Insuring Correlated Climate Risk: Evidence from Public Reinsurance

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Increasing climate risk has caused insurance in many locations to become unaffordable or unavailable. I study a novel policy response in Australian home insurance: government provided, mandatory, actuarially fair, reinsurance for cyclone damage. In this scheme, the government reinsures the cyclone risk, while the private market covers the remaining idiosyncratic risk. I find that public reinsurance leads to a 21% decrease in home insurance premiums and an 11% increase in the probability of insurance being offered at all. In terms of mechanisms, I rule out subsidization and show that the ambiguity of the risk has a minimal impact on premiums and insurance offerings. Instead, the entirety of the increase in insurance offered, and much of the decrease in premiums, comes from reducing the implicit costs associated with insuring spatially correlated risk. Increased competition due to insurer entry explains the remaining premium reductions. This isolates the cause of market dysfunction - correlated risk - and suggests that public reinsurance is a cost-effective policy to rehabilitate insurance markets for catastrophic climate risks.

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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. In regions prone to extreme weather shocks that do concentrated damage, such as cyclones, floods, and wildfires, these challenges have become particularly acute. Insurers around the world[1] have responded by dramatically increasing premiums and, in some cases, withdrawing from the market altogether. Homeowners are left struggling to find affordable coverage, or any coverage at all. This paper analyzes the precise cause of insurance market dysfunction and explores a novel policy solution: public reinsurance.

Governments have experimented with various policy responses to rising prices and reduced offerings in insurance markets. Governments have directly offered public insurance in markets not served by private firms (e.g. flood insurance and crop insurance in the US). These have typically become subsidy schemes with prices well below actuarial cost, potentially leading to moral hazard and encouraging excessive risk-taking and development in hazard-prone areas.[2] Other governments have created a public 'insurer-of-last-resort' to provide coverage to segments of the market that the private market cannot serve 'affordably' (e.g. Florida Citizens, California Earthquake Authority). These have often decoupled risk from prices and cannibalized the private market. [3] Finally, some regulators (e.g. US state insurance departments) have attempted to arrest price increases by requiring pre-approval for all premium changes, which has distorted prices away from accurately reflecting risk, caused insurer exit, exacerbated the insurance availability problem, and can lead to reduced insurer solvency.[4] Whether these schemes help or hinder the efficient allocation of risk and provide incentives for risk

[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 (2020), France Local (2021), New Zealand Herald (2020), South Africa Bloomberg (2021), and India Times (2021).

[2]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 Craig, Landry, and Li (2022); Hornbeck and Keniston (2022); Ostriker and Russo (2024).

[3]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.

[4]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.

mitigation is questionable.

In this paper, I analyze a novel policy solution: public, actuarially fair reinsurance. Reinsurance is insurance for insurers. Typically, reinsurance covers aggregate shocks (i.e tail risk): when losses are idiosyncratic, reinsurance doesn't pay, but when they occur in concentration, reinsurance covers total losses beyond a threshold (or 'deductible'). There are reasons to think that the government has a comparative advantage at holding aggregate risk. The government does not have an explicit capital constraint - they can print money or raise taxes as needed, at the marginal cost of public funds. Because private insurers who incur huge costs can declare bankruptcy and be protected by limited liability, they must credibly signal their solvency by holding enough (costly) capital to withstand aggregate shocks. Governments do not have this commitment problem. This paper tests whether, and by what mechanisms, the government can provide reinsurance for aggregate risk more efficiently than the private market. This functions as a limiting principle to government intervention: once the government reinsures the tail risk, does the private market for the remaining idiosyncratic risk function well? Or is there something else fundamentally different about climate risk?

My empirical setting (Section 2.1) 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 (2020)). This is largely driven by reinsurance costs that far exceed the rest of the country, and are rising rapidly.[5] The homeowners insurance market in Australia does not have any price controls. Insurers can increase prices or discontinue coverage at will. Regulation instead focuses on the capital adequacy and solvency of insurers.

I study the Cyclone Reinsurance Pool (CRP), a mandatory public reinsurance scheme run by the Australian federal government (Section 2.2). The CRP takes on only the cyclone risk from homeowners insurance policies. Operationally, once the meteorological

[5] Per Australian Competition and Consumer Commission (2020), reinsurance costs account for 30-40% of gross written premium in Northern Australia, compared to 5-15% in the rest of the country. Reinsurance costs have risen by up to 60% in some years. Causes for this include rising frequency and intensity of natural disasters, in Australia and globally, as well as limited competition in the reinsurance market.

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 all 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 behaviours such as building to higher cyclone resilience standards, retrofitting older homes, and implementing community-level mitigation measures [7]. The pool was announced in July 2023. 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 2.3) come from two sources. First, 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. 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 collect premiums for a randomly chosen address (again, fixed over time) in each zipcode, for a subset of the original insurers, and two additional. 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 2.5.1). 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 offering) 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

[6] Australian Government (2022)
[7] Australian Competition and Consumer Commission (2022)

variation.

Second, I leverage the staggered entry of insurers into the pool (Section 2.5.2). Of the 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 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 3). 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 decrease by 27%, and the probability of insurance being offered increases 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 \$3,408.67, 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 12 percentage point increase in insurance being offered is equivalent to 21.4% of baseline. In Appendix A I demonstrate that these findings are robust to data and specification choices made in the main paper.

I analyze four possible mechanisms for the observed reductions in premiums: an implicit 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.

I do not find evidence of any implicit subsidy in the reinsurance pool's pricing (Section 4). The pool is required, by legislation, to be budget neutral 'over the medium term' (Australian Reinsurance Pool Corporation (2023c)). Nevertheless, one might be concerned that the premium reductions observed are due to prices being set too low relative to true risk, perhaps due to analytical errors. To study this, I contrast three insurers who are Australian subsidiaries of global insurance groups, with the remaining domestic insurers. The former have access to internal reinsurance at cost (Allianz Re (2024); Cummins and Weiss (2000)), whereas the latter have to purchase reinsurance on the open market. If the pool was priced below cost, this subsidy would accrue to both the foreign and domestic insurers. In both empirical specifications, allowing for heterogeneous treatment effects, I find that the pool has a zero or slightly positive effect on the premiums of foreign insurers. All of the decrease observed in the main specifications is driven by domestic insurers. This shows that the pool is priced actuarially fairly: it had no impact for insurers who already had access to actuarially fair internal reinsurance, and a large impact on insurers who previously had to buy marked-up reinsurance on the open market.

I show that the pool primarily affects premiums and insurance offerings by reducing the cost of insuring spatially correlated risk (Section 5). Standard models assume that insurers are risk neutral and care only about the expected cost of a risk. This is unrealistic in practice. Insurers have to hold sufficient capital to stay liquid. Therefore, a risk that is correlated across policyholders, and therefore realizes for many of them, or none, at once, is much costlier to insure than an idiosyncratic risk with the same expected loss. To quantify this, I use a catastrophe model that simulates the damage in each zipcode from thousands of hypothetical cyclones. From this, I compute the expected risk in every zipcode and the correlation of risk in that zipcode with all other zipcodes.

I show that prior to the reinsurance pool the impact of spatial correlation on premiums and offerings is substantial, but this pool almost completely vitiates this. Consider two zipcodes, with the same local risk, but different degrees of correlation with the other locations in the sample. Two locations are correlated when most simulated cyclones hit both, or neither locations, but are unlikely to hit one and not the other. Prior to the pool, a zipcode whose risk is perfectly correlated with the remaining locations has 80% higher premiums and 11% less chance of being offered insurance than a zipcode whose risk is uncorrelated with the remaining locations. After the pool is introduced, the perfectly correlated zipcode is only 37% more expensive, and equally likely to be quoted insurance, than the uncorrelated zipcode. This demonstrates that the pool operates by reducing the substantial costs of insuring correlated risk. It suggests that governments, which are not capital constrained and do not have a commitment problem stemming from limited liability, have a comparative advantage at holding correlated tail risk over the private (re)insurance market.

I show that the effect of the ambiguity of risk on insurance prices and offerings is small and unimpacted by the reinsurance pool. Ambiguity refers to uncertainty around the underlying true probability of loss. There have been numerous papers[8] conjecturing that insurers charge more for or are less likely to insure ambiguous risks. The risk posed by natural catastrophes is ambiguous, even with state-of-the-art models.[9] I measure ambiguity by the uncertainty in the catastrophe model's estimates of cyclone risk. I show that prior to the reinsurance pool, going from the zipcode with minimal ambiguity to the zipcode with mean ambiguity is associated with a 5.2% increase in premiums and a 1.2% decrease in the chance insurance is offered. These are statistically significant but an order of magnitude lower than the effects of correlation. These effects are unchanged after the introduction of the reinsurance pool.

I show that the increase in competition caused by insurer entry was an important contributor to lower premiums (Section 7). Prior to the pool, prices were high because of the challenging reinsurance conditions, but also because few insurers were competing. I analyze the impact on premiums when a new insurer enters a zipcode, controlling for the direct effect of the reinsurance pool. Insurer entry is endogenous to unobserved market conditions, such as expected profitability. I instrument for insurer entry with the proportion of insurers in a zipcode prior to the insurance pool. This strongly predicts entry (i.e the first stage). Exogeneity is plausible, since after controlling for insurer x address fixed effects, pre-treatment market conditions should not affect post-treatment premiums except through the direct effect of the pool or the indirect competition effect. I find that of the total treatment effect on premiums, between 1/4 and 1/3 is due to the increased competition.

Literature Review

This 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 distorted risk signals and risk mitigation behaviour Wagner (2021a); Ostriker and Russo (2024). Similarly, government provided crop insurance provides risk protection value to farmers, but

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

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

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 Nielson (2006)). 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 (2023c)) 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.

Secondly, 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 (2008); Michel-Kerjan, Raschky, and Kunreuther (2006); Dieckmann (2011)). Analogous problems[10] exist for aggregate consumption risk in other financial markets. Frictions that can lead to insurance market dysfunction include adverse selection (e.g. Einav, Finkelstein, and Cullen (2010); Hendren (2013); Solomon (2024)), informational frictions and an associated winner's curse on the supply side (e.g. Boomhower et al. (2024)) moral hazard (e.g. Ehrlich and Becker (1972); Shavell (1979)), and behavioral factors such as ambiguity aversion, myopia, and limited attention on both the demand and supply sides (e.g. Kunreuther, Pauly, and McMorrow (2013); Meyer and Kunreuther (2016); Browne, Knoller, and Richter (2015); Solomon (2023)). Relative to this literature, my contribution is to quantify the impact of the correlation in risk on insurer behaviour, and demonstrate how a targeted government policy can alleviate this impact.

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

Related and concurrent work by Keys and Mulder (2024) shows that home insurance prices have risen sharply in the US due to the increasing cost of insuring disasters. The find, by exploiting between-state differences in the proportion of risk ceded to reinsurers, that these price increases are driven by increasing reinsurance costs that are largely passed through to consumers. I clarify the underlying mechanisms behind increasing reinsurance costs, and show that this impact of rising reinsurance rates can be entirely nullified by public reinsurance.

2. Setting, Data and Empirical Strategy

2.1. Setting

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.[11]. 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)).

[11] 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).

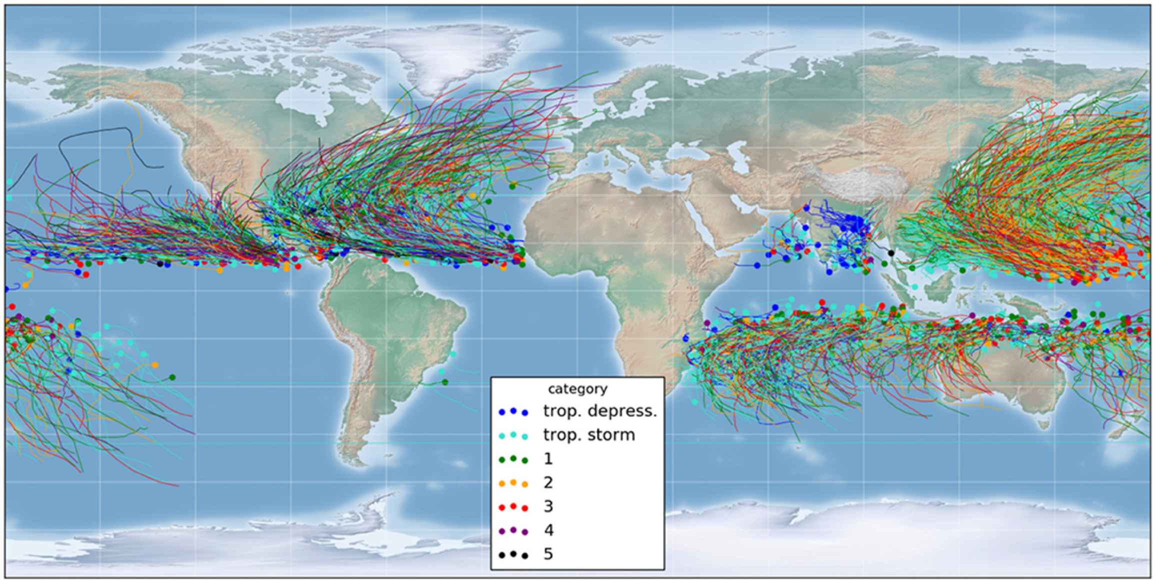

FIGURE 1. Map of global cyclones/hurricanes/typhoons since 1979 (reproduced from Giffard-Roisin et al. (2020)).

2.1.1. 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.[12] 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)).

General insurance is regulated at the national level by the Australian Prudential Regulation Authority (APRA), Australian Securities and Investment Commission (ASIC) and the Australian Competition & Consumer Commission (ACCC). Unlike the U.S., there is no state-by-state regulation. Crucially, *general insurers can set any prices* they wish, and do not need regulatory approval for a price change. Regulation focuses on capital adequacy for systemic stability, prudential standards and competition (Australian Law Reform Commission (2012)), which are discussed further below.

The affordability of home insurance, especially in areas with high natural disaster

[12] Full details of the coverage of the policies in the dataset are discussed in section 2.3.

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 (2020)), 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.

2.2. Policy Change - Cyclone Reinsurance Pool

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

Insurers had to join the CRP by the end of 2023, but could do so earlier. Of the insurers under study, three joined in January 2023, seven joined in July 2023, and the final two in November 2023. The staggered entrance 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 (2023e)). 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).

2.2.1. Relationship to Existing Reinsurance and Capital Regulations

The regulation of general insurers in Australia is focused on capital adequacy to ensure systemic stability. There are two regulations of direct relevance to the CRP.

First, GPS 116 (Australian Prudential Regulation Authority (APRA)) stipulates the stress testing required on insurance portfolios. At a high level, it requires that insurers hold capital and reinsurance sufficient to cover a 1-in-200-year loss on their entire portfolio. For the purposes of this regulation, reinsurance from the CRP was counted in the same way as commercial reinsurance obtained prior. Insurers can still take out additional reinsurance on top of the CRP, and some have.

Second, GPS 114 (Australian Prudential Regulation Authority (APRA)) specifies the capital that needs to be held against various assets. In particular, the capital that needs to be held against reinsurance assets due to counterparty risk. The capital requirement for reinsurance depends on the credit rating of the reinsurer. The S&P credit ratings for the 10 largest reinsurers range from (Atlas Magazine (2023)) A to AA. GPS 114 prescribes a capital charge of 2% to 6% respectively for all reinsurance receivables to account for counterparty risk.

Reinsurance provided by the CRP, since it is guaranteed by the Australian government, has a 0% capital charge. This is a potential mechanism for cost-savings: capital costs are reduced since capital requirements have been loosened by the CRP.

2.3. Data

2.3.1. 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 (2023d)). 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.

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).

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.

2.3.2. 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 geographic location are recorded.

The CHAD summarizes risk by expected maximum wind speeds in 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.2 I show results are robust to using a 2, 5 or 100 year period. To illustrate, Figure 2 shows the maximum wind speeds expected over a 100-year period, as predicted by the CHAD. 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.

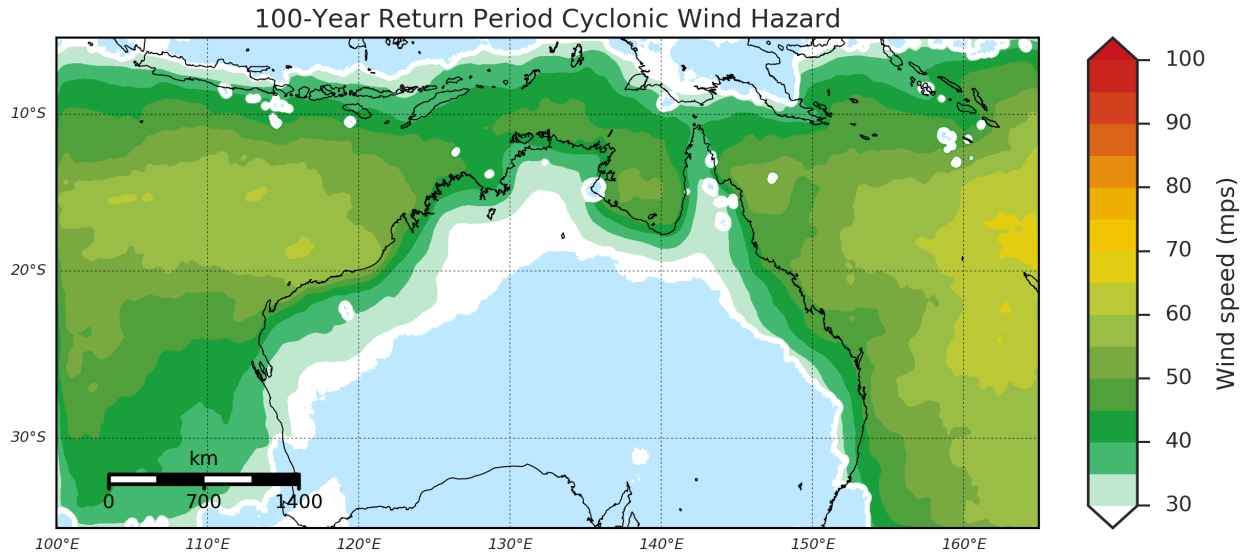

FIGURE 2. Map of predicted maximum wind speeds (in m/s) over a 100-year period for Northern Queensland, Australia Reproduced from the National Tropical Cyclone Hazard Assessment Data (CHAD) model Geoscience Australia (2018). The CHAD model uses historical cyclone data to generate plausible future cyclone scenarios and estimate the associated wind speeds at each location.

2.4. Summary Statistics

Summary statistics are in Table 3. Table 3 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. Low zipcode cyclone risk is defined as the bottom quartile, high risk are the top three quartiles. Additionally, I divide the sample into insurer-time periods pre and post treatment.

In the pre-treatment period, premiums are higher and less insurance is offered in high risk zipcodes. After treatment, the there is little change in premiums n 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.

TABLE 2. Building Insurance Premium Percentiles Summary by Treatment and Percentile/Mean

		Pre-treatment			Post-treatment		
Cyclone Risk		Mean	SD	N	Mean	SD	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 3. 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

2.5. Empirical Strategies

2.5.1. 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.2 I show these results are robust to alternate measures of cyclone risk. For interpretability, I normalize this measure of cyclone risk to be one. Standard errors are clustered at the zipcode level.

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

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

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.

2.5.2. 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. These expiration of these treaties was 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.

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 t, i, z, c, s 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, thr log of the premium quoted by $Log(Premium)_{a,t,i,z,p}$.

I estimate a difference-in-difference 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, in Appendix A.3 I show that the results are robust to including more granular fixed effects. 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.

3. Effects of the CRP

3.1. Premium Reductions

Did the reinsurance pool reduce insurance premiums? To study this, I estimate equations (2) and (4). The results are in Table 4. Recall that the tabulated coefficient for specification (2) is $\tau_{Jan,2024}$, the effect after all insurers have entered the reinsurance pool. The coefficients for the event study version of (2) are in Figure 3. The event study version of (4) is in Appendix A.4

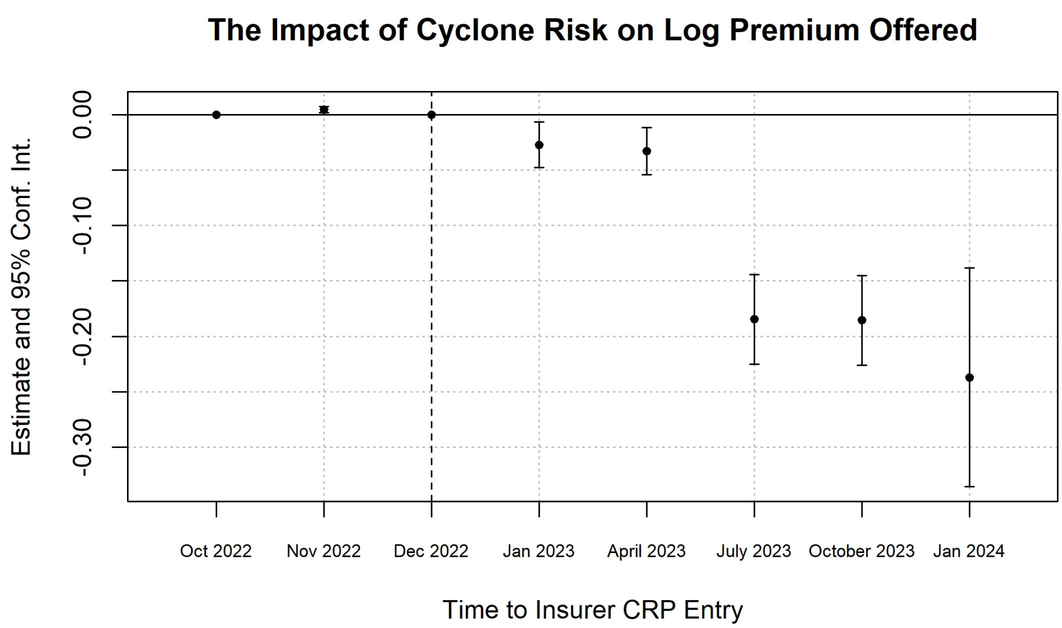

FIGURE 3. Event study coefficients for the effect of the reinsurance pool on log insurance premiums, based on the differential exposure specification (2). The figure plots the estimated coefficients τ_t and their 95% confidence intervals The vertical dashed lines indicate the dates when the first insurers entered the reinsurance pool: January 2023. Seven more entered in July 2023, and the final two in November 2023.

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 4. 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) only insurer fixed effects.

Figure 3 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.

Table 4 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 of risk. In section **??** I rule out any implicit subsidy, and give evidence that the mechanism for premium reductions is a combination of easing frictions in reinsurance markets that come from the concentration of risk and increased competition, although the latter is substantially larger.

3.2. 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) and the display the event study version of the former. The results are in Table 5.

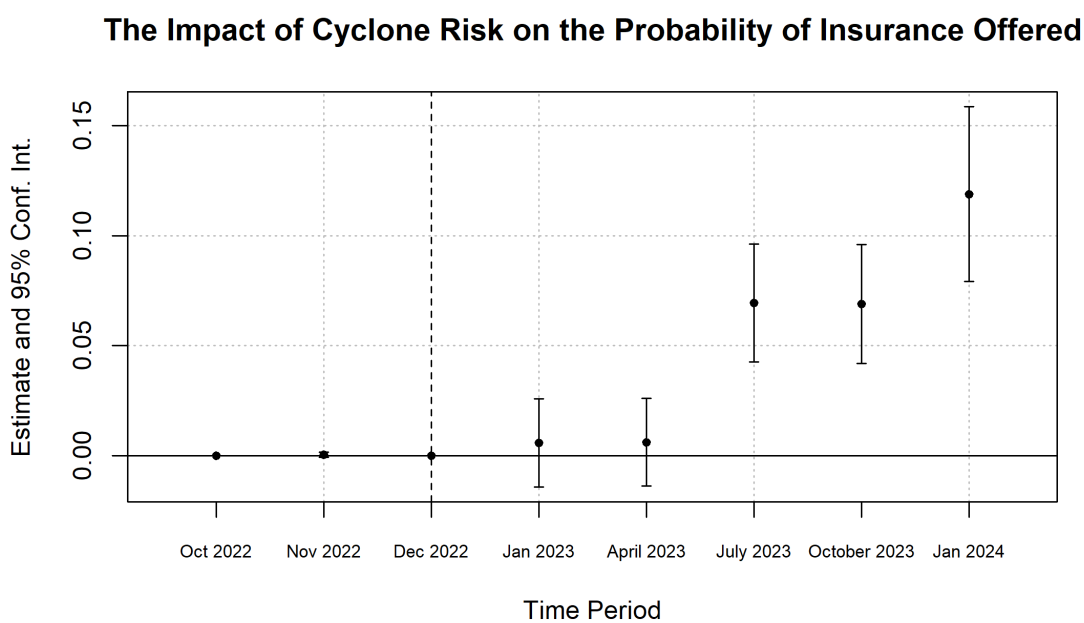

FIGURE 4. Event study coefficients for the effect of the reinsurance pool on whether insurance is quoted or not, based on the differential exposure specification (1). The figure plots the estimated coefficients τ_t and their 95% confidence intervals. The vertical dashed lines indicate the dates when the first insurers entered the reinsurance pool: January 2023. Seven more entered in July 2023, and the final two in November 2023.

Empirical Strategy	Differential Exposure (1)	(2)	Staggered Treatment (3)	(4)
Effect Of CRP Participation On Whether Insurance Is Quoted	0.112*** (0.017)	0.110*** (0.017)	0.052 (0.053)	0.052 (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
R2	0.79	0.14	0.75	0.12

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

TABLE 5. 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) only insurer fixed effects.

Table 5 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 low risk. 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, of which there are only 12.

This is evidence for supply-side frictions in the home insurance market. A risk-neutral insurer, should be willing to offer insurance to anyone at some price. In this market insurers have substantially better information than the insured, and so adverse selection is unlikely to explain this. Before the policy change, insurers refused to offer insurance to some individuals at any price. This suggests that insurers are not behaving as the risk-neutral model predicts they should.

In section 5 I show that costs associated with the correlation in risk, even after controlling for expected loss, entirely explain these insurer frictions. Prior to the reinsurance pool, the zipcodes who are not offered insurance are exactly those whose risk is correlated strongly with other zipcodes. The reinsurance pool removes the most concentrated risk - cyclones - from the basket of risks homes face. After the introduction of the pool, the correlation of risk no longer makes any difference to the chance of insurance being offered.

4. Mechanism I: Is it just a subsidy?

The reinsurance pool is, by statute, designed to be budget neutral ”over the longer term”. Despite these assurances there is a concern that the premium savings and insurance expansions documented above are driven by mis-pricing. If the pool set reinsurance premiums to be lower than actuarially fair, this could cause the effects observed in section 3. If the pool is only working by paying an implicit subsidy to insurers, this reduces the novelty of the policy as a means to combat insurance market failure. That a subsidy in the reinsurance market can lead to dramatic improvements in the functioning of the insurance market would still be interesting, but a different question.

I provide evidence that there is no implicit subsidy in the reinsurance pool - it does offer actuarially fair reinsurance. 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 foreign insurers have internal reinsurance which provide actuarially fair reinsurance to subsidiaries (Allianz Re (2024)). The other nine insurers are Australian with no direct international affiliation and who must obtain reinsurance on the open market.

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.

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

$$(6)\quad Premium^{q}_{t,i,z,c,s} = \gamma_t + \alpha_i + \tau^0 \times \text{Insurer } i \text{ in the pool}_{i,t}$$

$$+ \tau_F \text{Insurer } i \text{ in the pool}_{i,t} \times \text{Insurer is a foreign subsidiary}_i,$$

The results are in Table 6.

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
R2	0.87	0.04	0.82	0.03

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

TABLE 6. 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.

The results in Table 6 are inconsistent with the pool offering an implicit subsidy to all insurers. The effects on the global firms, who already have low or zero cost reinsurance access, are small in magnitude or in the opposite direction to domestic firms. If the pool was simply a subsidy, foreign subsidiaries would also have received it.

These results, that all the treatment effects come from Australian insurers with costlier access to foreign reinsurance, are consistent with high markups in the reinsurance market owing to the correlated nature of the risk. This is explored in greater detail in Section 5.

5. 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 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 paying 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 2.3. CHAD summarizes risk 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:

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

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

The coefficients of interest are κ and κ_{Post}. κ measures the baseline difference in premium/probability of insurance offered in 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 pf correlation due to the introduction of the reinsurance pool. In all cases, I control for risk in zipcode z, so that κ and $\kappa Post$ 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 4 and 5. Specifications (3) and (4) allow for insurer-time specific pricing of risk. Specifications (5) and (6) include a richer set of risk measures[13] 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.

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

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
R2	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
R2	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 (7 amd 8). The coefficient κ represents 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 coefficient κ_{Post} captures 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.

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.

6. 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.[14] 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.[15] 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.

I test the extent to which the ambiguity of estimates of risk affect the prices and avail-

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

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

ability of home insurance, and whether these impacts are reduced by the introduction of the reinsurance pool.

Data on Risk Ambiguity. I use the same 10,000 raw simulated cyclone data from the CHAD that I used in Section 5. By sub-sampling from the set of simulated cyclones, I bootstrap a sampling distribution of my primary measure of cyclone risk: the expected maximum 25-year wind speed in a zipcode.[16] I use the standard deviation of the bootstrapped distribution as a measure of ambiguity.

Method. Analogously to Section 5, 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:

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

The coefficients of interest are $\aleph$ and $\aleph_{Post}$. $\aleph$ measures the baseline difference in the premium/probability that insurance is offered when the risk ambiguity (the standard deviation of the sampling distribution of cyclone risk) increases by one unit. $\aleph_{Post}$ 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 analagous to those in Section 5. 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.

[16] See Appendix **??** for further details

Outcome: Log Premium	(1)	(2)	(3)	(4)	(5)	(6)
Pre-CRP Effect Of Risk Ambiguity	0.015***	0.014***	0.015***	0.014***	0.015***	0.014***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Post-CRP Change In The Effect Of Risk Ambiguity	0.000	0.000	0.000	0.000	−0.002	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(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	−0.003**	−0.003**	−0.003**	−0.003**	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post-CRP Change In The Effect Of Risk Ambiguity	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(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 coefficient $\aleph$ represents the baseline difference in premiums or probability of being offered insurance when the standard deviation of the distribution of cyclone risk increases by one unit. The estimating equations are (9 amd 10). The coefficient $\aleph_{Post}$ captures 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.

These effects are economically small and often statistically insignificant. The measure of ambiguity (the standard deviation of the bootstrapped sampling distribution of cyclone risk) has a range of 0.6 to 18.9 with a mean of 4.6 and median of 4.3. Thus, moving from the lowest ambiguity zipcode to the mean ambiguity zipcode is associated with 5.2% higher premiums and 1.2% less insurance offered prior to the reinsurance pool. These are statistically different from zero, but an order of magnitude lower than the correlation effects. There is no impact of the reinsurance pool on the cost of ambiguity. In Appendix A.7, I show these, and the results from Section 5 are robust to jointly estimating the effects of correlation and ambiguity in the same specification.

7. 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 is 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 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.

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	−0.177***	−0.175***	−0.074*	−0.066**
	(0.017)	(0.017)	(0.036)	(0.028)
Additional Effect of CRP Participation on Log(Premium) With New Entry	−0.021***	−0.106**	−0.049**	−0.025**
	(0.002)	(0.044)	(0.019)	(0.012)
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
R2	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.

Table 9 shows that the indirect effects of increased competition contributed significantly to the impact of the reinsurance pool. Depending on the specification, the competition channel accounts for between 11% and 47% of the baseline treatment effects in Table 4. 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.

8. Conclusion

Increasing climate risk has caused insurance market dysfunction worldwide. Areas exposed to natural disasters have seen insurance increase in price or become unavailable altogether. This paper studies a novel government response: public, actuarially fair, reinsurance for cyclone risk within the Australian home insurance market. The government charges each insurer an actuarially fair premium and, in exchange, covers any losses to the property (due to wind, water and so on) caused by a cyclone event. The private market continues to cover the remaining risk.

Using two empirical strategies, I find that the reinsurance pool had a substantial effect on the homeowners insurance market. Prices fell by as much as 20%, and the probability that insurance was offered at all increased by over 10%. I study four possible mechanisms for these effects: inadvertent subsidies, the effect of reduced costs of insuring correlated risks, the effect of reduced costs of insuring ambiguous risks, and the indirect effect on prices of increased insurer entry.

First, comparing insurers with differential exposure to reinsurance, I give evidence consistent with the reinsurance pool being priced actuarially fairly. That is, there is no implicit subsidy. Second, I compare the impact of premiums of insuring risk that is spatially correlated (controlling for the *level* of local risk) before and after the reinsurance pool. I find a) the cost of correlation is high before the reinsurance pool - fixing local risk, as correlation between local risk and the rest of the insurers portfolio changes from zero to one, the premium rises by 80% and the probability that insurance is offered decreases by 11%. And b) after the reinsurance pool is introduced, this impact of correlation on prices is halved, and the impact of correlation on whether insurance is offered is entirely nullified. Similarly, the cost of insuring ambiguous risk is a cause, albeit much smaller, of reduced offerings and increased prices prior to the reinsurance pool. Unlike the cost of correlated risk, this is not affected by the reinsurance pool. Finally, I show that insurer entry due to the pool had the general equilibrium effect of further reducing prices due to increased competition.

My findings are relevant to the current policy debate regarding property insurance market collapse and regulatory interventions that might reverse this. I show that government reinsurance can be actuarially fair (i.e. not cost the taxpayer anything) and still have a substantial effect on the home insurance market. This speaks to the broader question of which risks the private market can insure well, and which insurance markets require government intervention to support. When the government takes on the correlated tail risk, it allows the market for the remaining idiosyncratic risk to function markedly better.

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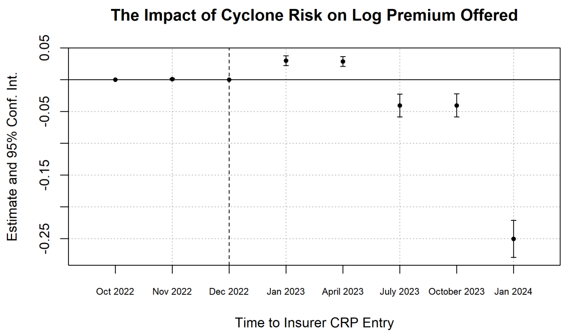
Appendix A. Empirical Appendix

A.1. Robustness Checks

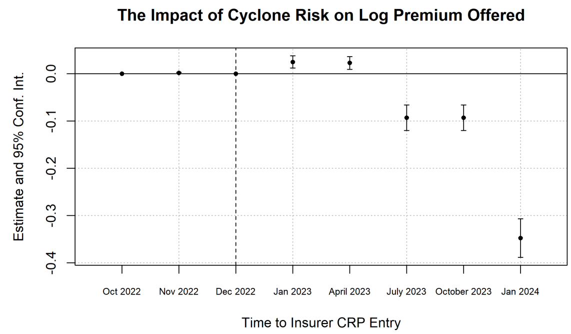
A.2. Robustness of main results to alternate measures of cyclone risk

I re-run the analyses first presented in Figures 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.

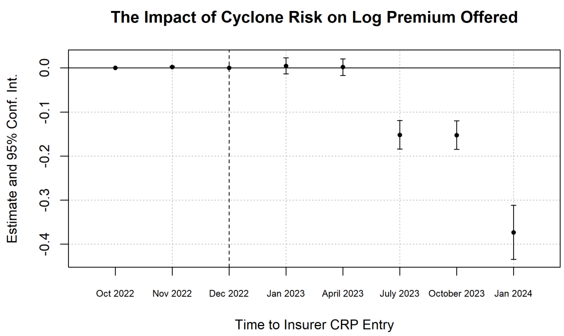
First, for the premiums offered. The results are in Figure A1. The general pattern is very robust to the measure of wind risk.



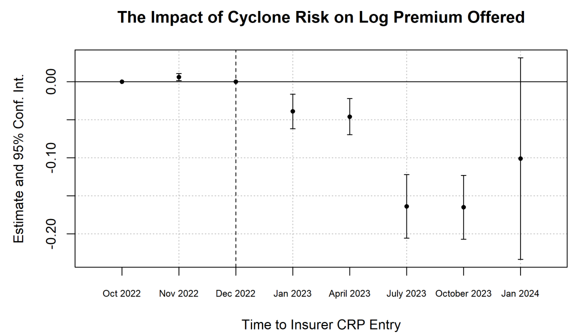
A. 2 Year Wind Speed



B. 5 Year Wind Speed



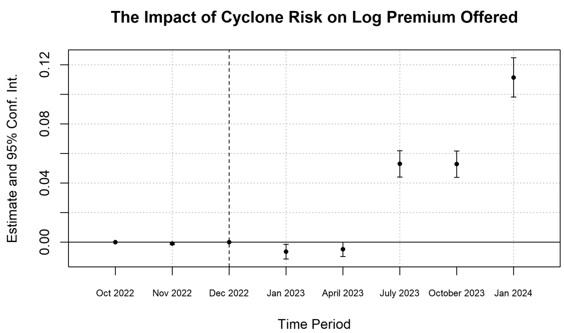
C. 10 Year Wind Speed



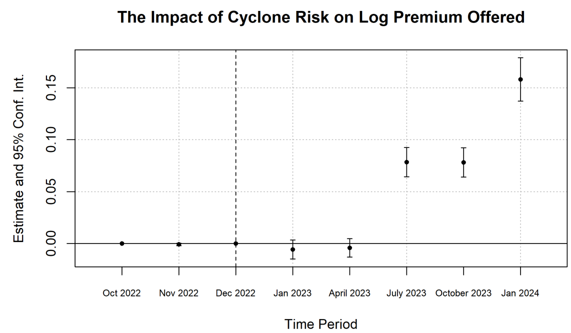
D. 50 Year Wind Speed

FIGURE A1. 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.

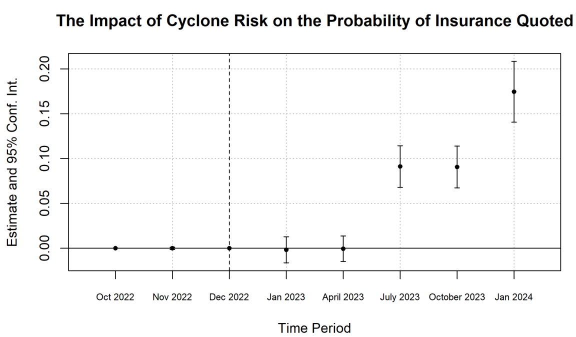
Second, for the probability of insurance being offered. The results are in Figure A2. The results are qualitatively unchanged when different measures of wind risk are used.



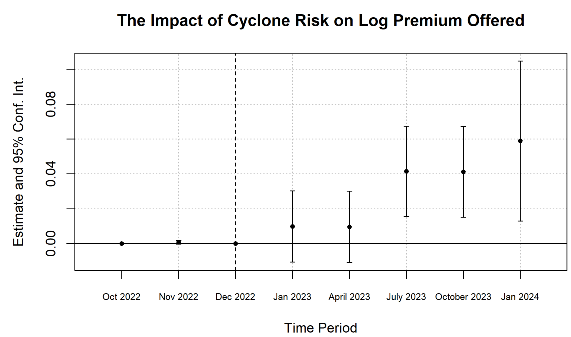
A. 2 Year Wind Speed



B. 5 Year Wind Speed



C. 10 Year Wind Speed



D. 50 Year Wind Speed

FIGURE A2. 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.3. Robustness of main results to alternate fixed effects

Here I estimate specifications analogous to equations (3) and (4) except with fixed effects at the level of address a insurer i, zip z cover level c and sum insured s.

First, the results for the premiums.

Empirical Strategy	Differential Exposure		Staggered Treatment	
	(1)	(2)	(3)	(4)
Estimate of τ	−0.220***	−0.168***	−0.107*	−0.074*
	(0.044)	(0.045)	(0.049)	(0.039)
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer x Policy x Address		✓		✓
N	1 963 614	1 963 614	4 266 658	4 266 658
R2	0.87	0.98	0.82	0.97

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

TABLE A1. 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) insurer x policy x address FEs.

The results are very similar to those in the main paper, if a little attenuated. Next, the results for whether insurance is quoted.

Empirical Strategy	Differential Exposure		Staggered Treatment	
	(1)	(2)	(3)	(4)
Estimate of τ	0.112***	0.122***	0.052	0.052
	(0.017)	(0.019)	(0.053)	(0.053)
Clustering	Zip	Zip	Insurer	Insurer
FE: Time	✓	✓	✓	✓
FE: Insurer x Policy	✓		✓	
FE: Insurer x Policy x Address		✓		✓
N	3 320 015	3 320 015	7 244 523	7 244 523
R2	0.79	0.90	0.75	0.91

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

TABLE A2. 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) only insurer fixed effects.

The results are identical to the main specifications.

A.4. Event Study Estimation of the Staggered Entry Specification

The event study versions of staggered entry specifications (4) and (3) are below.

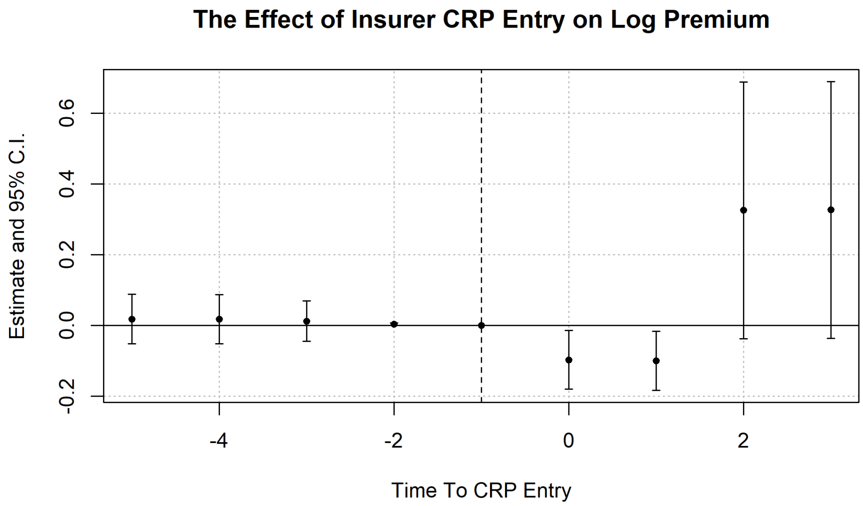


FIGURE A3. Event study coefficients, with the Sun and Abraham (2021) correction, for the effect of the reinsurance pool on log of the insurance premium, based on the staggered specification (4). The figure plots the estimated coefficients τ_t and their 95% confidence intervals. To estimate the Sun and Abraham (2021) correction, only time periods in which a non-treated insurer remains are included (i.e. January 2024 is excluded).

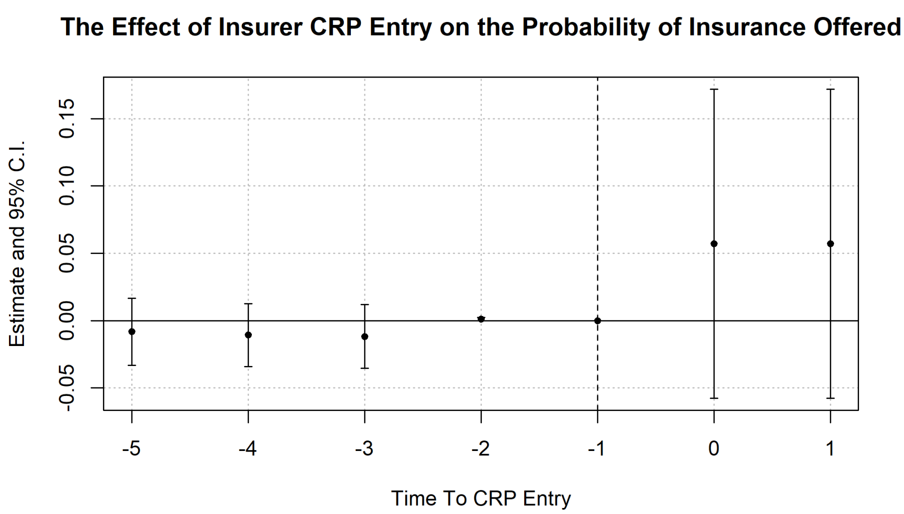


FIGURE A4. Event study coefficients, with the Sun and Abraham (2021) correction, for the effect of the reinsurance pool on whether insurance is quoted or not, based on the staggered specification (3). The figure plots the estimated coefficients τ_t and their 95% confidence intervals. To estimate the Sun and Abraham (2021) correction, only time periods in which a non-treated insurer remains are included (i.e. January 2024 is excluded).

There are two oddities. First, there are two extra post-period treatments for the log premium specifications than for the insurance quoted specifications. This is because, as explained in the main paper and in greater detail in A.5, the January 2023 treated insurers rolled out their price changes instantly, but their increased insurance offerings gradually. See, for example All (2023b). The fact that I code treatment on prices as earlier than insurance offered explains the difference in the number of post-treatment periods. I explore robustness to this coding in Appendix A.6.

Second, the premiums seem to increase in periods 3 and 4 post-treatment. This is driven by Allianz, Sure and Westpac, foreign insurers who were treated in January 2023. As shown in Section 4, these foreign insurers raise their prices after entering the pool. Because the only insurers treated in January 2023, for whom these three and four post period treatment effects can be estimated, are foreign, the event-study coefficients for these periods are weakly positive.

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.[17] For this reason, in my primary specification, I code treatment for these January 2023 insurers as occurring in January for premiums, and in April for whether insurance is quoted at all.

I check robustness to these choices in Appendix A.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

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

2023 (which is when they fully rolled out the changes to addresses quoted). The results are in Table A3 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 A3. 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) 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 to effects of risk correlation and risk ambiguity estimated respectively in Sections 5 and 6. I estimate the combined specifications.

$$\begin{aligned} Premium_{a,t,i,z,p} = \gamma_t + \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \aleph \times \text{Risk Ambiguity}_{z,-z} \\ + \kappa \times \text{Risk Correlation}_{z,-z} \\ + \aleph_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Ambiguity}_{z,-z} \\ + \kappa_{Post} \times 1\,[t = \text{Post-treatment}] \times \text{Risk Correlation}_{z,-z} + \epsilon, \end{aligned} \tag{A1}$$

$$Quoted_{a,t,i,z,p} = \gamma_t + \alpha_{Insurer} + \beta \times \text{Cyclone Risk}_z + \aleph \times \text{Risk Ambiguity}_{z,-z} \tag{A2}$$

$$
\begin{aligned}
&+ \kappa \times \text{Risk Correlation}_{z,-z} \\
&+ \aleph_{Post} \times 1\left[t = \text{Post-treatment}\right] \times \text{Risk Ambiguity}_{z,-z} \\
&+ \kappa_{Post} \times 1\left[t = \text{Post-treatment}\right] \times \text{Risk Correlation}_{z,-z} + \epsilon,
\end{aligned}
$$

The results are in Table A4.

Outcome: Log Premium	(1)	(2)	(3)	(4)	(5)	(6)
Estimate of $\aleph$	0.005	0.004	0.003	0.002	0.003	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Estimate of $\aleph \times t = 7$	0.003	0.003*	0.004*	0.005**	0.006**	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Estimate of κ	0.631***	0.630***	0.792***	0.791***	0.792***	0.791***
	(0.168)	(0.161)	(0.166)	(0.160)	(0.166)	(0.160)
Estimate of $\kappa \times t = 7$	−0.142*	−0.163**	−0.266***	−0.282***	−0.478***	−0.484***
	(0.073)	(0.074)	(0.082)	(0.084)	(0.109)	(0.108)
N	497 986	497 986	497 986	497 986	497 986	497 986
R^2	0.89	0.06	0.89	0.06	0.90	0.06
Outcome: Insurance Offered	(1)	(2)	(3)	(4)	(5)	(6)
Estimate of $\aleph$	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Estimate of $\aleph \times t = 7$	0.000	0.000	0.000	0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Estimate of κ	−0.090	−0.090*	−0.102*	−0.102*	−0.102*	−0.102*
	(0.055)	(0.055)	(0.054)	(0.054)	(0.054)	(0.054)
Estimate of $\kappa \times t = 7$	0.101***	0.100***	0.097***	0.096***	0.143***	0.143***
	(0.025)	(0.025)	(0.026)	(0.026)	(0.037)	(0.037)
Risk Controls:	Basic	Basic	Basic	Basic	Rich	Rich
Insurer x t Specific Risk Pricing	✗	✗	✓	✓	✓	✓
Clustering	Zip	Zip	Zip	Zip	Zip	Zip
FE:	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x t	Insurer x Policy x t	Insurer x t
N	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 A4. 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 (A1) and (A2). The coefficients κ, κ_{Post} and $\aleph$, $\aleph_{Post}$ have the same definition and meaning as in Tables 7 and 8 respectively. 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.

These results are qualitatively identical to the separated analyses run in Sections 5 and 6. As in Section 5, 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 6, ambiguity has quantitatively minimal effects both pre- and post- the introduction of the reinsurance pool.

A.8. Full quotation parameters

Each address was quoted under five different contract and house characteristic scenarios. They are:

In addition, for all five scenarios, the quotes were obtained under the following assumptions, per NQH (2024):

TABLE A5. Insurance Profile Data

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	-

Table A5 continued from previous page

Question	Default Answer	Comment
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
Does property have any unrepaired damage including storm?	No	-
Has house been demolished/sold/relocated?	No	-
Prior claim refused?	No	-

Table A5 continued from previous page

Question	Default Answer	Comment
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	-

Table A5 continued from previous page

Question	Default Answer	Comment
Frameless shower screens?	No	-
Granite/marble/stone tiling?	No	-
Large windows?	No	-
Plantation shutters?	No	-
Curved walls?	No	-
Ducted air conditioning?	No	-