reinsurance Pool Corporation. 2025. "ARPC Annual Report 2024-25." Audited financial statements at pp. 99–101 separate cyclone-pool from terrorism-pool fee disclosures; Annual Performance Statement (Measure 3) at p. 52 confirms no draws on the Commonwealth guarantee through 30 June 2025.
Australian Securities and Investments Commission (ASIC). 2024. "North Queensland Home Insurance." Australian Government website (run by ASIC). Accessed: 2024-01-18.
Babcock, Bruce A. 2015. "Using cumulative prospect theory to explain anomalous crop insurance coverage choice." *American Journal of Agricultural Economics* 97 (5): 1371–1384.
Ben-Shahar, Omri, and Kyle D Logue. 2011. "The redistributional effects of risk-based pricing in property catastrophe insurance." *Journal of Legal Studies* 40 (2): 507–538.
Bloomberg. 2021. "South African Insurers Face Steep Costs From Unrest, Forcing Premium Hikes."
Boomhower, Judson, Meredith Fowlie, Jacob Gellman, and Andrew J Plantinga. 2024. "How Are Insurance Markets Adapting to Climate Change? Risk Selection and Regulation in the Market for Homeowners Insurance." *Working Paper*. PRELIMINARY AND INCOMPLETE.
Bouriaux, Sylvain, and William L. Scott. 2008. "Financial Innovations for Catastrophic Risk: Cat Bonds and Beyond."Technical report, Milken Institute.
Boyer, M. Martin, and Charles M. Nyce. 2013a. "An Industrial Organization Theory of Risk Sharing." *North American Actuarial Journal* 17 (4): 283–296.
Boyer, M. Martin, and Charles M. Nyce. 2013b. "Insuring catastrophes and the role of governments." *Natural Hazards and Earth System Sciences* 13 (8): 2053–2063.
Browne, Mark J, and Robert E Hoyt. 2000. "The demand for flood insurance: empirical evidence." *Journal of Risk and Uncertainty* 20 (3): 291–306.
Browne, Mark J, Christian Knoller, and Andreas Richter. 2015. "Behavioral bias and the demand for bicycle and flood insurance." *Journal of Risk and Uncertainty* 50 (2): 141–160.
Caballero, Ricardo, and Arvind Krishnamurthy. 2008. "Collective Risk Management in a Flight to Quality Episode." *Journal of Finance* 63 (5): 2195–2230.
Callaway, Brantly, and Pedro H. C. Sant'Anna. 2021. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics* 225 (2): 200–230.
Chien, YiLi, and Hanno Lustig. 2009. "The Market Price of Aggregate Risk and the Wealth Distribution." *The Review of Financial Studies* 23 (4): 1596–1650.
Collier, Benjamin L., Cameron M. Ellis, Anran Li, and Adam Solomon. 2026. "Capital Costs, Reinsurance, and the Price of Climate Risk." Working paper.
Commonwealth of Australia. 2022. "Proof Committee Hansard: Economics Legislation Committee - Estimates." Senate Economics Legislation Committee. Uncorrected proof of evidence taken before the committee.
Commonwealth of Australia. 2023. "Official Committee Hansard: Economics Legislation Committee - Estimates." Senate Economics Legislation Committee. Public hearing.
Compare the Market Pty Ltd. 2025. "Who We Compare." https://www.comparethemarket.com.au/who-we-compare/. Accessed: 2025-11-13.
Cummins, J. David. 2008a. "CAT Bonds and Other Risk-Linked Securities: State of the Art and Recent

Developments." *Risk Management and Insurance Review* 11 (1): 23–47.

Cummins, J David. 2008b. "CAT bonds and other risk-linked securities: State of the market and recent developments." *Risk Management and Insurance Review* 11 (1): 23–47.

Cummins, J. David, David Lalonde, and Richard D Phillips. 2004. "Assessing the capacity of the insurance industry to deliver catastrophe risk financing: Limitations of standard models." *Journal of Insurance Regulation* 23 (2): 109–140.

Cummins, J. David, and Gregory Nini. 2002. "Geographic concentration in the US insurance market: Evidence from the property-liability industry." *Journal of Financial Services Research* 21 (3): 251–277.

Dieckmann, Stephan. 2011. "Rare event risk and heterogeneous beliefs: The case of incomplete markets." *Journal of Financial and Quantitative Analysis* 46 (2): 459–488.

Dyson, Ben. 2025. "Good reinsurance market conditions to prevail despite Jan. 1 price drop." S&P Global Market Intelligence, News & Insights. Accessed: 2025-07-28.

Eeckhoudt, Louis, and Christian Gollier. 1995. "Ambiguity and insurance decisions." *The Geneva Papers on Risk and Insurance Theory* 20 (2): 175–186.

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

Einav, Liran, Amy Finkelstein, and Mark R. Cullen. 2010. "Estimating Welfare in Insurance Markets Using Variation in Prices*." *The Quarterly Journal of Economics* 125 (3): 877–921.

Elsner, James B., and Bethany Kocher. 2000. "Global tropical cyclone activity: A link to the North Atlantic Oscillation." *Geophysical Research Letters* 27 (1): 129–132.

European Parliament and Council of the European Union. 2009. "Directive 2009/138/EC of the European Parliament and of the Council of 25 November 2009 on the Taking-up and Pursuit of the Business of Insurance and Reinsurance (Solvency II)." Official Journal of the European Union. Article 101 defines the Solvency Capital Requirement and its calibration to a one-year 99.5 percent Value-at-Risk of basic own funds.

Finity Consulting Pty Ltd. 2024. "Cyclone Pool – Premium determination applying from 1 April 2025."Technical report, Australian Reinsurance Pool Corporation. Table 7.2 reports estimated premium-adequacy ratios by risk tier.

Flood Re. 2022. "Quinquennial Review."Technical report, Flood Re.

Friedman, Karna, Susmita Mukherjee, and Vaishnavi Sridhar. 2021. "Decoupling insurance from risk: Evidence from India's crop insurance program." *Journal of Development Economics* 151: 102622.

Froot, Kenneth A. 1999. "The Limited Financing of Catastrophe Risk: An Overview." In *The Financing of Catastrophe Risk*, edited by Kenneth A. Froot, 1–13: University of Chicago Press.

Froot, Kenneth A. 2001. "The market for catastrophe risk: a clinical examination." *Journal of Financial Economics* 60 (2-3): 529–571.

Froot, Kenneth A. 2004. "Risk Management, Capital Budgeting and Capital Structure Policy for Insurers and Reinsurers."Technical report, NBER.

Froot, Kenneth A., and Paul G. J. O'Connell. 1999. "The Pricing of U.S. Catastrophe Reinsurance." In *The Financing of Catastrophe Risk*, 195–232: University of Chicago Press / NBER.

Geoscience Australia. 2018. "2018 National Tropical Cyclone Hazard Assessment Data." Accessed: May 1, 2024.

Giffard-Roisin, Sophie, Mo Yang, Guillaume Charpiat, Christina Kumler Bonfanti, Balázs Kégl, and Claire Monteleoni. 2020. "Tropical Cyclone Track Forecasting Using Fused Deep Learning From Aligned Reanalysis Data." *Frontiers in Big Data* 3.

Goodman-Bacon, Andrew. 2021. "Difference-in-Differences with Variation in Treatment Timing." *Journal of Econometrics* 225 (2): 254–277.

Grace, Martin F, and Robert W Klein. 2013. "Catastrophe risk and regulation." *Handbook of Insurance*: 683–714.

Grace, Martin F, Robert W Klein, and Paul R Kleindorfer. 2004. "Homeowners insurance with bundled catastrophe coverage." *Journal of Risk and Insurance* 71 (3): 351–379.

Grace, Martin F, Robert W Klein, and Richard D Phillips. 2007. "The future of insurance regulation in the United States." *Journal of Insurance Regulation* 25 (3): 177–193.

Gruber, Jonathan, and Adam Solomon. 2026. "Optimal Flood Insurance in a Second-Best World: Fiscal Spillovers, Reclassification Risk and Moral Hazard." Working paper, MIT and NYU Stern.

Harrison, Glenn W, and J Todd Swarthout. 2014. "The impact of ambiguity on insurance markets with compound risk." *Journal of Risk and Uncertainty* 49 (2): 185–221.

Hendren, Nathaniel. 2013. "Private information and insurance rejections." *Econometrica* 81 (5): 1713–1762.

Ibragimov, Rustam, Dwight Jaffee, and Johan Walden. 2009. "Nondiversification traps in catastrophe insurance markets." *Review of Financial Studies* 22 (3): 959–993.

Independent, The. 2021. "UK at risk of becoming 'uninsurable' due to climate change, insurance giant warns."

India Meteorological Department. 2023. "Cyclone Climatology for North Indian Ocean." http://www.rsmcnewdelhi.imd.gov.in/index.php?lang=en. Accessed: 2023-05-24.

Insurance Australia Group Limited. 2023a. "Annual Report 2023." 394 pages. Contains zero mentions of "Cyclone Reinsurance Pool", "ARPC" or "Reinsurance Pool Corporation", consistent with IAG still being in operational onboarding limbo at the date of release rather than executing a strategic wait-and-see; accessed 2026-04-14.

Insurance Australia Group Limited. 2023b. "IAG confirms 2023 reinsurance program and 10% quota share renewals." ASX release. Confirms main $10bn catastrophe tower placement finalised only after ARPC's December 2022 onboarding specification release; accessed 2026-04-14.

Insurance Australia Group Limited. 2023c. "IAG joins Cyclone Reinsurance Pool." Company announcement. Accessed 2026-04-14.

Insurance Council of Australia. 2023. "ICA Historical Normalised Catastrophe Data, November 2023." https://insurancecouncil.com.au/wp-content/uploads/2023/12/ICA-Historical-Normalised-Catastrophe-November-2023.xlsx. Accessed: 2024-01-17.

Insurance News Australia. 2023. "Another insurer joins cyclone reinsurance pool." Trade press. Quotes Sure Insurance Managing Director Bradley Heath on entering "earlier than required by our product issuers" in a "difficult reinsurance market"; accessed 2026-04-14.

Irina Demirag, et al. 2017. "An Integrated Approach to Pricing Catastrophe Reinsurance." *Risks* 5 (3): 51.

Jaffee, Dwight M, and Thomas Russell. 1997. "Catastrophe insurance, capital markets, and uninsurable risks." *Journal of Risk and Insurance* 64 (2): 205–230.

Japan Meteorological Agency. 2023. "RSMC Tokyo - Typhoon Center Climatology." https://www.jma.go.jp/jma/jma-eng/jma-center/rsmc-hp-pub-eg/climatology.html. Accessed: 2023-05-24.

Journal, Insurance. 2021. "Florida's Property Insurance Market Is 'Spiraling Towards Collapse' Because of Litigation: Report."

Kelly, M., A. Kleffner, and S. Li. 2013. "The impact of regulation on the availability and profitability of auto insurance in Canada." *Assurances et gestion des risques* 81 (3-4): 197–224.

Keys, Benjamin J., and Philip Mulder. 2024a. "Property Insurance and Disaster Risk: New Evidence from Mortgage Escrow Data." Working Paper 32579, National Bureau of Economic Research.

Keys, Benjamin J, and Philip Mulder. 2024b. "Property Insurance and Disaster Risk: New Evidence from Mortgage Escrow Data." Working Paper 32579, National Bureau of Economic Research.

Kim, Paul H. S., and Anran Li. 2025. "Reinsurance, Financial Frictions, and Subsidy Efficiency: Evidence from Health Insurance." Working paper.

Klosin, Sylvia, and Adam Solomon. 2024. "Optimal Insurance Scope: Theory and Evidence from US Crop Insurance." *Manuscript in preparation*.

Kousky, Carolyn. 2018. "Financing flood losses: A discussion of the National Flood Insurance Program." *Risk Management and Insurance Review* 21 (1): 11–32.

Kousky, Carolyn, and Roger Cooke. 2012. "Explaining the failure to insure catastrophic risks." *The Geneva Papers on Risk and Insurance-Issues and Practice* 37 (2): 206–227.

Kunreuther, Howard C, Mark V Pauly, and Stacey McMorrow. 2013. "Insurance and behavioral economics:

Improving decisions in the most misunderstood industry."
Kunreuther, Howard, Jacqueline Meszaros, Robin M Hogarth, and Mark Spranca. 1995. "Ambiguity and underwriter decision processes." *Journal of Economic Behavior & Organization* 26 (3): 337–352.
Kunreuther, Howard, and Erwann Michel-Kerjan. 2009. *At war with the weather: Managing large-scale risks in a new era of catastrophes.*: MIT Press.
Lee, Stephen, and Rade Musulin. 2022. "Cyclone Reinsurance Pool – Summary of the Actuarial Premium Rate Assessment." Summary Report Version 1.0, Finity Consulting Pty Limited. Australia. Reissued on 8 July 2022 with a revised Appendix B.4.
Leverty, J Tyler, and Martin F Grace. 2011. "The impact of rate regulation on claims: Evidence from Massachusetts automobile insurance." *Risk Management and Insurance Review* 14 (2): 173–199.
Meyer, Robert, and Howard Kunreuther. 2016. "Overcoming decision biases to reduce losses from natural catastrophes." *Behavioral Economics and Public Policy* 16: 398.
Michel-Kerjan, Erwann O. 2010. "Catastrophe Economics: The National Flood Insurance Program." *Journal of Economic Perspectives* 24 (4): 165–186.
Michel-Kerjan, Erwann, Paul A Raschky, and Howard Kunreuther. 2006. "Optimal risk sharing for law invariant monetary utility functions." *Journal of Risk and Uncertainty* 33 (3): 219–233.
Michel-Kerjan, Erwann, Paul Raschky, and Howard Kunreuther. 2017. "Flood risk and behavioral adaptation: micro-evidence from New York City." *Journal of Risk and Uncertainty* 55 (2): 95–126.
Morrison, Don. 2012. "Catastrophe Reinsurance: Understanding its Past, Present and Potential." Presentation at the Institute for Catastrophic Loss Reduction Workshop. ICLR Workshop, May 25, 2012.
MP, Stephen Jones. 2023. "More insurers join the cyclone reinsurance pool ahead of the 2023–24 cyclone season." Assistant Treasurer ministerial media release. Names QBE Insurance (Australia) Ltd as effective 21 June 2023; accessed 2026-04-14.
Météo-France La Réunion. 2023. "South-West Indian Ocean Cyclone Season Climatology." http://www.meteo.fr/temps/domtom/La_Reunion/webcmrs9.0/anglais/index.html. Accessed: 2023-05-24.
National Hurricane Center, NOAA. 2023a. "Atlantic Hurricane Season Climatology." https://www.nhc.noaa.gov/climo/. Accessed: 2023-05-24.
National Hurricane Center, NOAA. 2023b. "Eastern North Pacific Hurricane Season Climatology." https://www.nhc.noaa.gov/climo/. Accessed: 2023-05-24.
Newman, James, and Eric Christopherson. 2009. "Residual market mechanisms: Balancing catastrophic and attritional risks with affordability and availability." *Journal of Insurance Regulation* 28 (1): 25–50.
News, CBC. 2020. "Alberta's insurance market is 'unhealthy' and at risk of collapse, report says."
Oh, Sangmin S, and Ishita Sen. 2023. "Pricing of Climate Risk Insurance: Regulatory Frictions and Cross-Subsidies." *Journal of Finance, Revise & Resubmit*.
Ostriker, Abigail, and Anna Russo. 2024. "The Effects of Floodplain Regulation on Housing Markets." Working Paper.
Polacek, Andy. 2018. "Catastrophe Bonds: A Primer and Retrospective." *Chicago Fed Letter* (405).
QBE Insurance Group Limited. 2023. "Annual Report 2022." Australia Pacific section states QBE "commenced preparations for the introduction of the Northern Australia Reinsurance Pool" during 2022, pre-dating the 1 January 2023 Group reinsurance renewal; accessed 2026-04-14.
Queensland Government. 2024a. "Strengthening Far North Queensland." https://www.statedevelopment.qld.gov.au/regions/queenslands-regions/far-north-qld. Accessed: 14 May 2026.
Queensland Government. 2024b. "Strengthening Greater Whitsunday." https://www.statedevelopment.qld.gov.au/regions/queenslands-regions/greater-whitsunday. Accessed: 14 May 2026.
Queensland Government. 2024c. "Strengthening North Queensland." https://www.statedevelopment.qld.gov.au/regions/queenslands-regions/north-qld. Accessed: 14 May 2026.

RACQ Insurance Limited. 2023a. "Annual Report 2022–23." See Note 3.1(ii) on the reinsurance programme: "The Group entered the Australian Reinsurance Pool Corporation (ARPC) Cyclone Pool on 30 June 2023 . . . Excess of Loss and Per Risk reinsurance contracts renewal date was brought forward to 30 June 2023 from 1 July 2023 covering the 12 months ending 30 June 2024." Accessed 2026-04-14.

RACQ Insurance Limited. 2023b. "RACQ Insurance joins Cyclone Reinsurance Pool." Media release. Describes entry as "ahead of the 2023–24 cyclone season"; accessed 2026-04-14.

Reinsurance News. 2022. "Australia's CommBank sells general insurance arm to Hollard Group." Trade press. CBA completed the divestiture of its general insurance business to Hollard on 30 September 2022; accessed 2026-04-14.

Reinsurance News. 2023. "Youi opts out of aggregate reinsurance as market conditions harden." Trade press. Youi joined the CRP effective 1 July 2023 and simultaneously non-renewed its aggregate natural-perils reinsurance treaty, citing that aggregate covers were "no longer available at affordable rates"; accessed 2026-04-14.

Sastry, Parinitha, Ishita Sen, and Ana-Maria Tenekedjieva. 2024. "When Insurers Exit: Climate Losses, Fragile Insurers, and Mortgage Markets."Technical report. SSRN Working Paper No. 4674279.

Senate Economics References Committee. 2017. "The General Insurance Industry in Australia." government report, Parliament of Australia. Canberra, Australia.

Shavell, Steven. 1979. "On moral hazard and insurance." *The Quarterly Journal of Economics* 93 (4): 541–562.

Solomon, Adam. 2023. "Imperfect Private Information in Insurance Markets." *The Review of Economics and Statistics*: 1–46.

Solomon, Adam. 2024. "Bundling in Insurance Markets: Theory and an Application to Long-term Care."

Solomon, Adam. 2026. "Designing Public Reinsurance: Global Lessons for the U.S.." Working paper, NYU Stern School of Business.

Subramanian, Ajay, and Jinjing Wang. 2021. "Capital, aggregate risk, insurance prices and regulation." *Insurance: Mathematics and Economics* 100: 156–192.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics* 225 (2): 175–199. Themed Issue: Treatment Effect 1.

Suncorp Group Limited. 2023. "Suncorp joins Cyclone Reinsurance Pool." Company announcement. Accessed 2026-04-14.

Sure Insurance. 2023. "Sure Insurance — Participation in Federal Government Cyclone Reinsurance Pool." Company announcement. Accessed 2026-04-14.

Swiss Re Institute. 2022. "Natural catastrophes in 2021: the floodgates are open." Sigma 2/2022, Swiss Re Institute.

Texas Windstorm Insurance Association. 2024. "Residential Rate Adequacy Analysis Memorandum."Technical report, Texas Windstorm Insurance Association. Austin, TX. States that the provision for reinsurance expense is 44.0% of premium (net of expected recoveries).

The Hollard Insurance Company Pty Ltd. 2022. "Directors' Report for the year ended 30 June 2022." States: "In a recent meeting with ARPC, the Company indicated its intent to join the pool on 1 July 2023." Confirms reinsurance programme renewal 30 June / 1 July. Accessed via actuarial repository, 2026-04-14.

Times, The Economic. 2021. "Extreme weather events put focus back on climate change adaptation."

Tomunen, Tuomas. 2025. "Failure to Share Natural Disaster Risk." SSRN Working Paper, rev. Feb 2025.

U.S. Senate. 2025. "INSURE Act: Incorporating National Support for Unprecedented Risks and Emergencies Act." S. [bill number]. 119th Congress, 1st Session. Introduced by Sen. Schiff.

Wagner, Zachary. 2021a. "Rising sea levels and property insurance markets."

Wagner, Zachary. 2021b. "Risk management in insurance markets."

Wen, Jian, K. C. Chen, and Lifan Wu. 2015. "Empirical Study of Adverse Selection and Moral Hazard in the Property and Liability Reinsurance Market." *Journal of Finance and Accountancy* 19.

Yu, Jisang, and Aaron Smith. 2019. "Premium subsidies and moral hazard in crop insurance." *American*

Journal of Agricultural Economics 101 (4): 1216–1235.

Appendix A. Empirical Appendix

A.1. Reinsurance and Catastrophe Bond Markups

I have documented that the CRP led to premiums falling by 10-20 percent. Before attributing this to efficiency gains, I rule out an inadvertent subsidy. The reinsurance pool is, by statute, designed to be budget neutral "over the longer term". In the CRP's own modeling, they projected a premium adequacy ratio (premiums divided by expected loss) of 104.5 percent.[19] Despite these assurances, there is a concern that the premium savings and insurance expansions documented above are driven solely by mispricing. If the CRP was achieving favorable effects via a blanket subsidy, this would still be interesting, but less novel than achieving similar effects by reducing markups without running a fiscal deficit. In this section, I show that the markups on reinsurance and catastrophe bonds prior to the CRP were large, such that the CRP could be fiscally balanced and still plausibly achieve the premium reductions observed above. In the next section I give direct evidence consistent with actuarially fair pricing, i.e., no subsidy.

To study markups in reinsurance and catastrophe bonds prior to the CRP, I use two new data sources. Reinsurance information comes from quarterly insurer balance sheet filings with APRA, the Australian insurance regulator. The key variables observed are, for general insurers, premiums written (e.g., to homeowners), claims paid out, reinsurance premiums paid (to reinsurers), and reinsurance claims received. Data on catastrophe bond issuance come from artemis.fm. I focus on post-2017 data in which I can consistently identify the issuer. The critical variables are: the expected loss on the bond as modeled by a third-party modeling agency, the spread the bond pays (i.e., the coupon paid to investors minus risk-free rate on collateral), and the hazards and geographies the bond is exposed to. For further information on the general functioning of the reinsurance and catastrophe bond market, see Section 2.

Summary statistics for the reinsurance and catastrophe bond data sets are in Tables A1 and A2.

[19] See: Australian Reinsurance Pool Corporation (2024).

Variable	Overall	Domestic Reinsurer	Foreign Reinsurer
Premiums ($M)	829.86	948.84	543.12
	(801.40)	(854.65)	(564.44)
Claims ($M)	637.99	731.53	412.54
	(658.34)	(707.01)	(452.55)
Reinsurance Recovery Ratio	0.936	0.844	1.158
	(1.595)	(1.318)	(2.112)
Commissions ($M)	68.47	66.53	73.15
	(78.06)	(81.39)	(69.67)
Other Operating Expenses ($M)	28.26	27.76	29.49
	(36.61)	(38.15)	(32.81)
Net Profit/Loss ($M)	32.56	35.13	26.37
	(101.45)	(112.72)	(67.17)
Number of Observations	266	188	78

TABLE A1. Summary statistics for quarterly insurer–reinsurer flows from APRA filings, 2017–present. The sample is restricted to the APRA entities corresponding to the 12 insurers in the granular pricing data; firms are classified as domestic or foreign using the same rule as in the granular data (foreign = Allianz, Westpac and Sure; domestic = AAMI / Apia / Suncorp, CommInsure, NRMA, QBE, RACQ and Youi). Means are reported with standard deviations in parentheses; dollar amounts are AUD millions. The reinsurance recovery ratio equals reinsurance inflows (claims recovered) divided by reinsurance outflows (premiums ceded). N denotes firm–quarter observations.

Metric	All Bonds	Australia Only	Cyclones Only
Spread (%)	7.85 (5.31)	8.29 (4.48)	8.71 (5.57)
Expected Loss (%)	2.54 (3.82)	3.85 (2.55)	2.81 (4.20)
Excess Return (%)	5.46 (5.30)	4.45 (2.32)	6.05 (5.81)
Markup	6.05 (22.87)	1.38 (0.61)	5.11 (20.30)
Attachment Prob (%)	3.3 (4.6)	5.5 (4.3)	3.6 (5.0)
Deal Size ($ USD Millions)	63.11 (105.41)	16.20 (46.98)	60.14 (101.40)
Term Length (Years)	3.1 (1.1)	3.3 (0.5)	3.1 (1.0)
Number of Bonds	1164	25	889
Proportion Multi-Region (%)	10.6%	92.0%	13.3%
Proportion Multi-Peril (%)	49.2%	76.0%	63.7%

TABLE A2. Summary statistics for catastrophe bonds, 2017–present (Artemis). Means with standard deviations in parentheses. Columns split the sample into all bonds, Australian-exposed bonds, and cyclone-exposed bonds. All dollar amounts are in USD millions. Markup is defined as the spread divided by the expected loss.

These provide suggestive evidence that spreads and markups are high. The reinsurance recovery ratio - the share of ceded premiums subsequently received back as reinsurance claim payments - is approximately 0.94 overall. This is notably higher for insurers who are subsidiaries of foreign parents (1.158) than for domestic Australian insurers (0.844), consistent with the evidence in Section 6. Similarly, catastrophe bonds require a spread of 7.85 percent over and above the modelled expected loss of 2.54 percent, a markup of over 200 percent.

To further understand markups above expected loss in reinsurance and catastrophe bonds I run the following two regressions. Reinsurance outcomes are at the insurer i, quarter q level, with insurer and company fixed effects, and controlling for the volume of insurance written (premiums in and claims out). Cat bond outcomes are at the cat bond c, with fixed effects included for insurer ('issuer') i and calendar year of issue t, with further terms for a cyclone- and Australian-specific slope of spread with respect to expected loss.

$$\begin{aligned}\text{Reinsurance Claims}_{i,q} &= \beta_1 \text{Reinsurance Premiums}_{i,q} \\ &\quad + \beta_2 \text{Claims}_{i,q} + \beta_3 \text{Premiums}_{i,q} + \alpha_i + \gamma_q + \epsilon_{i,q}\end{aligned} \tag{A1}$$

$$
\begin{aligned}
\text{Spread}_c &= \beta_1 \text{ExpectedLoss}_{c,t} + \beta_5(\text{Cyclone}_c \times \text{ExpectedLoss}_{c,t}) \\
&\quad + \beta_3(\text{Australia}_c \times \text{ExpectedLoss}_{c,t}) + \gamma_t + \alpha_i + \epsilon_c
\end{aligned} \tag{A2}
$$

For reinsurance, the key coefficient is β_1. If $\beta_1 = 1$, this would imply actuarially fair reinsurance: every dollar paid in as premium is, on average, paid out as reinsurance claims. To the extent $\beta_1 \ll 1$, this suggests that reinsurance is priced well above expected risk. Similarly, for catastrophe bonds, which are fully collateralized, $\beta_1 = 1$ is consistent with actuarially fair pricing: the spread increases one-to-one with the expected loss. In contrast, $\beta_1 \gg 1$ implies a cost paid by issuers above expected loss. The results for various specifications are in Tables A3 and A4 below.

	(1)	(2)	(3)
Reinsurance Premiums	0.575***	0.624***	0.618***
	(0.123)	(0.066)	(0.067)
Claims		0.597***	0.611***
		(0.017)	(0.019)
Premiums		−0.399***	−0.252***
		(0.047)	(0.083)
FE: Company	✓	✓	✓
FE: Quarter	✓	✓	✓
Weighted by	-	-	Premiums
N	488	488	488
R^2	0.825	0.955	0.959

TABLE A3. Reinsurance claims vs. reinsurance premiums at the insurer–quarter level, estimated per Eq. (A1). The outcome is reinsurance claims (AUD millions). All columns include company and quarter fixed effects; columns (2)–(3) add controls for own claims and premiums; column (3) is weighted by premiums. Standard errors in parentheses.

	(1)	(2)	(3)
Expected Loss	1.456***	1.965***	1.651***
	(0.147)	(0.420)	(0.252)
Cyclone × Expected Loss		−0.596	−0.300
		(0.447)	(0.279)
Australia × Expected Loss			0.183
			(0.586)
FE: Issue Year	✓	✓	✓
FE: Issuer	✓	✓	✓
N	411	409	466
R^2	0.422	0.423	0.346

TABLE A4. Catastrophe bond spreads vs. expected loss, estimated per Eq. (A2). The outcome is the spread (percentage points over the collateral risk-free rate). All columns include issuer and issue-year fixed effects. Standard errors in parentheses.

Both reinsurance and catastrophe bonds exhibit prices far above expected risk. For every dollar of reinsurance premium paid, only about 60c is received back in claims; a markup of about 2/3. Similarly, the markup in catastrophe bonds is approximately 50 percent above expected loss (i.e., a typical bond with an expected loss of 5 percent will pay a spread of 1.456×5 percent = 7.28 percent).

Equation (A2) includes interaction terms between expected loss and whether the bond covers cyclone or Australian risk, reflecting the geographic coverage of the bond. It does not include an interaction between expected loss and the primary insurer's foreign-vs-domestic status, because catastrophe bond data are at the bond-coverage level: I observe what a bond protects against, not which Australian primary insurer would have sponsored it.

Markups in the pre-CRP tail-risk market of, conservatively, 50 percent, plausibly rationalize the price reductions of 10-20 percent in the prior section. As a back-of-the-envelope approximation, prior to the CRP, reinsurance accounted for between 32 percent (moderate cyclone risk) and 50 percent (high cyclone risk) of the premium.[20] If the CRP accurately priced at its stated markup of 4 percent, this would mechanically generate a premium saving of 14 percent for moderate-risk properties and 23 percent for high-risk properties.

A.2. Scraped Quotes versus Actionable Premiums

The NQHI-portal panel records insurer-supplied quotes for a representative house rather than transacted policy prices. These are required to be transactable prices. However, to check this, I hand-collected buyable premium quotations on randomly chosen real addresses in each zipcode for the three of the eleven analysis insurers (Allianz, RACQ, and Sure). Policy contract terms and modelled house characteristics are held fixed across snapshots to mimic the quotation parameters used on the NQHI portal.

Table A5 compares the prices quoted by the three insurers and one product common to both datasets. The second column shows the hand-collected buyable price from each insurers website. The remaining columns show the average percentage difference, across zipcodes, between that price for a random address and for the 10th, 50th and 90th percentile address quote scraped from NQHI. The buyable average premium sits about 12 percent above the low quote, about 3 percent below the median quote, and about 30 percent below the high quote. Across the three insurers separately the picture is qualitatively the same: realised premiums are not systematically clustered at either tail of the quoted distribution. The pattern is also broadly stable across cyclone-risk terciles, with some quantitative variation by insurer. This is consistent with NQHI-portal quotes spanning the realised-price level and supports interpreting the quote-based treatment effects as informative about prices households would actually pay.

[20] Per Australian Competition and Consumer Commission (2020b).

	N	Realized ($)	vs. Low Quote	vs. Median Quote	vs. High Quote
Overall	5822	4910	12.1%	−3.0%	−30.5%
By insurer					
Allianz	2052	4679	−0.6%	−13.9%	−40.0%
RACQ	1834	6945	5.7%	−9.7%	−22.6%
Sure	1936	3226	23.0%	7.4%	−32.3%
By cyclone-risk tercile					
Low	1678	4531	18.4%	2.9%	−27.2%
Medium	1822	5033	7.9%	−7.1%	−33.5%
High	2052	5388	13.7%	−2.6%	−28.1%

TABLE A5. Within-cell comparison of hand-collected realized premiums to NQHI quoted premiums. For each (insurer, zipcode, suburb, cover level, sum insured, insurance type, monthly snapshot) cell where both a hand-collected realized premium and NQHI quoted premiums are observed, we compute the percentage difference between the realized premium and each quoted percentile (low, median, high) and report cell-level means. The sample is restricted to the three insurers — Allianz, RACQ and Sure — that appear in both the hand-collected and NQHI-portal data. On average the realized premium sits approximately at the median of the quoted distribution: about 12% above the low quote, about 3% below the median quote, and about 30% below the high quote. The pattern is broadly stable across cyclone-risk terciles, with some variation across insurers.

A.3. Per-Insurer CRP Entry Timing: Documentary Evidence

This appendix catalogues the evidence underpinning the claim in Section 3.5.2 that CRP entry timing for the eleven insurers in the analysis sample was primarily determined by the expiration dates of pre-existing private reinsurance treaties, together with operational constraints of the ARPC onboarding process.

For nine of the eleven insurers, the evidence directly supports this story. The two exceptions are Sure Insurance, whose managing director publicly described entry as a voluntary decision taken "earlier than required by our product issuers" in light of the hard reinsurance market, and Youi Pty Ltd, which simultaneously joined the CRP and non-renewed its aggregate natural-perils reinsurance treaty citing that aggregate covers were "no longer available at affordable rates".

Insurance Australia Group (NRMA) is a mixed case: IAG's reinsurance programme runs on a split calendar (main $10bn catastrophe tower renewing 1 January, aggregate and whole-account-quota-share layers renewing 1 July), and the November 2023 entry date reflects a combination of IAG's 2023 January renewal having already been placed before ARPC's onboarding specification was published (15 December 2022), the 1 July 2023 aggregate-layer window being consumed by a separate restructuring, and the legislated 31 December 2023 large-insurer deadline. Table A6 summarises the per-insurer evidence with primary citations.

TABLE A6. Documented reasons for staggered CRP entry timing across the eleven insurers in the analysis sample. Effective entry dates are sourced from ARPC press releases, insurer corporate communications, audited annual reports, directors' reports, ASX releases, and Treasury ministerial statements. Nine of the eleven entrants (Allianz, Westpac, QBE, RACQ, AAMI, Apia, Suncorp, CommInsure, Youi) are documented with entry dates that either coincide with or were operationally forced by pre-existing private reinsurance treaty anniversary dates; NRMA is a mixed case driven jointly by IAG's split reinsurance calendar, ARPC onboarding constraints, and the legislated large-insurer deadline. Sure and Youi are the two insurers whose own public statements additionally invoke the 2023 hard reinsurance market as part of their rationale. In every case, however, the forces named — treaty anniversaries, ARPC's operational onboarding timeline, the 2023 global hard market, and the legislated 31 December 2023 large-insurer deadline — were fixed independently of any individual insurer's northern Australia cyclone premium dynamics, preserving exogeneity of entry timing with respect to the paper's outcome variables. A supplementary robustness check in Appendix A.14 re-estimates the headline price and quote effects on the nine-insurer sample that excludes the two insurers with mixed rationales.

Insurer	Effective Entry	Documented rationale for entry timing
Allianz	1 January 2023	Entry coincides with Allianz Group's documented 1 January property–catastrophe reinsurance renewal (Allianz Australia 2023a; Allianz SE 2025; Australian Reinsurance Pool Corporation 2023b).
Westpac	1 January 2023	Westpac-branded general insurance has been issued by Allianz Australia Insurance Ltd since Allianz's July 2021 acquisition of Westpac General Insurance under a 20-year distribution agreement; CRP entry is mechanically inherited from Allianz's 1 January 2023 entry (Allianz SE 2021; Allianz Australia 2023a).
Sure	1 January 2023	Sure's managing director publicly described entry as voluntary and "earlier than required by our product issuers," citing the "difficult reinsurance market" of the January 2023 hard renewal (Sure Insurance 2023; Insurance News Australia 2023; Australian Reinsurance Pool Corporation 2023b). This is the clearest case in which the rationale is partially strategic rather than purely mechanical.
QBE	21 June 2023	QBE's 2022 Annual Report confirms Australia Pacific "commenced preparations for the introduction of the Northern Australia Reinsurance Pool" during 2022, pre-dating QBE Group's 1 January 2023 reinsurance renewal (QBE Insurance Group Limited 2023). The 21 June 2023 effective date reflects execution via ARPC's "unexpired risk transfer" mechanism at a quarter-end, following preparations initiated at or before the 1 January 2023 renewal (Australian Reinsurance Pool Corporation 2022b; MP 2023). No QBE Australian cyclone sub-layer with a non-1-January anniversary is documented.

Continued on next page

TABLE A6 — continued from previous page

Insurer	Effective Entry	Documented rationale for entry timing
RACQ	30 June 2023	RACQ Insurance Limited's audited 2022–23 Annual Report (Note 3.1(ii)) states that its reinsurance treaty anniversary was 1 July and that the renewal date was "brought forward to 30 June 2023 from 1 July 2023" specifically to effect CRP entry (RACQ Insurance Limited 2023a,b). This is the only case in which an insurer publicly documents shifting its own treaty renewal date to align with CRP entry.
AAMI	1 July 2023	AAI Limited's (Suncorp Group's general insurance underwriter) main property–catastrophe reinsurance tower renews each 1 July aligned with Suncorp's financial year; CRP entry coincides exactly (Suncorp Group Limited 2023; Artemis.bm 2023a; MP 2023).
Apia	1 July 2023	Same underwriter (AAI Limited) and same single entry decision as AAMI (Suncorp Group Limited 2023).
Suncorp	1 July 2023	Same underwriter (AAI Limited) and same single entry decision as AAMI (Suncorp Group Limited 2023).
CommInsure	1 July 2023	Underwritten by Hollard Insurance Partners Ltd following Hollard's completion of the CBA general insurance divestiture on 30 September 2022 (Reinsurance News 2022). Hollard's FY22 Directors' Report (signed September 2022) explicitly stated: "In a recent meeting with ARPC, the Company indicated its intent to join the pool on 1 July 2023," and confirms the Hollard reinsurance programme renews 30 June / 1 July (The Hollard Insurance Company Pty Ltd 2022; MP 2023).
Youi	1 July 2023	Youi Pty Ltd runs a July–June financial year and renews its reinsurance programme each 1 July. Youi publicly announced CRP entry simultaneously with non-renewing its aggregate natural-perils reinsurance treaty, citing that aggregate covers were "no longer available at affordable rates" (Reinsurance News 2023; MP 2023). The entry date is mechanically anniversary-driven but the public rationale also cites hard-market conditions.

Continued on next page

TABLE A6 — continued from previous page

Insurer	Effective Entry	Documented rationale for entry timing
NRMA	13 November 2023	IAG's reinsurance programme has a split calendar: the main $10bn catastrophe tower renews 1 January (Insurance Australia Group Limited 2023b), while the aggregate cover and Hannover Re whole-account quota share renew each 1 July (Artemis.bm 2023b). ARPC's revised premium rates were finalised only on 1 October 2022 and its insurer onboarding specification (v2.01) was published on 15 December 2022 (Australian Reinsurance Pool Corporation 2022b), both downstream of IAG's 2023 main-tower placement window (confirmed to the market by ASX release on 10 January 2023 (Insurance Australia Group Limited 2023b)). The 1 July 2023 mid-year window was consumed by a separate aggregate-cover restructuring (Artemis.bm 2023b). November 2023 is therefore the first operationally feasible window for IAG between a hard-market January 2023 placement already locked in and the legislated 31 December 2023 large-insurer deadline (Insurance Australia Group Limited 2023c). IAG's 394-page FY23 Annual Report contains zero mentions of the CRP or ARPC, consistent with onboarding limbo rather than a strategic wait-and-see posture (Insurance Australia Group Limited 2023a).

A.4. Raw Premium Dynamics by Entry Cohort

Figure A1 provides a raw-dynamics companion to Figure A2, re-organised by the three CRP entry cohorts rather than by cyclone-risk category. Each row of the figure shows a cohort; within each panel, lines are coloured by the 10th, 50th, and 90th quote percentiles within a zipcode (i.e., the cheapest, median, and most expensive quoted addresses). The left column pools all quoted observations across the eleven analysis insurers; the right column restricts attention to the balanced subset of address-policy-insurer units that were quoted in every one of the eight observation snapshots, removing composition effects from entry and exit. The main dashed vertical line in each panel marks that cohort's effective CRP entry date; on Cohort 1 a thinner secondary line at t=5 marks the alternative treatment date used in the quote regressions for the January 2023 cohort, reflecting the price-versus-quote treatment-timing distinction discussed in Section 3.5.2. Parallel pre-treatment trends are visible in Cohort 2 through t=5, and the downward break at each cohort's CRP entry date is sharpest in the balanced panel where composition effects have been removed.

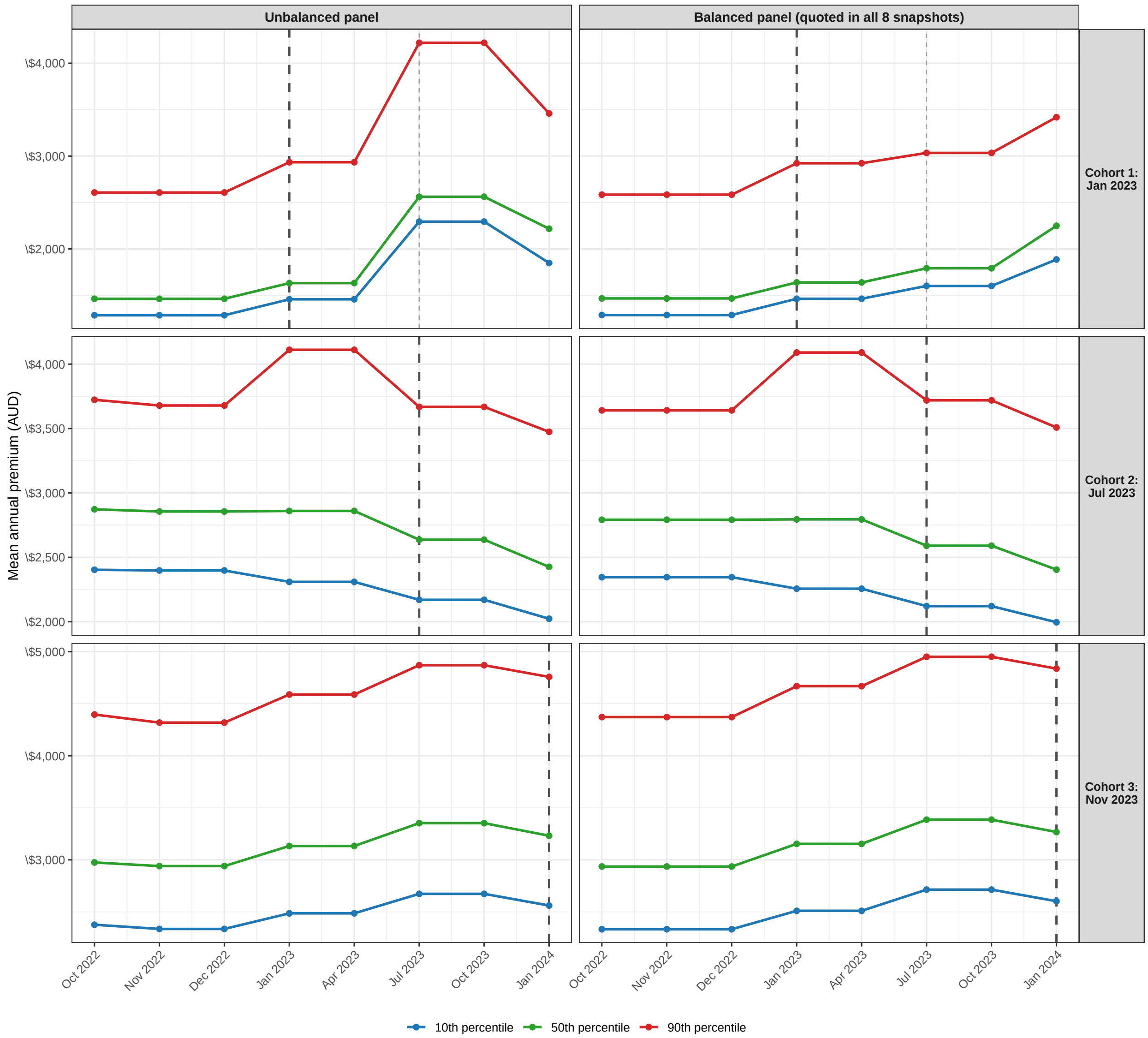


FIGURE A1. Mean annual premium by CRP entry cohort (rows) and within-zipcode address risk-percentile (line colour), across eight monthly quote snapshots (x-axis). Left column: all quoted observations across the eleven analysis insurers. Right column: balanced panel restricted to 422,943 address-policy-insurer units quoted in every one of the eight snapshots (50.5 percent of the full cross-section). The main dashed vertical line in each panel marks that cohort's CRP entry date (Cohort 1: January 2023; Cohort 2: July 2023; Cohort 3: November 2023); the thinner dashed line on Cohort 1 marks the alternative treatment date used in the quote regressions for Allianz, Sure, and Westpac.

A.5. Adjusted Time Series by Cyclone-Risk Category

Figure A2 is the cyclone-risk counterpart to Figure A1: it plots the adjusted time series of premiums (top panel) and the probability of being quoted (bottom panel) for low-, medium-, and high-cyclone-risk zipcodes, with all non-geographic policy-product variation absorbed by insurer-by-policy fixed effects. Premiums and quote rates in high-risk areas decline relative to low-risk areas, with the break compounding across the three CRP entry tranches and sharpest at the November 2023 cohort.

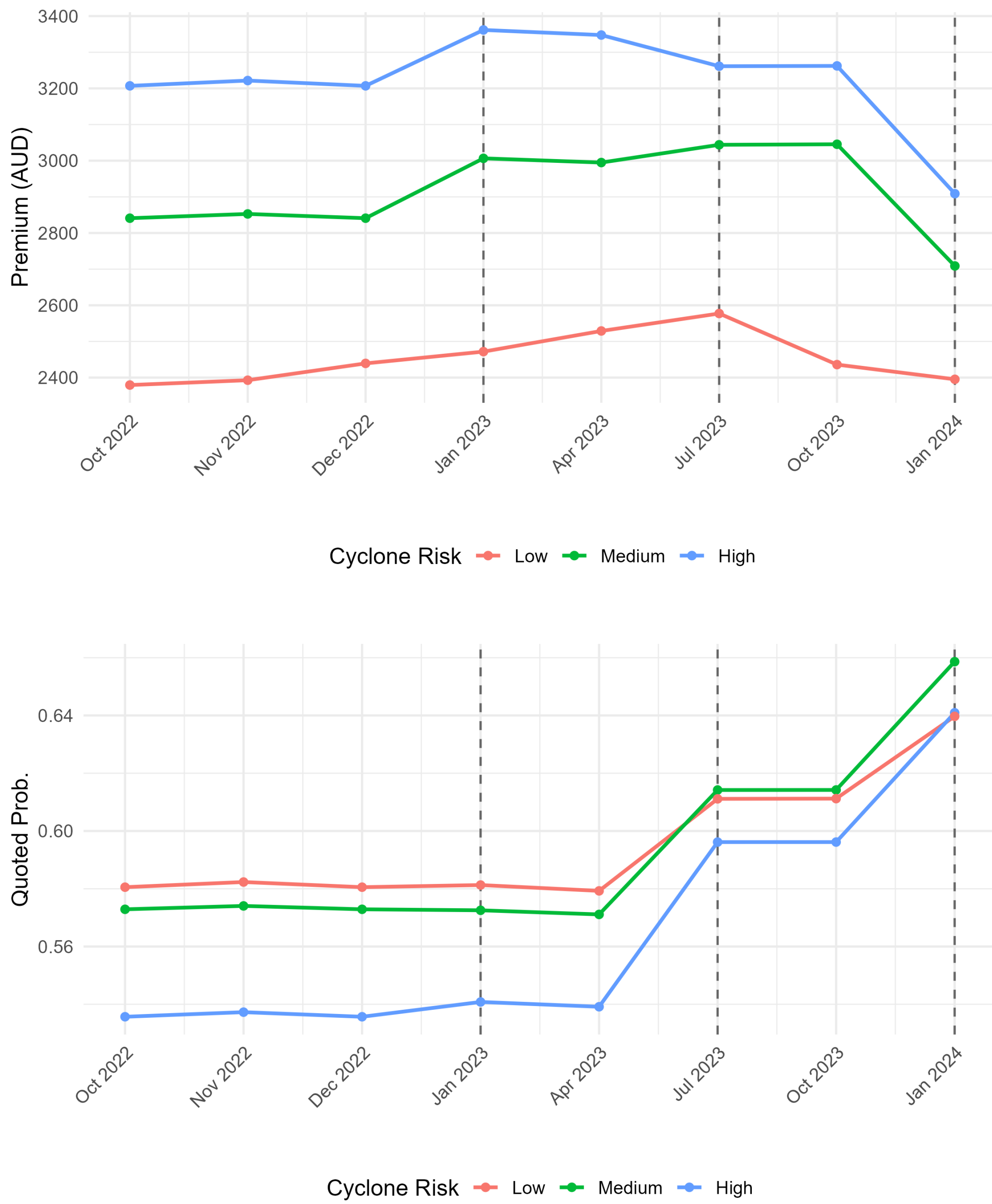


FIGURE A2. Adjusted time series by cyclone risk category. Top panel shows premiums; bottom panel shows quote rates. Each series is constructed by: estimating $y_{it} = \sum_s \beta_s \mathbb{1}(t = s) + \alpha_i + \varepsilon_{it}$ separately for each cyclone risk group, where y_{it} is the outcome (premium or quoted), α_i is a fixed effect for the full non-geographic policy cell indexing coverage level, sum insured, insurer, insurance type, and within-zipcode quote percentile - i.e., all policy-product variation except location, and t indexes time periods. Average predicted values by risk group and time period are plotted. Cyclone risk groups are defined based on the quantile of zipcode-average 25-year-maximum wind speed. Low-risk are the bottom decile, medium-risk the next four deciles, high-risk the top half of the risk distribution. Dashed vertical lines mark the three CRP entry cohort dates (January, July, and November 2023).

A.6. Global Tropical-Cyclone Activity

Figure A3 maps observed tropical-cyclone, hurricane, and typhoon tracks worldwide since 1979, providing global context for the Australian-region activity discussed in Section 3.1.

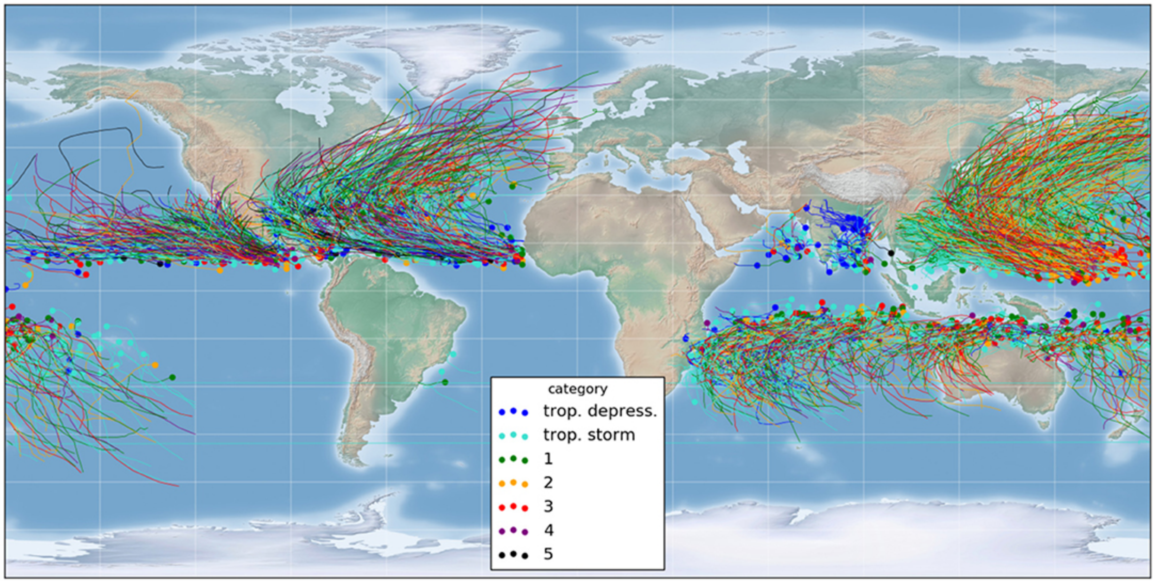


FIGURE A3. Map of global cyclones/hurricanes/typhoons since 1979 (reproduced from Giffard-Roisin et al. (2020)).

A.7. Appendix: Foreign Affiliation Heterogeneity in Correlation and Ambiguity Mechanisms

Section 6 showed that the CRP had a larger effect on prices for domestic Australian insurers relative to vertically integrated Australian subsidiaries of foreign reinsurers. Sections 7 and 8 showed that the price-reducing effects of the CRP were stronger, holding fixed expected risk, in locations with correlated and ambiguous risk, respectively. In this section, I test for the combination of these effects: were the effects of the CRP in reducing the costs associated with correlated or ambiguous risk, and by implication the pre-CRP frictions, sharper among domestic Australian insurers relative to vertically integrated foreign subsidiaries.

As in Sections 7 and 8, I restrict the sample to the first period (pre-treatment) and last period (post-treatment), and estimate for correlation

$$\begin{aligned}\log(\text{Premium})_{a,t,i,z,p} = {} & \text{FE} + \beta \cdot \text{Risk}_z + \kappa \cdot \text{Corr}_{z,-z} \\ & + \kappa_D \cdot \text{Corr}_{z,-z} \times \mathbb{1}\{\text{Domestic}_i\} \\ & + \Delta\kappa_D \cdot \text{Corr}_{z,-z} \times \mathbb{1}\{\text{Domestic}_i\} \times \mathbb{1}\{\text{Post}_t\} + \varepsilon_{a,t,i,z,p}. \end{aligned} \tag{A3}$$

And similarly for ambiguity:

$$
\begin{aligned}
\log(\text{Premium})_{a,t,i,z,p} = \text{FE} + \beta \cdot \text{Risk}_z + \aleph \cdot \text{Ambig}_z \\
+ \aleph_D \cdot \text{Ambig}_z \times \mathbb{1}\{\text{Domestic}_i\} \\
+ \Delta\aleph_D \cdot \text{Ambig}_z \times \mathbb{1}\{\text{Domestic}_i\} \times \mathbb{1}\{\text{Post}_t\} + \varepsilon_{a,t,i,z,p}.
\end{aligned}
\tag{A4}
$$

The coefficients of interest are κ_D ($\aleph_D$) and $\Delta\kappa_D$ ($\Delta\aleph_D$), the pre-CRP and post-CRP price premiums from correlation (ambiguity) for domestic insurers relative to foreign subsidiaries. The results are in Tables A7 and A8.

Outcome: Log Premium	(1)	(2)	(3)
Pre-CRP Effect Of Risk Correlation	0.619***	0.672***	0.686***
(Foreign Subsidiaries): κ	(0.036)	(0.042)	(0.047)
Additional Pre-CRP Effect For	0.300***	0.231***	0.197***
Domestic Insurers: κ_D	(0.070)	(0.063)	(0.060)
Post-CRP Change In Domestic Effect Of	−0.220***	−0.113***	−0.138***
Risk Correlation: $\Delta\kappa_D$	(0.031)	(0.005)	(0.005)
Risk Controls:	Basic	Basic	Basic
Insurer x t Specific Risk Pricing	✓	✓	✓
Clustering	Suburb	Suburb	Suburb
FE:	Insurer x t	Non-geo	Insurer
N	496 853	496 853	496 853
R^2	0.07	0.87	0.05

TABLE A7. Estimated effects of the spatial correlation in cyclone risk on insurance premiums, allowing for differential pricing and post-CRP changes for domestic insurers. The estimating equation is (A3). The first row reports the baseline (pre-CRP) effect of risk correlation for foreign subsidiary insurers, κ. The second row reports the additional pre-CRP correlation penalty for domestic insurers relative to foreign subsidiaries, κ_D. The third row reports the post-CRP change in the correlation penalty for domestic insurers, $\Delta\kappa_D$. Columns (1)–(3) present alternative fixed-effects designs, as indicated in the table. Standard errors, clustered at the suburb level, are reported in parentheses.

Outcome: Log Premium	(1)	(2)	(3)
Pre-CRP Effect Of Risk Ambiguity	0.160***	0.164***	0.173***
(Foreign Subsidiaries): $\aleph$	(0.035)	(0.038)	(0.039)
Additional Pre-CRP Effect For	−0.093***	−0.120***	−0.099***
Domestic Insurers: $\aleph_D$	(0.019)	(0.015)	(0.017)
Post-CRP Change In Domestic Effect Of	−0.077***	−0.072***	−0.089***
Risk Ambiguity: $\Delta\aleph_D$	(0.014)	(0.003)	(0.002)
Risk Controls:	Basic	Basic	Basic
Insurer x t Specific Risk Pricing	✓	✓	✓
Clustering	Suburb	Suburb	Suburb
FE:	Insurer x t	Non-geo	Insurer
N	936 805	936 805	936 805
R^2	0.05	0.85	0.03

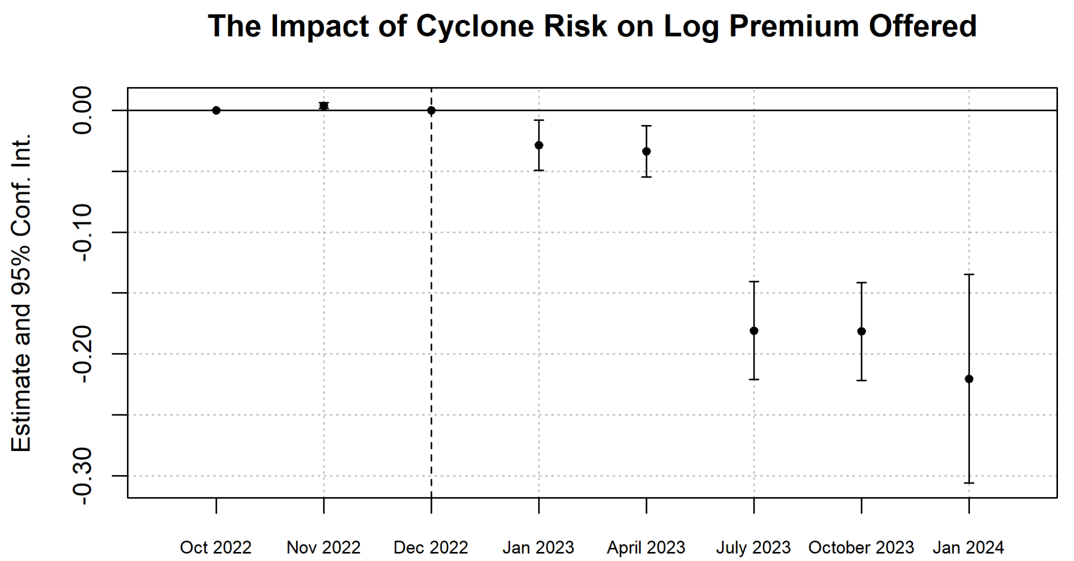
TABLE A8. Estimated effects of hazard uncertainty on insurance premiums, allowing for differential pricing and post-CRP changes for domestic insurers. The estimating equation is (A4). Hazard uncertainty is measured by the bootstrap standard deviation of the 25-year return-period wind speed at each postcode, derived from Geoscience Australia's cyclone simulation model. The first row reports the baseline (pre-CRP) uncertainty penalty for foreign subsidiary insurers, $\aleph$. The second row reports the additional pre-CRP uncertainty penalty for domestic insurers relative to foreign subsidiaries, $\aleph_D$. The third row reports the post-CRP change in the uncertainty penalty for domestic insurers, $\Delta\aleph_D$. Columns (1)–(3) present alternative fixed-effects designs, as indicated in the table. Standard errors, clustered at the suburb level, are reported in parentheses.

Table A7 shows a clear correlation heterogeneity. Holding cyclone risk fixed, and relative to foreign subsidiaries, domestic insurer prices are approximately 22-35 percent higher at a perfectly correlated zipcode than at an uncorrelated zipcode (κ_D ranges from 0.197 to 0.300 across the three columns; $e^{0.197} - 1 = 22\%$, $e^{0.300} - 1 = 35\%$). Much of this additional correlation penalty is nullified by the CRP: the post-CRP change in the domestic correlation slope is -0.113 to -0.220 log points, implying an 11-20 percent reduction in the additional penalty relative to foreign subsidiaries. This is consistent with correlated tail risk being most expensive for firms with the most constrained access to private tail-risk reinsurance, and with the CRP differentially easing this constraint. Table A8 tells a largely similar story for hazard-model uncertainty.

A.8. Event Studies

In this section, I present event study versions of the primary specifications in Tables 2 and 3.

First, I present the event study version of (1) and (2). These are the time-specific coefficients of the effects in high-risk zipcodes relative to low-risk zipcodes. The January 2024 coefficient is what was displayed in Tables 2 and 3.



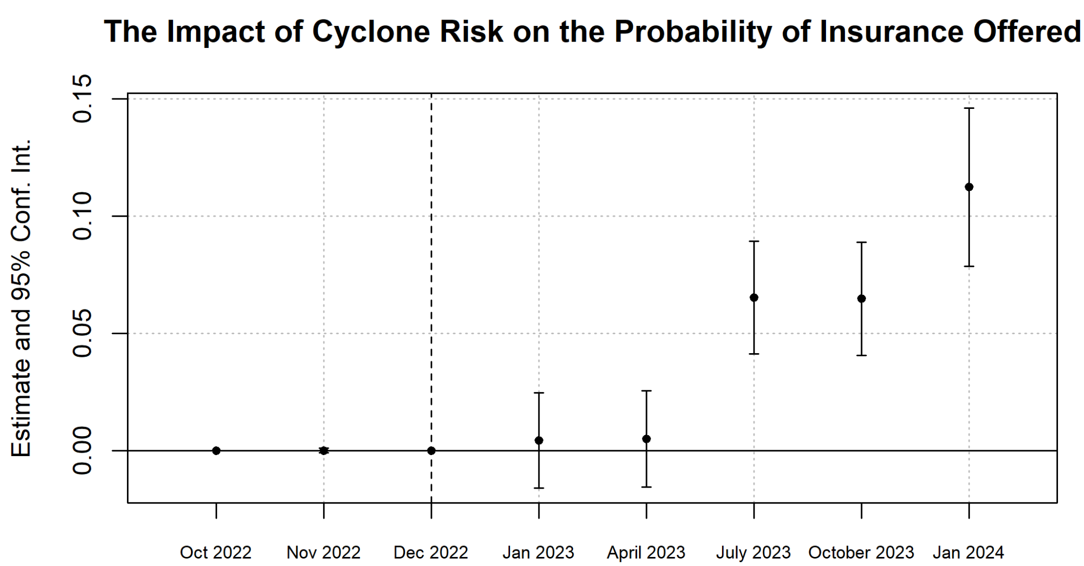


FIGURE A4. Event study coefficients for the effect of the reinsurance pool on log insurance premiums (top panel) and whether insurance is quoted or not (bottom panel), based on the differential exposure specification (2). The figure plots the estimated coefficients τ_t and their 95% confidence intervals. The vertical dashed lines indicate the dates when the first insurers entered the reinsurance pool: January 2023. Seven more entered in July 2023, and the final one in November 2023.

Figure A4 shows that the assumption of parallel trends between low- and high-risk zipcodes prior to treatment holds. As insurers enter the pool (three in January 2023, seven more in July 2023, and one in November 2023) the premium reductions get progressively larger, and the number of insurers entering the market gradually increases.

A.9. Robustness to Callaway-Sant'Anna Staggered-DiD Correction

One of my identification strategies leverages the staggered adoption of the CRP by different insurers. The TWFE specification used in the main text has been shown to be potentially misspecified under heterogeneous treatment effects across cohorts (Callaway and Sant'Anna 2021; Sun and Abraham 2021; Goodman-Bacon 2021). To check that the results are robust to this concern, I re-estimate the staggered design using the Callaway-Sant'Anna (2021) group-time ATT estimator, aggregated to a single pooled average treatment effect. Table A9 reports the pooled CS ATT alongside the TWFE estimate from the main text.

	Log(Premium)		Quoted	
	TWFE (1)	CS (2)	TWFE (3)	CS (4)
Average Treatment Effect	−0.140*** (0.062) [0.009]	−0.089 (0.064)	0.054 (0.051) [0.396]	0.059 (0.079)
Clustering	Insurer	Insurer	Insurer	Insurer
Inference	WCB	MB	WCB	MB
N	3 871 661	7056	6 706 245	8536

* p < 0.1, ** p < 0.05, *** p < 0.01

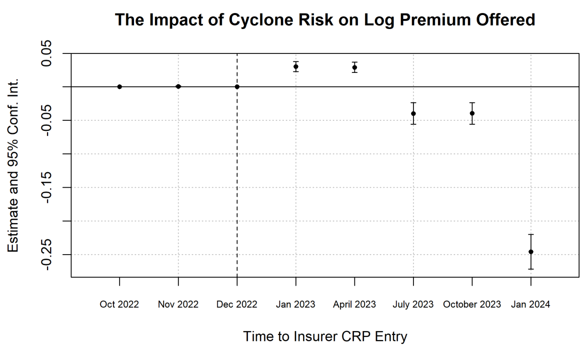
TABLE A9. Comparison of staggered difference-in-differences estimators. TWFE = two-way fixed effects (insurer × policy + time FE); CS = Callaway and Sant'Anna (2021), estimated on a balanced Insurer × Zip panel with not-yet-treated controls. Standard errors in parentheses, clustered at the insurer level. WCB = wild cluster bootstrap p-value (Rademacher weights, exact enumeration) in square brackets for the TWFE columns. MB = multiplier bootstrap at the insurer level (Callaway and Sant'Anna default) for the CS columns.

The Callaway-Sant'Anna pooled ATT is of the same sign as the TWFE estimate in both the price and quote regressions, with wider confidence intervals reflecting the CS estimator's smaller effective sample (it operates on a balanced insurer-zip panel with eight observation periods per unit, rather than the full unbalanced granular data used by the TWFE specification). The CS price ATT is not statistically distinguishable from zero at conventional levels under multiplier-bootstrap inference, but lies well within the confidence interval of the TWFE estimate and is directionally consistent with it. I therefore conclude that the headline staggered-DiD result is directionally robust to the Callaway-Sant'Anna correction.

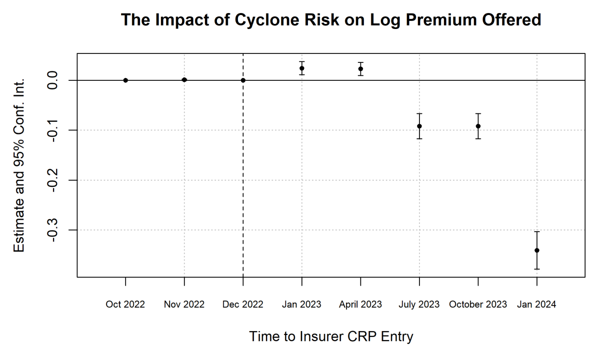
A.10. Robustness of Main Results to Alternate Measures of Wind Risk

I re-run the analyses first presented in Tables 2 and 3 with alternate measures of wind risk. Recall, the original figures used the maximum expected wind speed over a 25-year period, as calculated by the CHAD (Geoscience Australia 2018). As robustness, I use the maximum expected wind speed over 2-, 5-, 10-, and 50-year horizons.

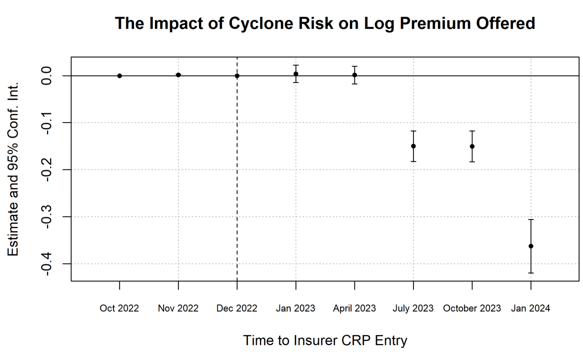
First, for the premiums offered: the results are in Figure A5. The general pattern is very robust to the measure of wind risk.



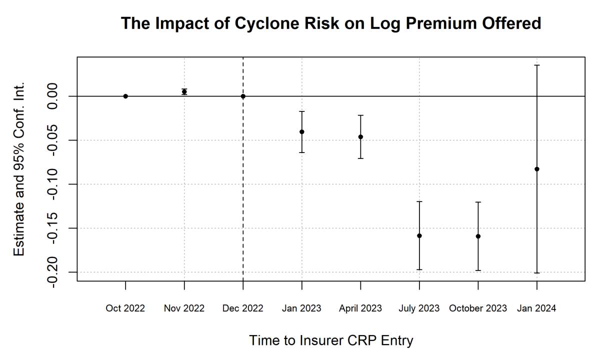
A. 2 Year Wind Speed



B. 5 Year Wind Speed



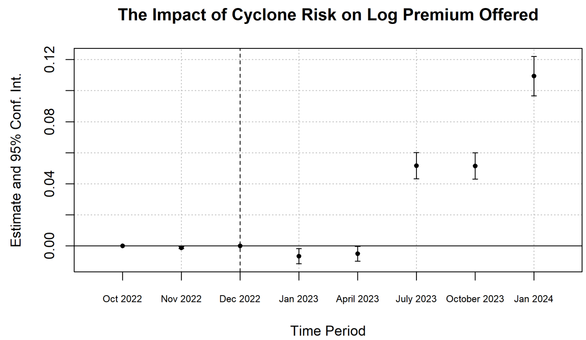
C. 10 Year Wind Speed



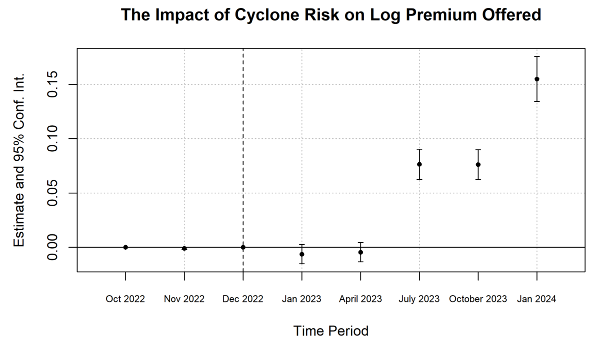
D. 50 Year Wind Speed

FIGURE A5. Event study coefficients for the effect of the reinsurance pool on log insurance premiums, based on the differential exposure specification (2). The different panels represent different measures of cyclone risk, as explained in the text above. The figures plot the estimated coefficients τ_t and their 95% confidence intervals. The vertical dashed lines indicate the dates when the first insurers entered the reinsurance pool: January 2023. Seven more entered in July 2023, and the final one in November 2023.

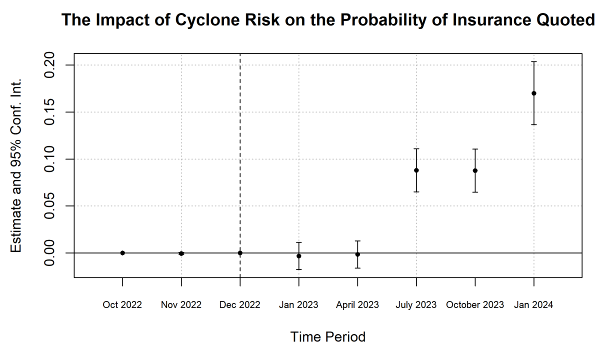
Second, for the probability of insurance being offered: the results are in Figure A6. The results are qualitatively unchanged when different measures of wind risk are used.



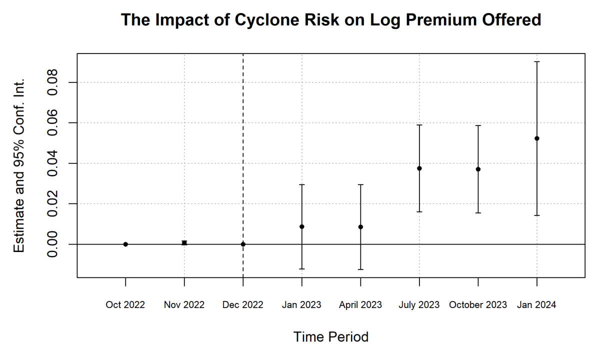
A. 2 Year Wind Speed



B. 5 Year Wind Speed



C. 10 Year Wind Speed



D. 50 Year Wind Speed

FIGURE A6. Event study coefficients for the effect of the reinsurance pool on the probability of reinsurance offered, based on the differential exposure specification (1). The different panels represent different measures of cyclone risk, as explained in the text above. The figures plot the estimated coefficients τ_t and their 95% confidence intervals. The vertical dashed lines indicate the dates when the first insurers entered the reinsurance pool: January 2023. Seven more entered in July 2023, and the final one in November 2023.

A.11. Robustness to Fixed-Effect Choice

Throughout the main text I report two-column or four-column regression tables that include two variants of the insurer fixed-effect structure side by side: a richer *insurer* × *policy* fixed effect (typically columns (1) and (3)) and a simpler *insurer-only* fixed effect (typically columns (2) and (4)). The narrative in the main text cites the insurer-only columns as the preferred specification, with the richer insurer × policy alternative reported in the adjacent columns for robustness. This appendix section explains the choice and summarises the cross-specification comparison.

The insurer × policy fixed effect absorbs any policy-type, coverage-level, or sum-insured variation that might otherwise load on the cyclone-risk or CRP-entry treatment variable. This is a stricter design: identification comes from within-policy-product-cell variation in cyclone risk or treatment, rather than from any across-policy-type variation. The stricter design is reassuring against the concern that policy composition might be correlated with treatment, but it also absorbs more of the data's variation, producing somewhat smaller point estimates and wider confidence intervals.

In every main-text table the two fixed-effect specifications give economically indistinguishable coefficients and do not change any significance conclusion. Compare, for example, the first row of Table 2: column (1) with insurer $\times$ policy fixed effects gives -0.178, while column (2) with insurer-only fixed effects gives -0.227; the staggered columns give -0.140 and -0.149. Both are highly significant and both imply a premium reduction in the high teens to low twenties. The same pattern holds for Tables 3, 4, 5, and for the correlation and ambiguity decompositions in Tables 8 and 9. I therefore cite the insurer-only specification as the headline and treat the richer specification as robustness, rather than presenting two separate sets of tables.

A.12. Treatment Timing

There is ambiguity about treatment timing for particular insurers because there is a lag between some insurers entering the CRP and adjusting their premiums or whether they quote. In particular, two of the three insurers who entered the pool in January 2023 updated their prices instantly, but updated the areas in which they offered insurance only in March-April 2023.[21] For this reason, in my primary specification, I code treatment for these January 2023 insurers as occurring in January for premiums, and in April for whether insurance is quoted at all.

I check robustness to these choices in Appendix A.13. And, more importantly, my primary empirical strategy - differential cyclone exposure - does not rely on the coding of treatment timing at all - only that all have entered the pool by January 2024, which was legally required.

A.13. Robustness to Treatment Timing Coding for the Insurers Treated in January 2023

I check the robustness of my main results against the somewhat ambiguous coding of the treatment timing of the insurers who entered the pool in January 2023. I rerun analyses (2) and (4) under the alternate coding that they were actually treated in June 2023 (which is when they fully rolled out the changes to addresses quoted). The results are in Table A10 below.

[21] See Allianz Australia (2023a) and Allianz Australia (2023b).

Empirical Strategy	Differential Exposure (1)	(2)	Staggered Treatment (3)	(4)
Estimate of τ	-0.178^{***}	-0.227^{***}	-0.078	-0.064
	(0.041)	(0.040)	(0.067)	(0.072)
			[0.284]	[0.441]
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	1 780 360	1 780 360	3 871 661	3 871 661
R^2	0.87	0.04	0.83	0.03

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE A10. Estimated effects of entering the reinsurance pool on quoted insurance premiums under alternate coding of treatment timing, using two empirical strategies: differential exposure (columns 1-2) and staggered treatment (columns 3-4). The coefficients tabulated are the average treatment effect in columns 3 and 4, and the treatment effect from the final period $\tau_{Jan2024}$ in columns 1 and 2. Standard errors, clustered at the zipcode or insurer level, are reported in parentheses. Wild cluster bootstrap p-values (Rademacher weights, exact enumeration) are reported in square brackets for insurer-clustered columns. Significance stars on insurer-clustered columns reflect bootstrap inference. Columns (1) and (3) include insurer x policy fixed effects, while (2) and (4) include only insurer fixed effects.

The results for the differential exposure specifications do not change, since they do not rely on any assumptions about treatment timing in January versus June 2023. The staggered-entry results are roughly half the size as in the main text and are no longer statistically distinguishable from zero under the wild cluster bootstrap (WCB p-values of 0.284 and 0.441 in columns (3) and (4), respectively, compared to 0.009 and 0.026 in Table 2), reflecting both the compositional shift - the January cohort contributes fewer post-treatment periods under the June coding - and the smaller effective staggered-design sample.

A.14. Robustness to Excluding Insurers With Reinsurance-Market Rationales

As discussed in Section 3.5.2, two of the eleven insurers in the analysis sample have public rationales for CRP entry that partially invoke reinsurance-market conditions rather than purely the expiration of pre-existing reinsurance treaties.

In this appendix I re-estimate the headline price and quote regressions (Tables 2 and 3) on the restricted nine-insurer sample that excludes Sure and Youi.

Every headline price coefficient grows in magnitude when Sure and Youi are excluded. The bootstrap p-value on column (4) of the staggered specification strengthens. Differential-exposure quote effects (Panel B) grow by approximately 40 percent. The staggered quote effect is statistically insignificant in both samples, as in the main text.

The interpretation is that the two insurers whose own public rationales are most exposed to the hard-market alternative explanation were, if anything, moderating the headline treatment effects; excluding them strengthens rather than weakens the paper's results.

Empirical Strategy	Differential Exposure		Staggered Treatment	
	(1)	(2)	(3)	(4)
Panel A. Effect of CRP participation on log**(Premium)**				
Main sample, 11 insurers (Sure Insurance 2023; Reinsurance News 2023 included)	−0.178*** (0.041)	−0.227*** (0.040)	−0.140*** (0.062) [0.009]	−0.149** (0.070) [0.026]
Excluding Sure and Youi, 9 insurers	−0.195*** (0.046)	−0.257*** (0.044)	−0.204*** (0.094) [0.000]	−0.219*** (0.112) [0.004]
Panel B. Effect of CRP participation on whether insurance is quoted				
Main sample, 11 insurers	0.125*** (0.019)	0.123*** (0.019)	0.054 (0.051) [0.396]	0.054 (0.051) [0.371]
Excluding Sure and Youi, 9 insurers	0.174*** (0.020)	0.172*** (0.020)	0.062 (0.064) [0.438]	0.062 (0.064) [0.438]
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer × Policy	✓		✓	
FE: Insurer		✓		✓
N (Panel A, 11 insurers)	1 780 360	1 780 360	3 871 661	3 871 661
N (Panel A, 9 insurers)	1 478 834	1 478 834	3 246 947	3 246 947
N (Panel B, 11 insurers)	3 070 809	3 070 809	6 706 245	6 706 245
N (Panel B, 9 insurers)	2 511 206	2 511 206	5 485 590	5 485 590

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE A11. Price and quote effect estimates with and without the two insurers (Sure, Youi) whose treatment timing was potentially endogenous to market conditions. Panel A replicates Table 2; Panel B replicates Table 3. Standard errors (parentheses) are clustered at zipcode or insurer; wild cluster bootstrap p-values (Rademacher, exact enumeration) are in brackets for insurer-clustered columns.

A.15. Policy Inclusions

Key features	AAMI	Allianz	Apia	CommInsure	NRMA	QBE	RACQ	Sure	Suncorp	Westpac	Youi
Cyclone	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Storm	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Flood	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Storm Surge	✓	✗	✓	✗	✓	✓	✓	✓	✓	✗	✗
Other Actions of the Sea	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Safety Net	✗	✗	✗	✓	✗	●	✓	✗	●	✗	✗
Total Replacement Cover	●	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗
Included coverage in each insurer's intermediate policy (Australian Securities and Investments Commission (ASIC)).											
Deductible	$400	$500	$400	$500	$500	$500	$500	$500	$400	$500	$500

TABLE A12. Comparison of key features and deductibles across cyclone insurance policies from major Australian insurers. The table indicates which perils and coverage options are included in each insurer's intermediate policy. Reproduced from Australian Securities and Investments Commission (ASIC).

A.16. Testing for the Impact of Correlation and Ambiguity Simultaneously

I test whether there is any interaction between the effects of risk correlation and risk ambiguity estimated respectively in Sections 7 and 8. I estimate the combined specifications.

$$\begin{aligned}
\text{(A5)} \qquad Premium_{a,t,i,z,p} = \gamma_t &+ \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \aleph \times \text{Risk Ambiguity}_{z,-z} \\
&+ \kappa \times \text{Risk Correlation}_{z,-z} \\
&+ \aleph_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Ambiguity}_{z,-z} \\
&+ \kappa_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Correlation}_{z,-z} + \epsilon,
\end{aligned}$$

$$\begin{aligned}
\text{(A6)} \qquad Quoted_{a,t,i,z,p} = \gamma_t &+ \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \aleph \times \text{Risk Ambiguity}_{z,-z} \\
&+ \kappa \times \text{Risk Correlation}_{z,-z} \\
&+ \aleph_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Ambiguity}_{z,-z} \\
&+ \kappa_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Correlation}_{z,-z} + \epsilon,
\end{aligned}$$

The results are in Table A13.

Outcome: Log Premium	(1)	(2)	(3)	(4)	(5)	(6)
Estimate of $\aleph$	−0.066	−0.041	0.009	0.032	0.009	0.032
	(0.041)	(0.039)	(0.048)	(0.045)	(0.048)	(0.045)
Estimate of $\aleph \times t = 7$	−0.057***	−0.063***	−0.125***	−0.128***	−0.144***	−0.146***
	(0.016)	(0.015)	(0.032)	(0.030)	(0.035)	(0.033)
Estimate of κ	0.666***	0.662***	0.823***	0.814***	0.823***	0.814***
	(0.146)	(0.139)	(0.145)	(0.139)	(0.145)	(0.139)
Estimate of $\kappa \times t = 7$	−0.136**	−0.153***	−0.272***	−0.280***	−0.479***	−0.477***
	(0.055)	(0.056)	(0.068)	(0.069)	(0.091)	(0.090)
N	471 278	471 278	471 278	471 278	471 278	471 278
R^2	0.90	0.06	0.90	0.06	0.90	0.06
Outcome: Insurance Offered	(1)	(2)	(3)	(4)	(5)	(6)
Estimate of $\aleph$	0.046***	0.046***	0.037***	0.037***	0.037***	0.037***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
Estimate of $\aleph \times t = 7$	−0.005	−0.005	−0.004	−0.004	−0.005	−0.004
	(0.008)	(0.008)	(0.009)	(0.009)	(0.011)	(0.011)
Estimate of κ	−0.102*	−0.102*	−0.123**	−0.123**	−0.123**	−0.123**
	(0.055)	(0.055)	(0.054)	(0.053)	(0.054)	(0.053)
Estimate of $\kappa \times t = 7$	0.113***	0.112***	0.116***	0.116***	0.158***	0.157***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.037)	(0.037)
Risk Controls:	Basic	Basic	Basic	Basic	Rich	Rich
Insurer x t Specific Risk Pricing			✓	✓	✓	✓
Clustering	Zip	Zip	Zip	Zip	Zip	Zip
FE:	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x t
N	782 118	782 118	782 118	782 118	782 118	782 118
R^2	0.86	0.16	0.86	0.16	0.86	0.16

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE A13. Joint estimation of hazard uncertainty and spatial correlation effects on insurance premiums (top panel) and availability (bottom panel), before and after the introduction of the reinsurance pool. The estimating equations are (A5) and (A6). The coefficients κ, κ_{Post} and $\aleph$, $\aleph_{Post}$ have the same definition and meaning as in Tables 8 and 9 respectively. Hazard uncertainty is measured by the bootstrap standard deviation of the 25-year return-period wind speed. Standard errors, clustered at the zipcode level, are reported in parentheses.

These results are qualitatively identical to the separate analyses in Sections 7 and 8. The CRP reduces the price premium associated with correlated and ambiguous risk.

A.17. Categorization of Domestic vs Foreign Subsidiaries for Reinsurance Analysis

For the reinsurance analysis in Section 6 and the per-insurer evidence in Appendix A.3, I classify three brands in the analysis sample as foreign subsidiaries of global insurer-reinsurer groups: Allianz Australia Insurance Ltd (parent: Allianz SE); Westpac General Insurance (underwritten by Allianz); and Sure Insurance (parent: Liberty Mutual Insurance Company). The remaining insurers have no foreign parent company and are therefore classified as Australian domestic insurers.

A.18. Full quotation parameters

Each address was quoted under five different contract and house characteristic scenarios. Additional parameters below were held fixed in all quotes per Australian Securities and Investments Commission (ASIC):

Question	Default Answer	Comment
Policyholder/occupant age	50	-
Flood cover?	Yes	Include flood cover
Fusion covered?	-	Premiums for different coverage levels (where applicable) are collected for this site
Accidental damage covered?	-	Premiums for different coverage levels (where applicable) are collected for this site
Additional personal belongings / valuables cover?	No	For example, jewellery
Claim history	None in last 3 years	-
Years insurance held	10 years (or maximum value allowed on the insurer's website)	-
Already covered under strata building insurance?	No	Applicable to building policies only
Strata Title?	No, Yes for Unit contents profiles	Applicable to contents policies only
Building Type	Detached house (except for 'Unit' profiles)	-
Is someone usually home during the day?	No	That is, all occupants work/are out during the day
Property usage	Private	-
Restricted access to property?	No	-
More than 5 people living at premises?	No	-
Currently unoccupied?	No	-
Currently under construction?	No	-
Constructed in last 6 months?	No	-

Table A14 continued from previous page

Question	Default Answer	Comment
Condition of building/construction quality?	Average/standard as default	Sometimes varied to achieve required sum insured
Does property have any unrepaired damage including storm?	No	-
Has house been demolished/sold/relocated?	No	-
Prior claim refused?	No	-
Denied purchase/refused insurance?	No	-
Criminal convictions/history?	No	-
Previous insurer	Other	-
Deadlocks	Yes	-
Key operated window locks	Yes	-
Smoke detector (back to base only)	No	-
Dangerous substances stored on premise?	No	-
Property below ground level	No	-
On stilts	No	-
Concierge	No	-
Home safe	No	-
Cover for portable contents?	No	Refer also to the comparison results for 'portable valuables' and 'items temporarily removed from the insured address' as these may be optional extras.
RACQ membership	No	-
Seniors card holder?	No	-
Large site?	No	For example, a farm
Water tanks?	No	-
Tennis court?	No	-
Architectural design?	No	-
European appliances?	No	-
Frameless shower screens?	No	-
Granite/marble/stone tiling?	No	-
Large windows?	No	-
Plantation shutters?	No	-
Curved walls?	No	-
Ducted air conditioning?	No	-

TABLE A14. Fixed parameters used in insurance quotations. All addresses were quoted with these standardized characteristics held constant, following the methodology in Australian Securities and Investments Commission (ASIC). Policyholder age was set to 50, flood cover was included, and the property was assumed to be a detached house (except for unit profiles) with no claim history in the prior three years.

Appendix B. Derivation and Proof of Proposition 1

Equilibrium condition

Let $z_\alpha := \Phi^{-1}(1-\alpha)$ and assume $\alpha < 1/2$, so $z_\alpha > 0$. Under the normal approximation to L_n, the survival constraint requires

$$k_n M P + a_n \geq k_n M \mu + z_\alpha \sqrt{\mathrm{Var}(L_n)}.$$

I focus on equilibria in which insurers optimally hold strictly positive capital, so this constraint binds. Thus

$$a_n^* = z_\alpha \sqrt{\mathrm{Var}(L_n)} - k_n M(P-\mu).$$

Substituting into expected profit gives

$$\Pi_n = k_n M(1+\tau)\big(P - \mathrm{MC}(k_n)\big),$$

where

$$\mathrm{MC}(k) := \mu + \frac{\tau z_\alpha}{1+\tau}\sqrt{\frac{V(kM)}{kM}}.$$

To derive the variance term, note that for an insurer with effective portfolio size $K = kM$,

$$\mathrm{Var}(L_n) = K\mu(1-\mu) + K(K-1)V_\infty,$$

where

$$V_\infty := \rho\,\mu(1-\mu) + (1-\rho)\sigma^2.$$

Equivalently, $\mathrm{Var}(L_n) = KV(K)$, where

$$V(K) := \mu(1-\mu) + (K-1)V_\infty.$$

Thus

$$\mathrm{MC}(k) = \mu + \frac{\tau z_\alpha}{1+\tau}\sqrt{\frac{V(kM)}{kM}}.$$

Here V_∞ is the non-diversifiable covariance component of losses. Since

$$\frac{V(kM)}{kM} = V_\infty + \frac{\mu(1-\mu) - V_\infty}{kM},$$

larger insurers have lower per-risk portfolio variance.

The Cournot first-order condition follows from differentiating $k_n M(1+\tau)(P - \mathrm{MC}(k_n))$ with respect to k_n, using $\partial P/\partial k_n = -1$. This gives

$$P = \mathrm{MC}(k_n) + k_n + k_n\mathrm{MC}'(k_n).$$

Imposing symmetry, $k_n = k^*$, and using $P^* = \bar{Q} - Nk^*$ gives the equilibrium condition

$$\bar{Q} = \mathrm{MC}(k^*) + (N+1)k^* + k^*\mathrm{MC}'(k^*). \tag{A7}$$

This equation implicitly defines the symmetric equilibrium quantity $k^*(\rho, \sigma, \tau, N, M)$ and price $P^* = \bar{Q} - Nk^*$.

Comparative statics

Let $W(k) := V(kM)/(kM) = V_\infty + \{\mu(1-\mu) - V_\infty\}/(kM)$, where $V_\infty = \rho\mu(1-\mu) + (1-\rho)\sigma^2$. Then $\mathrm{MC}(k) = \mu + g(\tau)\sqrt{W(k)}$, with $g(\tau) := \tau z_\alpha/(1+\tau)$. Write the equilibrium condition as $G(k^*;\theta) = \bar{Q}$, where

$$G(k;\theta) := \mathrm{MC}(k;\theta) + (N+1)k + k\,\mathrm{MC}'(k;\theta), \qquad \theta \in \{\rho, \sigma, \tau\}.$$

Since $\mu(1-\mu) - \sigma^2 = \mathbb{E}[p(1-p)] > 0$, we have $\mu(1-\mu) - V_\infty = (1-\rho)\{\mu(1-\mu) - \sigma^2\} > 0$ for $\rho < 1$. Hence $W_k < 0$: larger insurers have lower per-risk portfolio variance.

By the implicit function theorem, $dk^*/d\theta = -G_\theta/G_k$. Since $P^* = \bar{Q} - Nk^*$, it is enough to show $G_k > 0$ and $G_\theta > 0$.

First, $G_k = (N+1) + 2\mathrm{MC}'(k) + k\mathrm{MC}''(k)$. The firm's strict second-order condition is equivalent to $2 + 2\mathrm{MC}'(k) + k\mathrm{MC}''(k) > 0$, so

$$G_k = (N-1) + \{2 + 2\mathrm{MC}'(k) + k\mathrm{MC}''(k)\} > 0.$$

Now consider $\theta \in \{\rho, \sigma\}$, with the σ derivative holding μ fixed. Because $kM > 1$, $W_\rho = (1 - 1/(kM))\{\mu(1-\mu) - \sigma^2\} > 0$ and $W_\sigma = (1 - 1/(kM))2\sigma(1-\rho) > 0$. Also $W_{k\rho} > 0$ and $W_{k\sigma} > 0$. Since $W_k < 0$, differentiating $\sqrt{W}$ gives $(\sqrt{W})_{k\theta} = W_{k\theta}/(2\sqrt{W}) - W_k W_\theta/(4W^{3/2}) > 0$. Therefore both terms in $G_\theta = \mathrm{MC}_\theta + k\mathrm{MC}_{k\theta}$ are positive, so $G_\theta > 0$ for $\theta \in \{\rho, \sigma\}$.

Finally, consider τ. Since $g'(\tau) = z_\alpha/(1+\tau)^2 > 0$, we have

$$G_\tau = \frac{g'(\tau)}{2\sqrt{W}}\{2W + kW_k\}.$$

But $2W + kW_k = 2V_\infty + \{\mu(1-\mu) - V_\infty\}/(kM) > 0$, so $G_\tau > 0$.

Thus, for each $\theta \in \{\rho, \sigma, \tau\}$, $G_k > 0$ and $G_\theta > 0$. Therefore $dk^*/d\theta < 0$, and since $P^* = \bar{Q} - Nk^*$, $\partial P^*/\partial\theta > 0$. ■