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

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Increasing climate risk is making property insurance unaffordable and unavailable. I study a novel Australian policy response: government-provided, mandatory, risk-based reinsurance for cyclone damage in home insurance. Public reinsurance reduces premiums by 21% and increases insurance availability by 11%. These gains are not a subsidy but arise from eliminating large pre-existing markups in private reinsurance and catastrophe bond markets, flowing primarily to insurers most constrained by tail-risk exposure. The markup reduction stems from neutralizing the high premium for spatially-correlated and ambiguous risk, with increased competition providing additional benefits. This demonstrates that insurance market dysfunction originates from frictions in tail-risk reinsurance markets, and that targeted, cost-neutral interventions in these upstream markets can restore affordability and availability in home insurance.

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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 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 (insurance for insurers) 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 extreme markups—approximately 70% and 200% over expected losses, respectively. The failure of both mechanisms to efficiently price this diversifiable risk is therefore puzzling.

This paper makes three contributions. First, I empirically document the failure of

[1]Recent coverage of collapsing insurance markets includes: Florida Journal (2021), California Times (2020), Louisiana NOLA.com (2021), the United Kingdom Independent (2021), Canada News (2020, 2021), Germany Reuters (2021), Japan Asia (2020), Australia Australian Competition and Consumer Commission (2020a), France Local (2021), New Zealand Herald (2020), South Africa Bloomberg (2021), and India Times (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).

private risk-sharing in a setting where it ought to succeed: 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 whether upstream tail-risk frictions are a cause of downstream insurance-market dysfunction. I find that public reinsurance reduced premiums by 27% and increased insurer entry by 11%. 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, bearing spatially correlated and ambiguous risk was expensive relative to expected risk. The CRP eliminates approximately half of these correlation and ambiguity wedges, with additional price reductions arising from increased competition due to insurer entry. Critically, these gains arise from eliminating frictions in tail-risk markets rather than subsidizing risk. This demonstrates that insurance market dysfunction originates in upstream reinsurance markets, and that targeted interventions there can repair downstream retail markets without fiscal cost. 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 this policy - socializing the natural catastrophe tail risk —this paper offers a path forward in what has otherwise been a sequence of unsuccessful policy interventions. Governments have experimented with three broad approaches to rising insurance prices and reduced availability, all with significant drawbacks. First, direct public insurance provision (e.g. US flood and crop insurance) has typically devolved into subsidy schemes with prices well below actuarial cost, potentially leading to moral hazard and encouraging excessive development in hazard-prone areas.[3] Second, public 'insurers-of-last-resort' (e.g. Florida Citizens, California Earthquake Authority) have often decoupled risk from prices and cannibalized the private market.[4] Third, rate regulation requiring pre-approval for premium changes has distorted prices away from accurately reflecting risk, caused insurer exit, and can

[3] Michel-Kerjan, Raschky, and Kunreuther (2017); Babcock (2015); Klosin and Solomon (2024); Kousky (2018) discuss how prices are subsidized below actuarial cost, while the moral hazard distortions of public insurance are documented by Michel-Kerjan (2010); Ostriker and Russo (2024).

[4] Friedman, Mukherjee, and Sridhar (2021) examines the decoupling of risk from prices, Newman and Christopherson (2009) explores the cannibalization of the private market, and Ben-Shahar and Logue (2011) investigates cross-subsidies and inequitable outcomes.

reduce insurer solvency.[5] These interventions operate downstream - by regulating or providing consumer-facing primary insurance - rather than addressing the upstream constraint: the high shadow price of bearing and sharing 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 subsidizing 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% (reinsurance) and up to 200% (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 (along with the Caribbean/Gulf of Mexico and the Western Pacific) experiences multiple cyclone-force storms each year. Cyclone exposure has caused problems in the homeowners insurance market: premiums rose 122% from 2007 to 2019 (compared to 52% 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: I document that reinsurance has markups of 66% and catastrophe bond markups of 115%. 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 premium is set to be actuarially fair by statute[6], and is calculated using three state-of-the-art catastrophe models as well as

[5] Leverty and Grace (2011) examines the distortion of prices, Oh and Sen (2023) discusses insurer exit and exacerbated insurance availability problems, and Grace and Klein (2013) explores the potential impact on insurer solvency.

[6] Australian Government (2022)

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[7]. 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 NQH (2024), a government-run comparison website that collects quotes from twelve 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, and two additional 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 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

[7] Australian Competition and Consumer Commission (2022)

twelve insurers in my data, three entered in January 2023, seven entered in July and the remainder in November. The date of entry was determined by the expiration of existing reinsurance treaties, the anniversaries of which were long-standing and unaffected by the pool (Senate Economics References Committee (2017)). 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 (i.e., using the Sun and Abraham (2021) correction).

The reinsurance pool increased insurance availability and reduced premiums substantially (Section 4). Using the first empirical strategy, after insurers entered the pool, the probability of them offering insurance increases by 5%, and the premiums they quoted decline by 12%. The second empirical strategy shows that, once all insurers had entered the pool, the premiums in the highest cyclone risk zipcode decreased by 27%, and the probability of insurance being offered increased by 11 percentage points relative to the lowest risk areas. (I control for any pre-treatment differences in outcomes due to cyclone risk.) 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 27% premium decrease translates into \$920, over 1% of national average income in 2023 (\$98,812, per Australian Bureau of Statistics (2023)). A 11 percentage point increase in insurance being offered is equivalent to approximately 20% of the baseline.

To understand the mechanisms by which the CRP generates premium reductions and availability increases, I test four frictions in tail-risk intermediation that can generate high markups and rationing even when risk is diversifiable: an easing of reinsurance frictions for the most constrained local insurers rather than an implicit subsidy or cross-subsidy; a reduction in the cost of insuring correlated tail risk; a reduction in the cost of insuring ambiguous risk; and indirect competition effects from insurer entry.

First, I provide direct evidence that the CRP's primary effect was to remedy this market friction for constrained firms, ruling out an implicit subsidy (Section 5). I exploit the fact that several Australian insurers are subsidiaries of global firms, giving them access to at-cost internal reinsurance, while domestic insurers must rely on the high-markup external market. 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 with internal reinsurance access, the CRP had a zero, or even slightly positive, effect on prices. This heterogeneity demonstrates that the CRP worked by providing fairly-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 6). 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 80% higher premiums and was 11% less likely to be offered insurance than an uncorrelated zipcode. The introduction of the pool more than halved this premium penalty and eliminated the availability gap entirely. This shows that the CRP's core effect operates by reducing the cost of insuring correlated risk, a key driver of private market inefficiency.

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. Natural disaster risk is inherently ambiguous, at best approximated by uncertain models, and this has been posited as a reason for increased costs or insurer withdrawal.[8] I proxy for ambiguity using the dispersion in pre-CRP prices offered by different insurers in a zipcode, controlling for the level of risk. Disagreement among insurer prices, for the same underlying cyclone risk, is consistent with ambiguous or uncertain models that translate this risk into annualized economic damages. I find that, prior to the CRP, an increase in the ambiguity of risk (specifically, a $1,000 increase in the standard deviation across insurers) increases prices by 13% and reduces availability by 1.2%. After the CRP is introduced, half of the price penalty and three quarters of the availability penalty are removed. This result suggests the CRP's success stems in part from addressing the costs of ambiguous risk that had previously made tail-risk reinsurance expensive.

Fourth, I show that the CRP lowered prices not only directly by reducing reinsurance costs for incumbents, but also indirectly by inducing competition (Section 8). The pool's introduction enabled new insurers to enter high-risk markets they previously avoided. To isolate the causal effect of this entry, I use an exposure-based instrumental variable strategy, instrumenting for insurer entry with the proportion of insurers in a zipcode

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

prior to the insurance pool. I find this induced competition is a powerful secondary mechanism of the CRP, explaining between one-quarter and one-third of the total premium reduction.

These findings point to a diagnosis of insurance market dysfunction in catastrophe-exposed regions: high prices and a lack of availability at the retail level can be equilibrium outcomes of constrained 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. This forces them either to charge high premiums that reflect expensive reinsurance markups or to withdraw from high-risk markets entirely. By providing reinsurance at expected cost, the CRP demonstrates that governments can address the fundamental friction - 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, suggest targeted interventions to restore market function in other catastrophe-exposed insurance markets.

Literature Review

First, my paper relates to a literature on frictions in insurance markets that can lead to their collapse, often (but not exclusively) related to natural catastrophes. Since insurance is premised on the diversification of risk, concentrated/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)). Analogous problems[9] 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

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

(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)). Concurrent 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 drivers of high reinsurance costs, and show that public reinsurance can nullify their impact on premiums.

Second, my paper contributes to the literature on government regulation of insurance markets. Interventions such as publicly provided insurance, subsidies, and mandatory coverage have been implemented to address market failures and increase access to coverage. Public insurance schemes 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 'insurance-of-last-resort' entities, which have cannibalized the private markets they were designed to supplement (see, e.g. Froot (2001) and Grace, Klein, and Kleindorfer (2004) respectively). The most relevant studies are government reports (Flood Re (2022); Australian Reinsurance Pool Corporation (2023a)) on UK Flood Re (a reinsurer of last resort run by the UK government) and the CRP. 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 - public reinsurance - in which the government bears only tail risk, thereby reducing the expected cost of the program 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 realize) 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)).

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% - 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 (2199)). Second, reinsurers themselves face high capital costs to back correlated tail risk, which are passed through in their pricing (Froot (2004)). 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); AMB (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 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 100% higher than 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% or more. In Sections 5, 6, and 7 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.[10]. This study focuses on the northern Queensland region. The state of Queensland occupies the north-eastern portion of Australia, and North Queensland is approximately the portion 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 GDP of 17 billion and population of 250,000 (Queensland Government (2023)).

Figure 1 about here

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 damage due to theft, vandalism and fire, accidental damage, and 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% of market share, and the largest six for 87%. (Senate Economics References Committee (2017)).

[10] 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).

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

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 attracted public policy interest in recent years. From 2007 until 2019, home insurance premiums rose 122% in northern Australia (Australian Competition and Consumer Commission (2020a)), compared to 52% 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

[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.

by the Australian Government.

Insurers had to join the CRP by the end of 2023, but could do so earlier. Of the insurers under study, three joined in January 2023, seven joined in July 2023, and the final two in November 2023. The staggered entry will be the basis for identification. The timing of insurer entry was primarily determined by the expiration month of their prior reinsurance contracts (Commonwealth of Australia (2022)).

The CRP is statutorily required to be budget neutral (Commonwealth of Australia (2023) and Australian Reinsurance Pool Corporation (2023c)). To calculate the reinsurance premiums charged to insurers for each policy, the CRP combined catastrophe exposure datasets received from all insurers with 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 (2022)).

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, mitigation activities (roller door, window protection, roof replacement).

3.3. Data

3.3.1. Insurance Prices

Insurance price data primarily come from a government-run home insurance price comparison site (NQH (2024)). 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 postcode: the addresses at the 10th, 50th and 90th percentile of cyclone risk according to an underlying risk model. These addresses are constant over time.

Each address is quoted *as if* it 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 twelve insurers for a variety of different policy options (coverage levels, deductibles, etc). Collectively these insurers cover 95% of the home insurance market (Australian Reinsurance Pool Corporation (2023b)). Table 1 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.

Table 1 about here

To supplement the primary insurance data, premiums were hand collected for a randomly chosen address in each zipcode for a subset of three insurers. The characteristics of the policy quoted and the house quoted for are also held fixed over time. These data allow for estimates of changes to the mean-risk address in each zipcode.

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 11 quotes, they would need to go through 11 separate insurer processes that generally ask for different information. The leading comparison site only compares among 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.3.

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.4 I show results are robust to using a 2-, 5-, or 100-year period. The area of study, Northern 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 2. Table 2 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 median, and medium risk as the remainder in the middle. Additionally, I divide the sample into insurer-time periods pre and post treatment.

Table 2 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 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 low.

To understand the dynamics, Figure 2 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.

Figure 2 about here

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%, 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 they do. 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 zip-code 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.4 I show that these results are robust to alternative measures of cyclone risk. For interpretability, I normalize this measure of cyclone risk to be one. Standard errors are clustered at the zipcode level.

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

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

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 the remaining two in November 2023. This was driven primarily by the expiration of existing reinsurance treaties. The expiration dates of these treaties were fixed well before the cyclone pool was announced or implemented (see: Commonwealth of Australia (2023)).

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.5 and robustness checks to this coding are in Appendix A.6. An advantage of the other empirical strategy - differential cyclone exposure - is that it does not suffer from this ambiguity.

An additional concern is that, were the market to be perfectly competitive, 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 Figure 2 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 they do. 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 x 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.

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 3. The equivalent event studies are in Appendix A.3. Recall that the tabulated coefficient for specification (2) is $\tau_{Jan,2024}$, the effect after all insurers have entered the reinsurance pool.

Table 3 about here

Table 3 compares the treatment effects estimated from the staggered entry empirical strategy (columns (3) and (4)) with the differential exposure (columns (1) and (2)). Columns (3) and (4) indicate that once an insurer enters the pool, premiums drop by approximately 11%. Columns (1) and (2) show that after all insurers enter the pool, the premium for the highest risk zipcode has fallen by 22% more than for the lowest risk zipcode. These two sets of estimates broadly cohere: the median cyclone risk is approximately 0.7, and so the reduction in premiums in the median risk zipcode is approximately 15%.

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 concentration or ambiguity of risk. In Sections 5 to 8 I test all of these mechanisms. Additionally, in Appendix A.1 I demonstrate that the observed 20% 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.3, I test the robustness of the results that leverage staggered insurer entry to the Sun and Abraham (2021) method and find they are qualitatively similar, albeit slightly less precise.

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 4. The equivalent event studies are in Appendix A.3.

Table 4 about here

Table 4 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 11% higher in high-risk zipcodes than in low-risk zipcodes. This coheres with the less precisely estimated 5% increase in probability estimated from staggered entry. The lack of precision is due to the clustering at insurer level, of which there are only 12, and among which availability decisions are highly correlated. I test for robustness to the Sun and Abraham (2021) correction for staggered treatment in Appendix A.3.

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. This strongly suggests that modeling insurers as risk neutral is highly incomplete. 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. Mechanism I: Subsidy or Reducing Reinsurance Access Frictions?

The previous sections showed that private tail-risk cover carried large mark-ups, and insurance prices fell when the CRP began offering at-cost reinsurance. Here I close the loop: *insurers that faced the highest pre-CRP mark-ups experienced the largest premium reductions.*

To do so, I leverage heterogeneity in the insurers exposed to this policy. Of the twelve insurers, three are Australian affiliates of large global insurers - Allianz, Westpac and SURE (a subsidiary of Liberty Mutual). These subsidiaries have internal at-cost reinsurance with their corporate parents.[13] The other nine 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 (1), (2), (3) 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 5.

$$
\begin{aligned}
(5)\qquad Quoted^{q}_{a,t,i,z,p} &= \gamma_t + \alpha_i + \tau \times \text{Insurer } i \text{ in the pool}_{i,t} \\
&\quad + \tau_F \text{Insurer } i \text{ in the pool}_{i,t} \times \text{Insurer is a foreign subsidiary}_i + \epsilon, \\
(6)\qquad Premium^{q}_{a,t,i,z,p} &= \gamma_t + \alpha_i + \tau^0 \times \text{Insurer } i \text{ in the pool}_{i,t} \\
&\quad + \tau_F \text{Insurer } i \text{ in the pool}_{i,t} \times \text{Insurer is a foreign subsidiary}_i + \epsilon,
\end{aligned}
$$

Table 5 about here

The results in Table 5 demonstrate that the price reductions are entirely driven by domestic insurers without access to in-house reinsurance. For subsidiaries of foreign insurers that do have access to in-house reinsurance, the CRP effect causes no change or a moderate price increase, perhaps due to additional operational costs of compliance.

Because primarily reinsurance-constrained domestic insurers gain from the pool, the evidence rules out a blanket subsidy. If there was simply a universal subsidy, prices for

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

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 6 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.

Cross-Subsidy The preceding evidence confirms that, as designed, there was no overall subsidy in the CRP's pricing. However, there is the potential for a *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, computing the magnitude of any cross-subsidy is of independent interest.

To estimate the cross-subsidy effect, I leverage and extend the foreign versus domestic insurer strategy used above. Specifically, I rely on the fact that, prior to the CRP, foreign subsidiaries paid no markup on their reinsurance while domestic insurers paid market-negotiated markups. Thus, any change in risk-price gradient (high- versus low-risk properties) for foreign subsidiaries would be entirely caused by a cross-subsidy effect. In contrast, the change in risk-price gradient for domestic insurers would combine a 'pure' treatment effect of the CRP with a cross-subsidy effect. Therefore I estimate the triple difference specification:

$$
\begin{aligned}
\log(\text{Premium})_{a,t,i,z,p} = {} & \gamma_t + \alpha_i + \beta_1 \times \text{Cyclone Risk}_z \\
& + \beta_2 \times \text{Cyclone Risk}_z \times \text{Insurer } i \text{ in pool}_{i,t} \\
& + \beta_3 \times \text{Cyclone Risk}_z \times \text{Foreign subsidiary}_i \\
& + \beta_4 \times \text{Cyclone Risk}_z \times \text{Insurer } i \text{ in pool}_{i,t} \times \text{Foreign subsidiary}_i \\
& + \epsilon_{a,t,i,z,p},
\end{aligned} \tag{7}
$$

This yields four distinct risk-price gradients: pre-treatment domestic insurers ($RP_{pre,D} = \beta_1$), post-treatment domestic insurers ($RP_{post,D} = \beta_1 + \beta_2$), pre-treatment foreign subsidiaries ($RP_{pre,F} = \beta_1 + \beta_3$), and post-treatment foreign subsidiaries ($RP_{post,F} = \beta_1 + \beta_2 + \beta_3 + \beta_4$).

From these estimated risk price gradients, I estimate the cross-subsidy effect and the pure treatment effect: Cross-subsidy effect $= RP_{post,F} - RP_{pre,F} = \beta_2 + \beta_4$, and Isolated markup reduction $= [RP_{post,D} - RP_{pre,D}] - [RP_{post,F} - RP_{pre,F}] = -\beta_4$. The results are in Table 6 below.

Table 6 about here

Table 6 demonstrates a small, and statistically indistinguishable from zero cross-subsidy effect. In contrast, the pure treatment effect, having removed any cross-subsidy, is large and highly significant: the risk gradient flattens by 35% for treated insurers. This is further evidence that, even after accounting for any cross-subsidy, the CRP lead to substantial price reductions for the areas most exposed to cyclone risk.

6. Mechanism II: The Cost of Insuring Correlated Risk

The cost of insurance for catastrophic risks is often much higher than the expected loss. This is because catastrophic risks are concentrated in two senses. First, most years will not have a cyclone, but when one arrives it can cause an entire house to be destroyed. Second, when one house is destroyed it is likely many others nearby are. Insurers have to hold enough capital to be able to pay claims in years with correlated losses. This makes cyclone risk much more expensive than, say, auto insurance, in which risks are idiosyncratic and the right tail of the loss distribution is thin.

The concentration of risk does not pose the same cost challenge to government. Governments do not have to hold capital against tail risk because they can more plausibly commit to meeting their liabilities rather than declaring bankruptcy and seeking protection via limited liability.

In this section, I quantify the cost of the concentration of cyclone risk, over and above the expected loss. For the reasons above, when the cost of insurance is close to expected loss, private markets are likely to function well. To the extent the concentration of risk causes the cost of insurance to substantially exceed expected loss, the rationale for governments bearing that risk is stronger.

Broadly, the cost of providing insurance in zipcode z depends on risk in that zipcode, and the correlation of risk in that zipcode with other zipcodes.

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 as 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 their 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:

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

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.

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 3 and 4. Specifications (3) and (4) allow for insurer-time specific pricing of risk. Specifications (5) and (6) include a richer set of risk measures[14] 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 7 below.

Table 7 about here

Table 7 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 124% (=$e^{0.807}-1$) higher than a zipcode whose risk is uncorrelated. Similarly, the zipcode with perfectly correlated risk is 11.3% 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% (=$e^{0.807-0.433}-1$) 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 reduces by 2/3 relative to prior to the pool.

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 at holding correlated risk. They are not capital constrained and cannot declare bankruptcy or be shielded by limited liability if a disaster strikes.

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

In Section A.2, 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.

7. Mechanism III: The Cost of Insuring Ambiguous Risk

It has been hypothesized that some insurance markets do not exist because the probabilities of loss are ambiguous.[15] Cyclone risk is ambiguous - the ground truth probabilities of loss are estimated imperfectly. There is significant uncertainty, within and between state-of-the-art catastrophe models, as to the expected loss from a cyclone in a particular location.[16] This uncertainty arises from imperfect understanding of the physical processes, and uncertainty as to exactly how these are being altered by climate change. This ambiguity is less severe than for risks such as terrorism, but substantially worse than, for example, auto insurance, for which orders of magnitude more historical data can be relied upon and for which the underlying data generation process is plausibly stationary.

Additionally, even if the ambiguity is not severe enough to cause market collapse, it can still lead to higher pricing. This is a form of the 'winner's curse' (Milgrom and Weber (1982)). When an insurer attracts a policyholder by having the lowest price, this signals their competitors' estimates of true risk were likely higher, and therefore their own estimate likely too low. Consequently, in equilibrium, all insurers price above their estimates of true risk for informational-strategic reasons. This was documented in Californian home insurance by Boomhower et al. (2024).

I test the extent to which the ambiguity of estimates of risk affects the prices and availability of home insurance, and whether these impacts are reduced by the introduction of the reinsurance pool.

Measure of Risk Ambiguity. To proxy for the ambiguity of risk in a way that doesn't get entangled with the risk itself, I use the standard deviation (in thousands of dollars) in

[15] For example, Kunreuther, Pauly, and McMorrow (2013) posit this as the reason why there is no insurance for terrorism in the US.

[16] See, for example, Knutson et al. (2010); Lee and Musulin (2022).

pre-CRP prices in a zipcode. Disagreement among insurer models due to ambiguous risk will, all else equal, lead to greater dispersion in prices. As noted in Section 3.3.1, price dispersion persists (i.e. Bertrand-style competition does not occur) through a combination of slightly differentiated products and substantial search frictions.

Method. Analogously to Section 6, 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:

$$\begin{aligned}(10)\qquad Premium_{a,t,i,z,p} &= \gamma_t + \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \aleph \times \text{Risk Ambiguity}_z \\ &\quad + \aleph_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Ambiguity}_z + \epsilon,\\ (11)\qquad Quoted_{a,t,i,z,p} &= \gamma_t + \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \aleph \times \text{Risk Ambiguity}_z \\ &\quad + \aleph_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Ambiguity}_z + \epsilon,\end{aligned}$$

The coefficients of interest are $\aleph$ and $\aleph_{Post}$. $\aleph$ measures the baseline difference in the premium/probability that insurance is offered when the standard deviation of pre-CRP prices in a zipcode increases by \$1,000. $\aleph_{Post}$ 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 6. 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 8 about here

Table 8 shows that ambiguity caused higher prices and lower availability, but that these effects were moderately attenuated by the CRP. Prior to the CRP, controlling for risk, a \$1,000 increase in the standard deviation of premiums offered across insurers was associated with 13% higher premiums and 1.2% lower availability, per specification (5)[17]. After the CRP was introduced, half of the price penalty and three quarters of the availability reduction were negated.

This shows that, controlling for risk levels, the pre-CRP pricing of tail risk penalizes

[17]Here, unlike in all other specifications, the choice of fixed effects alters the results. I use the more granular fixed effects (odd numbered columns rather than even) as my preferred

ambiguity. Although economically significant, these effects are an order of magnitude smaller than the effects of correlation. In Appendix A.7, I estimate the effects of correlation and ambiguity together and obtain identical estimates to this and the prior section individually.

Similarly to the correlation analysis, in Section A.2, I show that both the pre-CRP ambiguity premium and 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.

8. Mechanism IV: Competition Effects

The reinsurance pool induced insurers to offer insurance to addresses they previously did not. The increased competition could lead to additional premium reductions, further mitigating the market failure the pool was introduced to fix.

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. The coefficient τ represents the treatment effect in zipcodes in time periods in which there was no new insurer entry. The new coefficient represents the treatment effect in zipcodes in time periods with new entry.

Insurer entry is potentially endogenous. Insurers may strategically choose to enter zipcodes based on unobserved factors that also influence premiums, such as expected profitability or market conditions. This self-selection could bias the estimates of the effect of new entry on premiums. To overcome this endogeneity issue, I instrument for the entry of new insurers with the proportion of insurers quoting in a zipcode in the time periods before the reinsurance pool was introduced. The pre-treatment proportion of insurers serves as a proxy for the lack of competition in a market, which is correlated with the subsequent entry of new insurers. However, the pre-treatment market conditions that influenced this proportion should not have a direct effect on premiums in the current period, other than through the direct or indirect competition effects of the reinsurance pool. In Table 9 I present estimates of the core specifications augmented with the entry indicator, with and without the IV.

Table 9 about here

Table 9 shows that the indirect effects of increased competition contributed significantly to the impact of the reinsurance pool. The IV results show that the additional price reduction with new entry is 79% (column (2)) or 131% of the baseline price reduction effect with no new entry. Put another way, for markets with new entry, between 44% and 56% of the total price reduction effect comes indirectly from new entry; the remainder is the direct effect of cheaper reinsurance. This shows that frictions in the reinsurance market that lead to depressed insurance offerings have a compound effect. Prices are high because reinsurance costs are high, and because there is limited competition. The reinsurance pool directly targeted the former, but had the knock-on effect of improving the latter, which then further reduced prices.

9. Conclusion

Increasing climate risk has caused insurance market dysfunction worldwide, demonstrating the failure of reinsurance markets and catastrophe bonds to globally diversify local risk. This paper studies a novel government response: public, risk-based, reinsurance for cyclone risk within the Australian home insurance market. By assuming the tail risk, this government program reduced premiums by over 20% and increased availability by over 11%. I show that these effects are primarily driven by a reduction in the reinsurance markup associated with correlated risk, with additional indirect effects through increased competition and reduced ambiguity.

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.

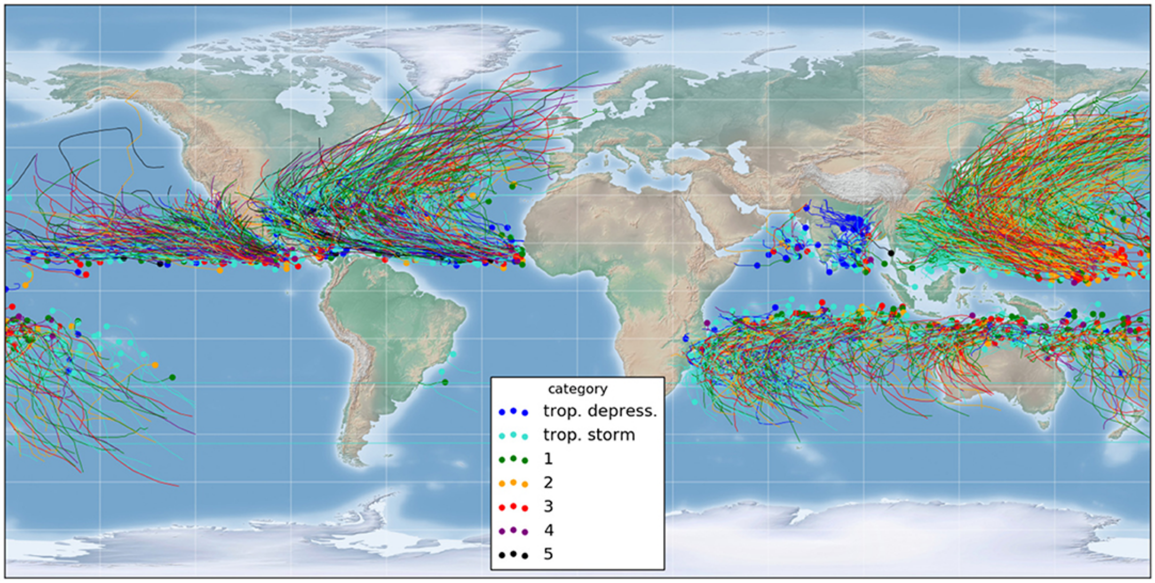

FIGURE 1. Map of global cyclones/hurricanes/typhoons since 1979 (reproduced from Giffard-Roisin et al. (2020)).

Key features	AAMI	Allianz	ANZ	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 (NQH (2024)).												
Deductible	$400	$500	$500	$400	$500	$500	$500	$500	$500	$400	$500	$500

TABLE 1. 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 NQH (2024).

Cyclone Risk		Pre-treatment Mean	Pre-treatment SD	Pre-treatment N	Post-treatment Mean	Post-treatment SD	Post-treatment N
Low Risk	Premium ($)	2439.15	2277.16	137874	2401.84	2196.59	69524
	Proportion of Insurers Quoting	0.60	0.49	228158	0.62	0.48	111357
Medium Risk	Premium ($)	2934.30	2582.85	541302	2866.98	2582.06	279114
	Proportion of Insurers Quoting	0.59	0.49	910764	0.63	0.48	443406
High Risk	Premium ($)	3408.67	2958.70	641001	3070.74	2646.78	336421
	Proportion of Insurers Quoting	0.56	0.50	1137126	0.61	0.49	553644

TABLE 2. 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

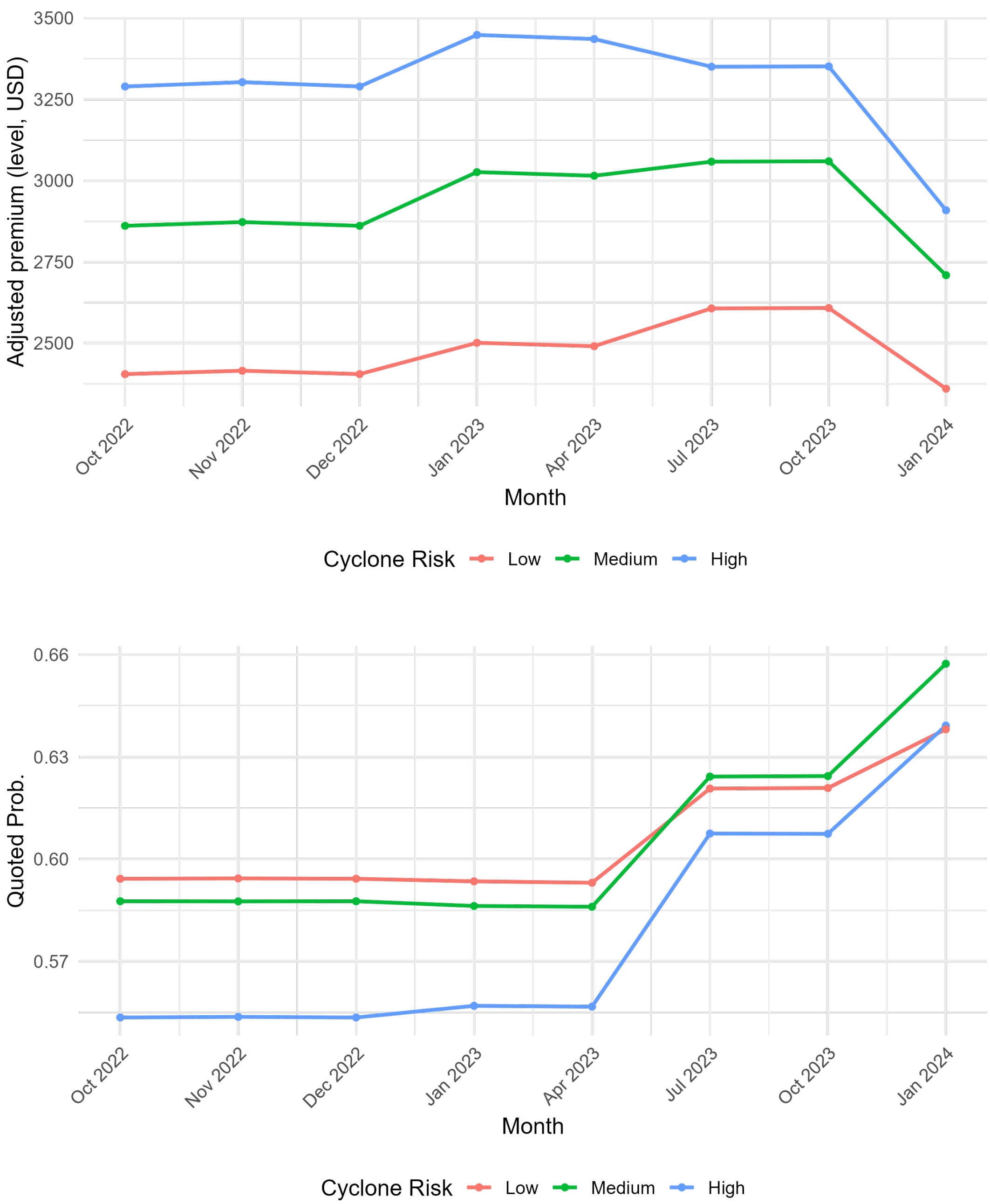

FIGURE 2. Adjusted time series by cyclone risk category. Top panel shows premiums; bottom panel shows quote rates. Each series is constructed by: estimating $y_{it} = \sum_s \beta_s \mathbb{1}(t = s) + \alpha_i + \varepsilon_{it}$ separately for each cyclone risk group, where y_{it} is the outcome (premium or quoted), α_i represents non-geographic fixed effects, 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.

Empirical Strategy	Differential Exposure (1)	(2)	Staggered Treatment (3)	(4)
Effect Of CRP Participation On Log(Premium)	-0.220^{***} (0.044)	-0.266^{***} (0.043)	-0.107^{*} (0.049)	-0.116^{**} (0.053)
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	1 963 614	1 963 614	4 266 658	4 266 658
R^2	0.87	0.04	0.82	0.03

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

TABLE 3. 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. 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 Whether Insurance Is Quoted	0.112***	0.110***	0.052	0.052
	(0.017)	(0.017)	(0.053)	(0.053)
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	3 320 015	3 320 015	7 244 523	7 244 523
R^2	0.79	0.14	0.75	0.12

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

TABLE 4. 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. 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 All Insurers	-0.296^{***}	-0.356^{***}	-0.213^{***}	-0.235^{***}
	(0.039)	(0.038)	(0.069)	(0.076)
Additional Effect Of CRP Participation For Foreign Subsidiaries	0.390^{***}	0.460^{***}	0.384^{***}	0.431^{***}
	(0.020)	(0.022)	(0.081)	(0.095)
Clustering	Suburb	Suburb	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	1 963 614	1 963 614	4 266 658	4 266 658
R^2	0.87	0.04	0.82	0.03

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

TABLE 5. 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. Columns (1) and (3) include insurer x policy fixed effects, while columns (2) and (4) include only insurer fixed effects.

Outcome: Log Premium	(1)	(2)
Cross-Subsidy Effect	0.11	0.07
	(0.09)	(0.07)
Pure Treatment Effect	-0.35^{***}	-0.37^{***}
	(0.13)	(0.12)
Clustering	Insurer	Insurer
FE: Time	✓	✓
FE: Insurer		✓
FE: Insurer x Policy	✓	
N	1 963 614	1 963 614
R^2	0.87	0.04

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

TABLE 6. Tests for cross-subsidies versus pure markup reduction. The estimating equation is 7 and the displayed effects are Cross-subsidy effect = $RP_{post,F} - RP_{pre,F} = \beta_2 + \beta_4$, and Isolated markup reduction = $[RP_{post,D} - RP_{pre,D}] - [RP_{post,F} - RP_{pre,F}] = -\beta_4$. Standard errors, clustered at the insurer level, are reported in parentheses.

Outcome: Log Premium	(1)	(2)	(3)	(4)	(5)	(6)
Pre-CRP Effect Of Risk Correlation	0.671***	0.664***	0.815***	0.807***	0.815***	0.807***
	(0.155)	(0.148)	(0.153)	(0.146)	(0.153)	(0.146)
Post-CRP Change In The Effect Of Risk Correlation	−0.126**	−0.144**	−0.235***	−0.249***	−0.428***	−0.433***
	(0.062)	(0.063)	(0.072)	(0.073)	(0.091)	(0.090)
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	497 986	497 986	497 986	497 986	497 986	497 986
R^2	0.77	0.06	0.77	0.06	0.78	0.07

Outcome: Insurance Offered	(1)	(2)	(3)	(4)	(5)	(6)
Pre-CRP Effect Of Risk Correlation	−0.103*	−0.103*	−0.113**	−0.113**	−0.113**	−0.113**
	(0.053)	(0.053)	(0.052)	(0.052)	(0.052)	(0.052)
Post-CRP Change In The Effect Of Risk Correlation	0.099***	0.099***	0.095***	0.094***	0.137***	0.136***
	(0.023)	(0.023)	(0.024)	(0.024)	(0.033)	(0.033)
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	818 746	818 746	818 746	818 746	818 746	818 746
R^2	0.86	0.15	0.86	0.16	0.86	0.16

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

TABLE 7. 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 (8 and 9). 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 Ambiguity	0.127***	0.676***	0.138***	0.679***	0.138***	0.679***
	(0.010)	(0.017)	(0.011)	(0.017)	(0.011)	(0.017)
Post-CRP Change In The Effect Of Risk Ambiguity	−0.036***	−0.033***	−0.045***	−0.034***	−0.062***	−0.032***
	(0.004)	(0.002)	(0.006)	(0.003)	(0.007)	(0.003)
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	497 986	497 986	497 986	497 986	497 986	497 986
R^2	0.89	0.06	0.89	0.05	0.89	0.06

Outcome: Insurance Offered	(1)	(2)	(3)	(4)	(5)	(6)
Pre-CRP Effect Of Risk Ambiguity	−0.011***	−0.026***	−0.012***	−0.026***	−0.012***	−0.026***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Post-CRP Change In The Effect Of Risk Ambiguity	0.006***	−0.006***	0.006***	−0.006***	0.009***	−0.005***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
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	818 746	818 746	818 746	818 746	818 746	818 746
R^2	0.86	0.15	0.86	0.16	0.86	0.16

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

TABLE 8. Estimated effects of the ambiguity of risk on insurance premiums (top panel) and availability (bottom panel), before and after the introduction of the reinsurance pool. The coefficients in the first row represent the baseline difference in premiums or probability of being offered insurance when the standard deviation of the distribution of pre-CRP premiums increases by $1,000. The estimating equations are (10 and 11). 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.

Empirical Strategy	Differential Exposure		Staggered Treatment	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Effect of CRP Participation on Log(Premium) With No New Entry	−0.183***	−0.180***	−0.074*	−0.064**
	(0.017)	(0.017)	(0.036)	(0.028)
Additional Effect of CRP Participation on Log(Premium) With New Entry	−0.021***	−0.143***	−0.053**	−0.084**
	(0.003)	(0.035)	(0.020)	(0.033)
Clustering	Suburb	Suburb	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Address x Insurer x Policy	✓	✓	✓	✓
N	1 723 774	1 722 909	3 741 522	3 630 972
R^2	0.87	0.87	0.87	0.87

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

TABLE 9. Estimated direct effects of entering the reinsurance pool and indirect effects of increased competition on 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. Columns (1) and (3) present OLS estimates, while columns (2) and (4) use an instrumental variable (IV) approach to address potential endogeneity in insurer entry. The instrument is the pre-treatment proportion of insurers quoting in a zipcode. Standard errors, clustered at the suburb or insurer level, are reported in parentheses. All specifications include address x insurer x policy and time fixed effects.

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Appendix A. Empirical Appendix

A.1. Reinsurance and Catastrophe Bond Markups

I have documented that the CRP led to premiums falling by 10-20%. 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%.[18] 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.

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

Variable	Overall	Domestic Reinsurer	Foreign Reinsurer
Premiums ($M)	489.08	531.95	341.40
	(702.39)	(736.38)	(547.63)
Claims ($M)	375.54	408.73	261.18
	(566.56)	(596.52)	(431.35)
Reinsurance Outflows ($M)	132.07	155.38	51.75
	(345.65)	(387.89)	(68.79)
Reinsurance Inflows ($M)	98.14	114.02	43.45
	(273.69)	(305.48)	(88.64)
Reinsurance Recovery Ratio	0.798	0.695	1.153
	(1.597)	(1.347)	(2.227)
Commissions ($M)	42.25	41.70	44.15
	(66.11)	(65.35)	(68.93)
Other Operating Expenses ($M)	18.70	18.75	18.55
	(29.87)	(29.81)	(30.24)
Net Profit/Loss ($M)	19.27	20.45	15.21
	(76.43)	(81.14)	(57.40)
Number of Observations	489	379	110

TABLE A1. Summary statistics for quarterly insurer–reinsurer flows from APRA filings, 2017–present. Means are reported with standard deviations in parentheses; dollar amounts are AUD millions. Columns divide observations by reinsurer domicile (domestic vs. foreign). 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 ratio of reinsurance claims reimbursed (inflows) relative to reinsurance premiums paid (outflows) is approximately 0.8. This is notably higher for insurers who are subsidiaries of foreign parents (1.153) than for domestic Australian insurers (0.695), consistent with the evidence in Section 5. Similarly, catastrophe bonds require a spread of 7.85% over and above the modeled expected loss of 2.54%; a markup of over 300%.

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.

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

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

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***
	(0.069)	(0.119)	(0.106)
Claims		0.597***	0.611***
		(0.020)	(0.020)
Premiums		−0.399***	−0.252***
		(0.030)	(0.079)
FE: Company	✓	✓	✓
FE: Quarter	✓	✓	✓
Weighted by	-	-	Premiums
N	489	489	489
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.

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

	(1)	(2)	(3)
Expected Loss	1.456***	1.965***	1.651***
	(0.351)	(0.162)	(0.086)
Cyclone × Expected Loss		−0.596	−0.300*
		(0.315)	(0.131)
Australia × Expected Loss			0.183
			(0.357)
FE: Issue Year	✓	✓	✓
FE: Issuer	✓	✓	✓
N	443	442	466
R^2	0.435	0.438	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.

markup of about 2/3. Similarly, the markup in catastrophe bonds is approximately 50% above expected loss (i.e. a typical bond with an expected loss of 5% will pay a spread of $1.456 \times 5\% = 7.28\%$.)

Markups in the pre-CRP tail-risk market of, conservatively, 50%, plausibly rationalize the price reductions of 10-20% in the prior section. As a back-of-the-envelope approximation, prior to the CRP reinsurance accounted for between 32% (moderate cyclone risk) and 50% (high cyclone risk) of the premium[19] If the CRP accurately priced at their stated markup of 4%, this would mechanically generate a premium saving of 14% for moderate-risk properties and 23% for high-risk properties.

A.2. Appendix: Foreign Affiliation Heterogeneity in Correlation and Ambiguity Mechanisms

Section 5 showed that the CRP had a larger effect on prices for domestic Australian insurers relative to vertically integrated Australian subsidiaries of foreign reinsurers. Sections 6 and 7 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 implications

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

the pre-CRP frictions , sharper among domestic Australian insurers relative to vertically integrated foreign subsidiaries.

As in Sections 6 and 7, I restrict the sample to the first period (pre-treatment) and last period (post-treatment), and estimate for correlation

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

And similarly for ambiguity:

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

The coefficients of interest are κ_D ($\aleph_D$) and $\Delta\aleph_D$ ($\Delta\aleph_D$), the pre-CRP and post-CRP price preimums from correlation (ambiguity) for domestic insurers relative. The results are in Tables A5 and A6.

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	0.329***	0.249***	0.216***
Domestic Insurers: κ_D	(0.079)	(0.069)	(0.066)
Post-CRP Change In Domestic	−0.249***	−0.114***	−0.139***
Effect Of Risk Correlation: $\Delta\kappa_D$	(0.041)	(0.005)	(0.004)
Risk Controls:	Basic	Basic	Basic
Insurer x t Specific Risk Pricing	✓	✓	✓
Clustering	Suburb	Suburb	Suburb
FE:	Insurer x t	Non-geo	Insurer
N	524 569	524 569	524 569
R^2	0.07	0.87	0.06

TABLE A5. 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	0.603***	0.121***	0.608***
(Foreign Subsidiaries): $\aleph$	(0.011)	(0.008)	(0.011)
Additional Pre-CRP Effect For	0.097***	0.049***	0.107***
Domestic Insurers: $\aleph_D$	(0.003)	(0.004)	(0.004)
Post-CRP Change In Domestic	−0.026***	−0.060***	−0.058***
Effect Of Risk Ambiguity: $\Delta\aleph_D$	(0.002)	(0.002)	(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	1 035 314	1 035 314	1 035 314
R^2	0.52	0.84	0.51

TABLE A6. Estimated effects of risk ambiguity on insurance premiums, allowing for differential pricing and post-CRP changes for domestic insurers. The estimating equation is (A4). Risk ambiguity is proxied by the zipcode-level dispersion in pre-CRP premiums (scaled as in the main text). The first row reports the baseline (pre-CRP) ambiguity penalty for foreign subsidiary insurers, $\aleph$. The second row reports the additional pre-CRP ambiguity penalty for domestic insurers relative to foreign subsidiaries, $\aleph_D$. The third row reports the post-CRP change in the ambiguity 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.

Tables A5 and A6 show that domestic insurers face a substantially higher cost of bearing correlated or ambiguous risk relative to foreign subsidiaries. Prior to the CRP, holding risk fixed, and relative to foreign subsididiaries, domestic insurer prices are 22-33% (5-11%) higher as correlation (ambiguity) increases from 0 to 1.

Much or all of this penalty is nullified by the CRP: the premium is reduced by 12-25% (3-6%), representing about half or more of the pre-CRP penalty. This implies that the costs of bearing tail risk, caused either by correlation or ambiguity (i.e. model risk), are highest among firms that have more constrained access to tail-risk sharing through reinsurance. The CRP, by reducing the costs of tail-risk sharing, reduces the implicit tail-risk premium caused by correlation or ambiguity, has the largest effect among the firms and in the places where tail-risk is highest and where the constraints to reinsure tail risk are sharpest.

A.3. Event Studies and Robustness to Sun and Abraham (2021) Correction

In this section, I present event study versions of the primary specifications in Tables 3 and 4.

First, for 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 3 and 4.

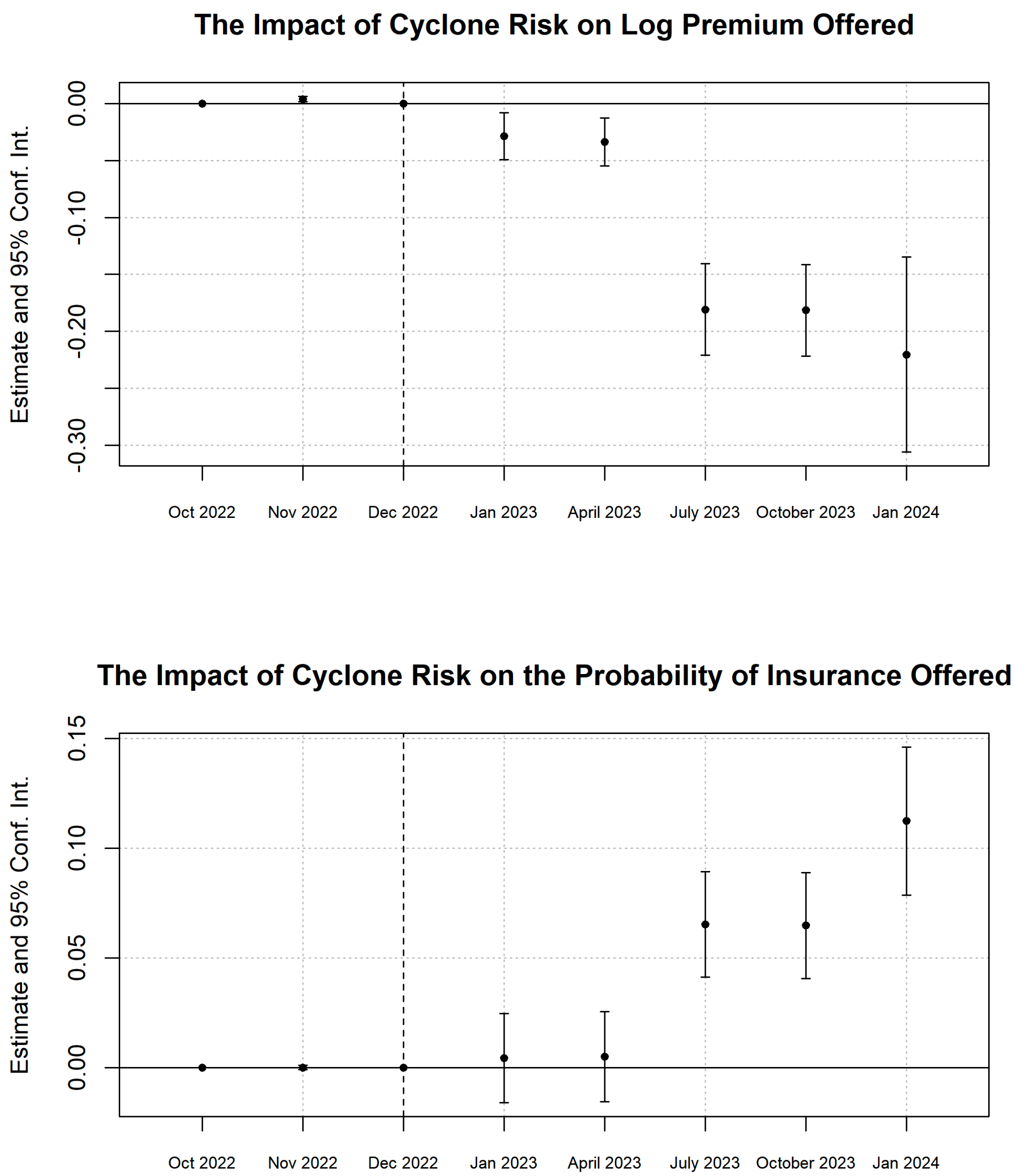
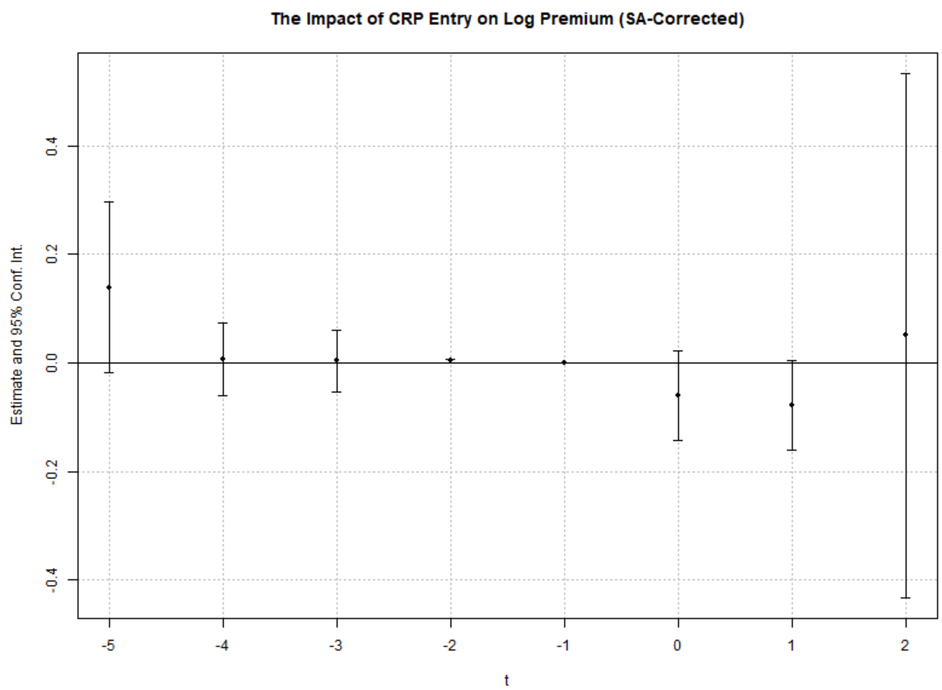


FIGURE A1. Event study coefficients for the effect of the reinsurance pool on log insurance premiums (top panel) and whether insurance is quoted or not (bottom panel), based on the differential exposure specification (2). The figure plots the estimated coefficients τ_t and their 95% confidence intervals. 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 two in November 2023.

Figure A1 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, the final two in November 2023) the premium reductions get progressively larger, and the number of insurers entering the market gradually increases.

One of my identification strategies leverages the staggered adoption of the CRP by different insurers. The TWFE specification I use in the primary analysis has been shown to be potentially misspecified due to a problem of ’bad controls’. To check that the results from this specification are robust to these concerns, I estimate the Sun and Abraham (2021)-corrected procedure. For power and to avoid collinearity, I pool all treated periods with relative time more than 5 periods before treatment and more than two periods afterwards. The results are in Figure A2.



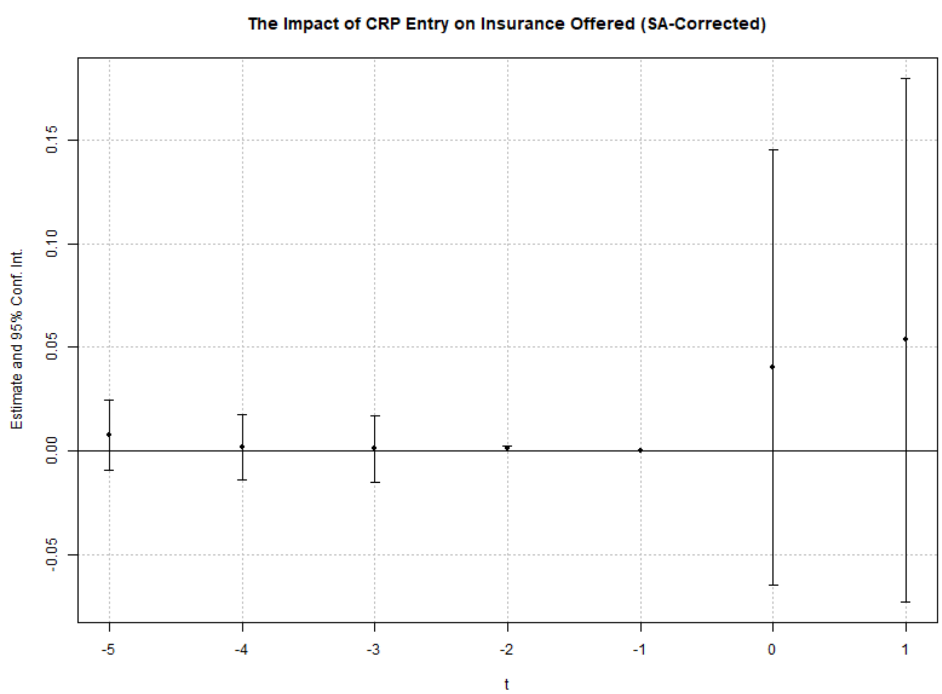


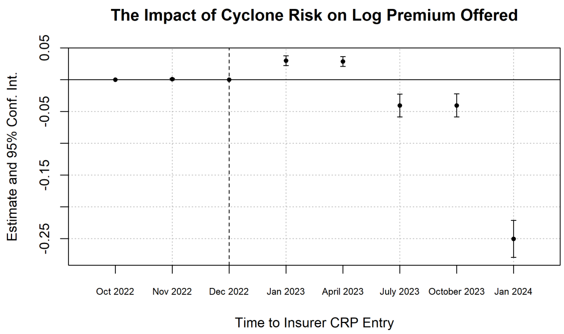
FIGURE A2. Event-study estimates from the Sun–Abraham (2021) staggered-adoption estimator. The outcome is log premium (top panel) and whether insurance is quoted or not (bottom panel). Coefficients are normalized relative to $\tau = -1$; leads with $\tau \leq -5$ and lags with $\tau \geq 1$ (2 for log premium) are pooled for power. Specifications include insurer and calendar-time fixed effects. 95% confidence intervals are shown and are clustered by insurer.

Figure A2 shows that the qualitative results in Tables 3 and 4 are robust. The event studies are naturally less precisely estimated than the difference-in-differences coefficients, especially for the very early and very late relative time periods (even with the pooling described above).

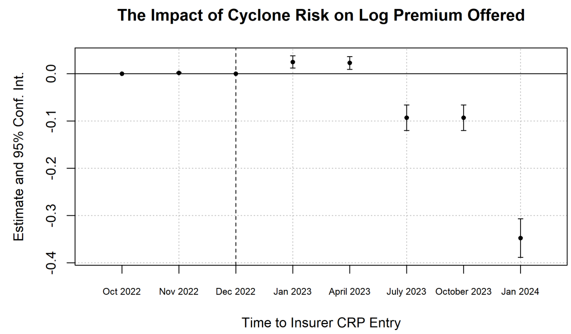
A.4. Robustness of Main Results to Alternate Measures of Wind Risk

I re-run the analyses first presented in Tables 3 and 4 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.

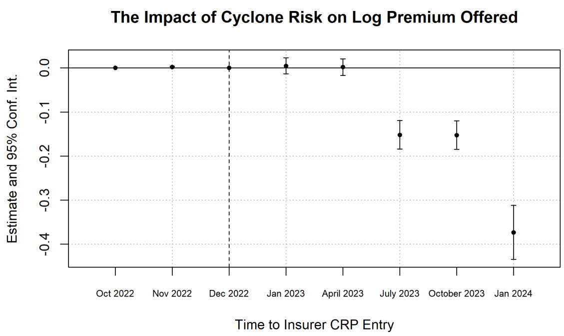
First, for the premiums offered. The results are in Figure A3. The general pattern is very robust to the measure of wind risk.



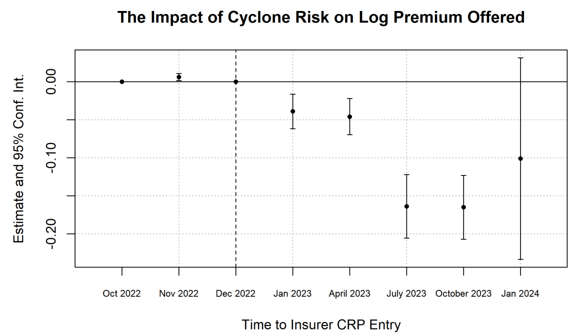
A. 2 Year Wind Speed



B. 5 Year Wind Speed



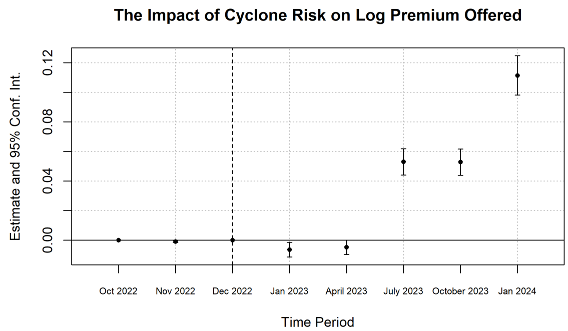
C. 10 Year Wind Speed



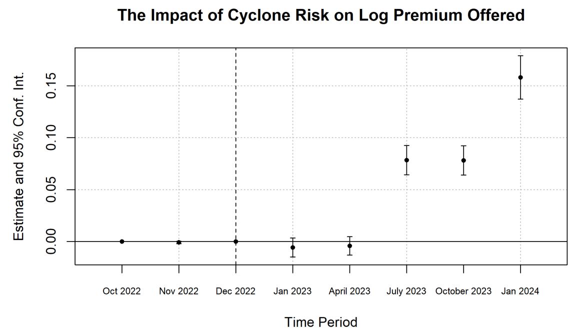
D. 50 Year Wind Speed

FIGURE A3. 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 two in November 2023.

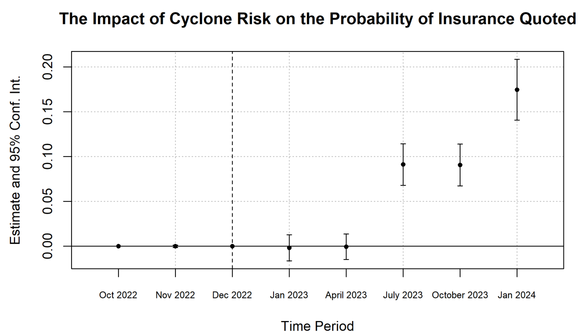
Second, for the probability of insurance being offered. The results are in Figure A4. The results are qualitatively unchanged when different measures of wind risk are used.



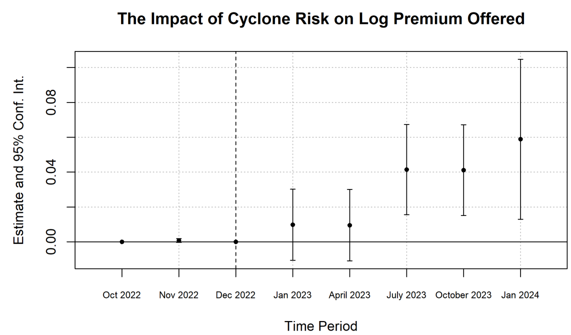
A. 2 Year Wind Speed



B. 5 Year Wind Speed



C. 10 Year Wind Speed



D. 50 Year Wind Speed

FIGURE A4. 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 two in November 2023.

A.5. 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 only updated the areas in which they offered insurance only in March - April 2023.[20] For this reason, in my primary specification, I code treatment for these January 2023 insurers as occurring in January for premiums,

[20] See All (2023a) and All (2023b).

and in April for whether insurance is quoted at all.

I check robustness to these choices in Appendix A.6. 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.6. 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 A7 below.

Empirical Strategy	Differential Exposure		Staggered Treatment	
	(1)	(2)	(3)	(4)
Estimate of τ	-0.220***	-0.266***	-0.044	-0.040
	(0.044)	(0.043)	(0.072)	(0.075)
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer		✓		✓
N	1 963 614	1 963 614	4 266 658	4 266 658
R^2	0.87	0.04	0.82	0.03

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

TABLE A7. 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. 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 results for the staggered entry specification are about half the size as before.

A.7. 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 6 and 7. I estimate the combined specifications.

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

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

The results are in Table A8.

Outcome: Log Premium	(1)	(2)	(3)	(4)	(5)	(6)
Estimate of ℵ	0.117***	0.674***	0.122***	0.675***	0.122***	0.675***
	(0.010)	(0.017)	(0.010)	(0.017)	(0.010)	(0.017)
Estimate of $\aleph \times t = 7$	−0.033***	−0.032***	−0.038***	−0.032***	−0.045***	−0.027***
	(0.004)	(0.002)	(0.005)	(0.003)	(0.007)	(0.003)
Estimate of κ	0.617***	0.363***	0.746***	0.431***	0.746***	0.431***
	(0.141)	(0.080)	(0.139)	(0.079)	(0.139)	(0.079)
Estimate of $\kappa \times t = 7$	−0.107*	−0.094	−0.202***	−0.132**	−0.352***	0.006
	(0.059)	(0.058)	(0.068)	(0.065)	(0.081)	(0.052)
N	496 294	496 294	496 294	496 294	496 294	496 294
R^2	0.90	0.53	0.90	0.53	0.90	0.54
Outcome: Insurance Offered	(1)	(2)	(3)	(4)	(5)	(6)
Estimate of ℵ	−0.009***	−0.025***	−0.009***	−0.025***	−0.009***	−0.025***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Estimate of $\aleph \times t = 7$	0.003*	−0.007***	0.003	−0.007***	0.007**	−0.006***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Estimate of κ	−0.134*	−0.129*	−0.146**	−0.138**	−0.146**	−0.138**
	(0.070)	(0.067)	(0.069)	(0.066)	(0.069)	(0.066)
Estimate of $\kappa \times t = 7$	0.133***	0.138***	0.127***	0.128***	0.179***	0.167***
	(0.031)	(0.032)	(0.033)	(0.033)	(0.043)	(0.042)
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	611 892	611 892	611 892	611 892	611 892	611 892
R^2	0.71	0.43	0.72	0.43	0.72	0.44

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

TABLE A8. Estimated effects of the ambiguity of risk and the spatial correlation of risk 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 7 and 8 respectively. Standard errors, clustered at the zipcode level, are reported in parentheses.

These results are qualitatively identical to the separated analyses run in Sections 6 and 7. As in Section 6, prior to the pool, correlation dramatically pushes up premiums and reduces insurance availability. After the introduction of the pool, the effect for availability is fully nullified, and the effect for premiums is half the size. As in Section 7, ambiguity has quantitatively minimal effects both pre- and post- the introduction of the reinsurance pool.

A.8. Categorization of Domestic vs Foreign Subsidiaries for Reinsurance Analysis

Insurer (short)	Foreign	Foreign_Re	Explanation (parent and reinsurance status)
AAI (Suncorp)	0	0	Australian listed Suncorp; no reinsurance arm.
Aioi Nissay Dowa Aust.	1	1	MS&AD (Japan) owns MS Amlin reinsurer.
Aioi Nissay Dowa JP	1	1	Same MS&AD / MS Amlin group.
Allianz Aus General	1	1	Allianz SE (Germany) with Allianz Re.
Allianz Aus Insurance	1	1	Allianz SE; Allianz Re covers group.
Auto & General	1	0	BHL / Budget Direct (UK/SA); direct only.
CIC Allianz	1	1	Allianz JV; Allianz Re in group.
Commonwealth Ins.	1	0	Hollard (South Africa); cedes only.
Credicorp	1	0	Credicorp Ltd (Peru); no reinsurer.
Great Lakes	1	1	Munich Re group reinsurer.
Hallmark	0	0	St Andrews (Australia); no reinsurer.
Hollard Partners	1	0	Hollard group; direct writer only.
IAG (IAL)	0	0	Australian IAG; cedes externally.
IMA (IAG/RACV)	0	0	70% IAG, 30% RACV; no reinsurer.
LFI Group	0	0	Small AUS lender-insurer; none.
OnePath GI	1	1	Zurich (CH) with internal reinsurer.
Optus Insurance	1	0	Singtel (SG) telecom; no reinsurer.
Progressive Direct	1	0	Progressive (US); direct writer only.
QBE Australia	0	0	QBE headquartered in Sydney.
QBE International	0	0	Same Australian QBE parent.
RAA / RAC / RACQ / RACT	0	0	Member owned AUS motoring clubs.
Southern Cross	1	0	NZ health insurer; no reinsurer.
St Andrews	0	0	AUS creditor insurer; no reinsurer.
Hollard Insurance Co.	1	0	Hollard (SA); no reinsurer.
Westpac GI	1	1	Sold to Allianz SE; Allianz Re covers.
Youi	1	0	OUTsurance (SA); direct only.

TABLE A9. Ownership and reinsurance status of selected Australian direct and personal-lines insurers. These are used in the categorization of domestic versus foreign insurers.

A.9. 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 NQH (2024):

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	-
Condition of building/construction quality?	Average/standard as default	Sometimes varied to achieve required sum insured

Table A10 continued from previous page

Question	Default Answer	Comment
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 A10. Fixed parameters used in insurance quotations. All addresses were quoted with these standardized characteristics held constant, following the methodology in NQH (2024). 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.