Stormy Futures? The Impact of Climatic Shocks on Retirement Savings

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Stormy Futures?
The Impact of Climatic Shocks on Retirement Savings

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Abstract

Climatic shocks introduce additional complexities to individuals' lives and influence their critical decisions, both present and into the future. We utilise longitudinal administrative data on Australian individual retirement contributions to present the first estimated effects of natural disasters on retirement savings. Using the 2010-2011 Queensland floods as a natural experiment, we document that retirement contributions increase following the disaster. We show that individuals update their risk perceptions post-disaster, which drive changes in their portfolio choices across retirement savings, investment property ownership, and other interest-generating financial instruments. Our findings offer important insights into the relationship between individuals' planning horizons, retirement savings and their adaptive strategies in maintaining retirement welfare amidst demographic changes and increased environmental risks.

JEL: D14, D91, Q54

Keywords: retirement savings; risk perceptions; climate shocks

1 Introduction

Retirement funds are pivotal in shaping individuals' well-being during their retirement years, but they are also significant in driving a country's economic growth. They increase the amount of capital available to financial markets and provide investors with additional opportunities. As of 2023, retirement funds in the 22 major pension markets of the world comprise around US$ 48 trillion, with Australia, Canada, Japan, Netherlands, Switzerland, UK and US commanding 92% of these funds (Thinking Ahead Institute, 2023).

Over the past few decades, the accumulation of retirement savings has become increasingly vulnerable to challenges posed by global economic shocks, changes in the composition

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of the workforce, aging populations, and shifts in the retirement choices of different generations.[1] For example, it is reported that millennials aspire to retire in their 50s, approximately 15 years earlier than their parents; however, their prospects of fulfilling this goal are uncertain given that they reached adulthood during global economic shocks, including the 2009 global financial crisis and the COVID-19 pandemic (The New York Times, 2022).[2] Thus, millennials have struggled to accumulate sufficient retirement funds because their real wages have not kept up with inflation, volatile housing markets, and mounting student debts. Milenials have also increased their uptake of freelance and part-time employment, meaning that only 55% of the generation has access to retirement plans, compared with 77% of Generation X and 80% of Baby Boomers (The Economist, 2019). An additional dynamic in retirement savings relates to recent trends in 401(k) plan participation and contribution. Generation Z contributes more to their retirement plans than millennials in order to avoid the pitfalls that the latter experienced in their early adulthood (Fortune, 2023).

Recent years have shown that climatic shocks introduce an additional layer of complexity to the accumulation of retirement savings, due to their significant economic and psychological consequences, as well as their multi-faceted repercussions that reverberate rapidly through the economy.[3] The key problem is that natural disasters may influence the saving behaviour of traumatised future retirees and pose a significant threat to wealth holdings. For example, thousands of American workers have tapped their retirement savings since the Internal Revenue Service allowed hardship withdrawals from 401(k) plans in 2020, putting their retirement well-being at risk (The Wall Street Journal, 2022).[4] Given the rising frequency and severity of climate-change-induced disasters, the literature presents a significant vacuum as to whether and how disasters shape retirement savings as well as individuals' adaptive strategies to maintain retirement welfare amid demographic changes and environmental risks.

The principal objective of this paper is to study the changes in retirement savings following an unexpected catastrophic disaster, the 2010-2011 Queensland floods in Australia, which had profound impacts on the economy, the workforce, and economic activity in disaster-stricken areas. To the best of our knowledge, this is the first study to investigate the impact of a natural disaster on retirement savings. Our pursuit sheds light on the trajectory of retirement savings post-disaster by offering nuanced insights into the differential responses

[1]See for example Poterba, 2014; Poterba, 2015; Aguila, 2011; Rabaté, Jongen and Atav, 2024; Coile and Levine, 2007.

[2]Aucejo et al. (2020) find that the COVID-19 pandemic had a lasting impact on college students' educational achievement and labor market participation, showing that major shocks in adulthood can have substantial implications on future earnings.

[3]For example, Luechinger and Raschky (2009) show robust findings on floods' negative impacts on people's reported life satisfaction.

[4]Fidelity Investments, the largest 401(k) plan administrator in the United States, reports that about 250,000 workers have withdrawn funds from their retirement plans since January 2021 due to natural disasters, compared with 1.6 million workers who did the same in 2020 because of COVID-19. (The Wall Street Journal, 2022)

by age group, as well as the portfolio choices through which a disaster's impacts are likely to be manifested.

Theoretically, the effect of natural disasters on retirement savings is ambiguous due to opposing mechanisms. An average individual might reduce their retirement savings in the wake of disasters for at least three reasons. First, affected individuals may reallocate financial resources from savings to rebuilding and renewing their damaged tangible assets. Second, individuals with recent experience of significant material loss may prefer to hold easily accessible precautionary funds rather than investing in less liquid retirement savings which they would access only in the distant future (Beshears et al., 2015; Briere, Poterba and Szafarz, 2022). Third, reduced wealth holdings following a disaster can change individuals' reference points when estimating future losses, leading to underestimated future risks and reduced savings. The latter phenomenon aligns with the principles outlined in prospect theory, as proposed by Kahneman and Tversky (1979).[5] Conversely, individuals may increase their retirement savings post-disaster for at least two reasons. First, they may allocate investments from tangible assets such as real estate (which are perceived to be vulnerable to disasters) to financial markets, including pension funds. Second, they may update their perceived background risk, rendering them more risk averse and driving up retirement savings (Gollier and Pratt, 1996).[6]

We employ high-quality longitudinal administrative data on Australian individual tax records and retirement contribution statements to examine the effects of the 2010-2011 Queensland Floods on retirement savings. These floods were the worst ever to hit Australia in terms of total material damage caused, and were among the major disasters of the decade globally. They inundated around 25,000 homes and businesses (Deloitte Access Economics, 2016) and caused an estimated total AU$15.9 billion of damage (World Bank, 2011).[7,8,9] Our dataset comprises critical indicators such as contributions made into retirement saving accounts, some individual taxpayer characteristics, sources of income, and insurance coverage such as private health insurance.

Our analysis is predicated on a difference-in-differences (DID) design, which defines the treatment group as individuals living in the most heavily flooded areas around metropolitan

[5] Page, Savage and Torgler's (2014) findings confirm the status quo of prospect theory, suggesting that flood victims whose properties were directly affected are more likely to accept a risky gamble than their unaffected neighbours.

[6] Evidence on the impact of natural disasters on risk preferences has been inconclusive. For example, the studies by Cameron and Shah (2015), Cassar, Healy and Von Kessler (2017) and Callen (2015) find an increase in risk aversion following disasters, whereas Hanaoka, Shigeoka, and Watanabe (2018), Kuroishi and Sawada (2024), and Kahsay and Osberghaus (2018) find decreased risk aversion following natural disasters.

[7] 70% of this figure represents damage to the housing and infrastructure sectors, while the remaining 30% comprises losses in forgone revenue and production losses

[8] According to the Queensland Reconstruction Authority, the total estimated costs associated with the flood were AU$5 billion (Queensland Reconstruction Authority, 2011).

[9] The probability of a flood occurring in the region was estimated to be one in 2000 years (Queensland Government, 2014).

Brisbane and the control group as those living in comparable suburbs of four other major Australian cities: Sydney, Melbourne, Adelaide and Perth. Several detailed diagnostic analyses confirm the comparability of our treatment and control groups, and support the parallel trends assumption in the pre-disaster period. Our investigation proceeds in three steps. First, we estimate the aggregate effects of the disaster on contributions made to retirement savings. Second, we illuminate the retirement savings behaviour of different age groups following the floods. Third, to the extent that our dataset permits, we offer insights into the potential mechanisms at play by investigating some risk perceptions and portfolio choices. This includes shifts in private health insurance uptake, investment property ownership, and income earned from interest-generating financial instruments.

Our results document several important findings. First, the average individual in the flooded area increases their retirement savings following the disaster. The estimated effect is about 5%, which is economically meaningful and indicates an additional AU$300 being invested in retirement savings. While this effect is partly driven by changes in income post-disaster, the effect persists even after controlling for income. Second, we identify crucial variations by age groups. The surge in savings is most prominent, and persists for several years, for individuals aged 21-29 years. Specifically, contributions to retirement savings among the 21-29 and 30-39 age groups increase by 4-6%, while individuals from the 40-49 and 50-57 age groups, respectively, exhibit no significant change and reduce their pension contributions post-disaster. Third, in an effort to shed light on these findings, we examine the changes in private health insurance uptake. We find a statistically significant increase in uptake in disaster areas, pointing to altered risk perceptions as a probable factor influencing retirement savings. Our subsequent analysis of portfolio choices across investment property ownership and income earned from interest-generating financial instruments highlights that changes in risk perceptions play a crucial role in portfolio choices post-disaster, one of which is increased retirement savings. The changes in portfolio choices likewise display differential patterns across age groups.

Our findings suggest several factors that should be taken into consideration when investigating the effects of natural disasters on retirement savings. These include individuals' planning horizons and life-cycle stage. For example, younger populations are less likely to have experienced devastating natural disasters than older generations. Their first major shock causes them to update their background risk, and thus to choose safer investment options such as retirement savings. Individuals in their 30s and 40s at the time of the disaster, who have a higher average income than those in their 20s, invest more in alternative saving instruments, with an updating of background risk seeming to play a significant role. Older generations, on the other hand, might have experienced several shocks in their lifetime and accumulated sufficient retirement savings by the time of a given shock. Thus, they seem to choose to hold precautionary savings instead of locking their savings in less liquid investment instruments.

This paper makes several important contributions to the extant literature. First, we are the first study to examine whether and how natural disasters impact retirement savings. Second, we contribute to the literature on natural disasters and individual savings (see for example Noy, Nguyen and Patel, 2021; Udry, 1995; Skidmore, 2001; Ersado, Alderman and Alwang, 2003; and Berlemann, Steinhardt, and Tutt, 2015) and add to the literature on household finances following natural disasters (see, for example, Deryugina, Kawano and Levitt, 2018; Gallagher and Hartley, 2017; Gallagher, 2014). Using mostly self-reported survey data (in some cases non-financial measures of savings), in general from developing countries, this literature suggests that geological and climatic catastrophes can both increase and decrease household savings, depending on the context and location.[10] We contribute to this literature by investigating the disaster-savings dynamic using high-quality administrative data from a developed country.

Third, our pursuit to illuminate the changes in retirement savings contributes to the literature on risk perceptions in the wake of natural disasters. Thus far, insights on risk perceptions after natural disasters have been limited to experimental findings (e.g., Page, Savage and Torgler, 2014; Hanaoka, Shigeoka and Watanabe, 2018; Cameron and Shah, 2015).[11] These studies offer mixed evidence on risk perception, highlighting the importance of the severity, location (rural vs. urban areas) and type of disaster in altering risk aversion.[12] Most closely related to our context, Page, Savage and Torgler (2014) find that, from a sample of 220 homeowners, individuals who were victims of the 2010-2011 Queensland Floods and faced large property value losses were more likely to opt for a risky gamble. Our contribution to this literature is to employ a large administrative dataset and uncover an increase in risk aversion post-disaster. This occurs in the form of higher private health insurance uptake, as an insight into increased risk perceptions that ultimately result in higher retirement savings.[13]

The remainder of this paper proceeds as follows. Section 2 provides an overview of the Australian superannuation system. Sections 3 and 4 present the empirical methodology and the results, respectively. Section 5 includes robustness checks, and Section 6 concludes.

[10]For instance, negative effects are attributed to changes in risk perceptions and the effects of post-disaster aid, known as the Samaritan's Dilemma (see Berlemann, Steinhardt, and Tutt, 2015).

[11]Charness, Gneezy and Imas (2013), Dohmen et al. (2011), and Chuang and Schechter (2015) study the advantages and drawbacks of the prevailing methods.

[12]For example, Hanaoka, Shigeoka and Watanabe (2018) find that individuals become more risk-tolerant after the Great East Japan Earthquake. However, Cassar, Healy and Von Kessler (2017) and Cameron and Shah (2015) find increased risk aversion and an updating of background risk following natural disasters in rural areas of Thailand and Indonesia, respectively.

[13]Gallagher (2014) also finds an increase in flood insurance uptake following regional floods, which spikes the year after a flood and gradually declines to baseline levels later.

2 The Australian Private Pension System

The superannuation system, established in the 1980s, is Australia's national private pension system (Australian Prudential Regulation Authority, 2021). In 1992, participation in the superannuation system became compulsory for all employed individuals, except self-employed individuals. This occurred through the introduction of the superannuation guarantee, which required all employers to contribute 3% of their employees' salaries to a super fund on their behalf. While the superannuation guarantee has changed over time and the system has been modified frequently, the main idea of requiring individuals to save for their retirement during their years of employment via the superannuation system has not changed.

Payments into the superannuation system are called superannuation contributions and can be made from both pre-tax and post-tax income. These are referred to as concessional and non-concessional contributions, respectively. Concessional contributions are subject to a 15% tax before being deposited into superannuation accumulation funds and are subject to a cap (Chan et al., 2022). Non-concessional contributions are also subject to a cap; however, since they are sourced from after-tax income, they are not taxed, to prevent double taxation. Over time, both caps have undergone numerous adjustments, with the prevailing trend being a reduction in size. Appendix A1 provides an overview of the changes in superannuation policy over the study period, which have primarily impacted the cap limits for concessional and non-concessional contributions. The nationwide implementation of these changes ensures that their influence on total contributions by individuals in the treatment and control groups remains consistent, avoiding posing a hindrance to the achievement of parallel trends.[14]

Superannuation funds become accessible to individuals at or close to the age of 65. Having reached that age, individuals can access their superannuation savings, regardless of whether or not they continue to work. Individuals under the age of 65 can access their superannuation savings if they have stopped working and reached their preservation age, which is determined based on their birth year and determines when they can access their retirement savings.[15] In addition, individuals who are past their preservation ages have the option to withdraw while continuing to work at their existing job via the 'transition to retirement' scheme. Lump-sum withdrawals of the taxed components are tax-free up to a threshold, after which they are taxed at the marginal tax rate minus 15%. Taxable withdrawals made as part of an income stream are taxed at the marginal tax rate minus 15% with a requirement that at least 2% of

[14]Superannuation co-contributions, initiated by the Australian Government to incentivise low- and middle-income earners to save for retirement, are exempt from taxation and do not count towards the concessional and non-concessional contribution caps. Under this scheme, eligible individuals who make personal non-concessional contributions receive a co-contribution from the Australian Government, deposited automatically into their superannuation account. The specific amount of the co-contribution depends on the year the contribution is made.

[15]The preservation age is 55 years for individuals born prior to 1960 and 60 years for individuals born after 1964 (ATO, 2021a).

the balance be paid each year. Since July 2007, superannuation withdrawals and investment earnings in the pension phase have been tax free.

Prior to the access stage of retirement savings, the superannuation system allows for early withdrawals under certain very limited circumstances, including severe financial hardship.[16] Given the effects of the 2010-2011 Queensland Floods, if individuals had incurred severe losses and found themselves in extreme financial distress, they could have been permitted to access their superannuation funds early given that they met relevant the criteria.

In summary, superannuation savings are rather less liquid than other investments, due to being only accessible in later life. They have a high investment return, in part due to all the tax concessions and subsidies, and are relatively safe, which makes them an attractive option for wealth accumulation purposes (e.g., Kingston and Thorp, 2019). This study focuses on the reported total annual contributions.

3 Empirical Analysis

3.1 Dataset and Variable Construction

We use the Australian Longitudinal Information Files (ALife) dataset from the Australian Taxation Office (ATO), which consists of a random 10% sample of all registered tax filers.[17,18] Employing a quasi-experimental design, we assess the impact of the 2010-2011 Queensland floods on retirement savings by utilising longitudinal data on superannuation contributions from superannuation records linked with other variables from individual tax-returns for the fiscal years 2008-2014.[19]

The main outcome variable of interest is total contributions, which captures the total amount contributed to retirement saving accounts.[20] We then analyse total draw-down, to investigate whether individuals residing in the flooded areas had to rely on their retirement savings to cope with the financial implications of the disaster. We treat monetary variables before the analysis by deflating them at the respective state inflation rates, winsorising at the top and bottom 1%, and log-transforming. Following the literature, we log-transform

[16] The ATO provides a detailed list of these circumstances (2021b).

[17] Tax record data for the sample is available for each year from 1990-1991 to 2016-2017, and superannuation records are available for each year from 1996-1997 to 2016-2017, linked via everyone's unique tax file number. For more details of the ALife data and its construction, see Polidano et al. (2020).

[18] While lodging a tax return is only compulsory for those with taxable incomes above the tax-free threshold, most individuals who earn less than the tax-free threshold still file a tax return in order to have tax withheld by their employer refunded. The tax-free threshold over the period of analysis was AU$6,000 from 2007-2008 to 2011-2012 and AU$18,200 from 2012-2013 onwards.

[19] The data correspond to Australian fiscal years, which cover the period from 1 July of the previous year to 30 June of the given year.

[20] Until 2013, fund managers of superannuation accounts were only obliged to report member contribution statements of accounts that received contributions during that particular financial year. Therefore, missing observations for superannuation contributions can be interpreted as no contributions made, so we input zero values for all missing observations for superannuation contributions prior to 2013 (Chan et al., 2022).

zero-values by adding one.[21]

Before applying our sample selection criteria, we address inconsistencies related to reporting requirements for superannuation contributions made to superannuation funds with a defined benefit interest. Prior to the 2013 financial year, such contributions were not always linked to individuals. However, post-2013, individuals receiving defined benefit interest from a superannuation fund were obliged to report their contributions as notional taxed contributions (ATO, 2018), which created reporting discrepancies. We identify these individuals by constructing a total contributions variable using the components of total contributions and comparing it with the reported figures. Individuals with a difference greater than AU$2,000, approximately 1% of the sample, are excluded to eliminate reporting discrepancies.

3.2 Treatment and Control Groups

We construct our treatment group by including individuals residing in the most heavily flooded areas of Brisbane at the time of the disaster, i.e., in 2011. Our ArcGIS work identifies the most-flooded SA4 regions as Brisbane East, Brisbane North, Brisbane South, Brisbane West, Brisbane Inner City and Ipswich, which are all located along the Brisbane River, given the riverine nature of the flood (shown in Fig. 1).

Working with SA4-level granularity has several advantages for the purpose of this study. First, unlike smaller statistical area levels, SA4s enable all flooded areas to be included in the sample. Our Statistical Area-2 (SA2s)-level GIS mapping shows that drawing individuals only from the flooded SA2s that lie along the Brisbane River leaves out those residing in other flooded SA2s not neighbouring the riverside. This poses a challenge because including the latter SA2s in the treatment group makes it difficult to identify comparable SA2s in the control group. Second, focusing on smaller statistical areas leaves out the effects experienced by commuters.[22] Third, focusing on SA4s when defining the treatment group allows us to not only analyse the disaster's effect at the local level but also capture the dynamics in the regional economies. While SA4s are larger, meaning that the intensity of the disaster experience varies within the region, the scale and severity of the 2010-2011 Queensland floods mean it is not unreasonable to assume that an individual's home or workplace was affected by the flood.[23]

[21]With only about 6% of total contributions observations being zero and our residuals not showing heteroskedasticity (Silva and Tenreyro, 2006), we are not concerned at the risk of bias from log-transforming by adding one to our true zero values. In addition, in line with the findings of Chen and Roth (2023), we show that the disaster has a negligible effect on participation in the retirement system (see Figure 4 and Appendix A2.)

[22]As an average SA2 comprises between 3,000 and 10,000 residents, drawing individuals from the flooded riverside SA2s would imply our sample excludes commuters (ABS, 2021).

[23]Spatial variation of flood height within and between SA4s is of no great concern, as we are focusing on the most heavily flooded areas.

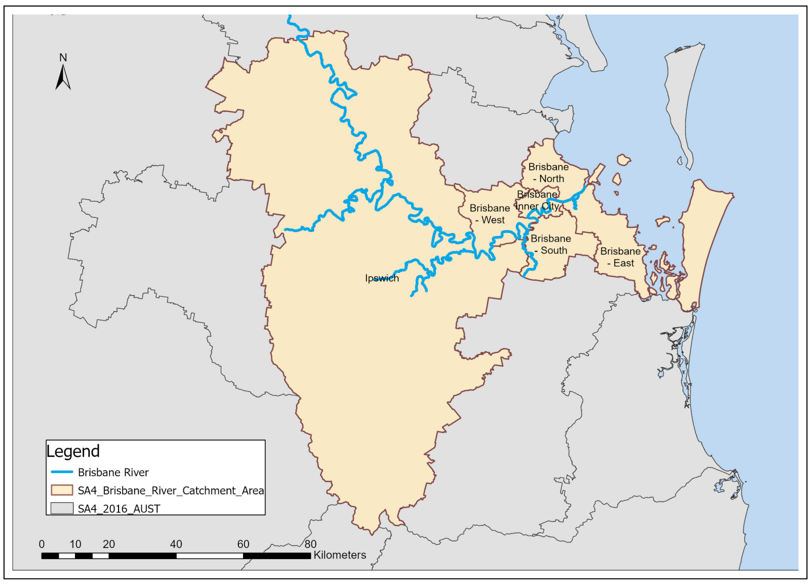
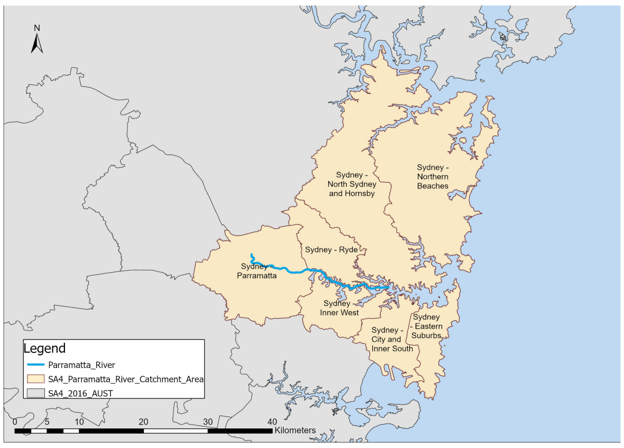


Figure 1: Map of SA4s comprising the treatment group

We construct the control group of individuals from comparable SA4s in the cities of Sydney, Melbourne, Perth and Adelaide. Our ArcGIS work has identified a group of comparable SA4s along the four respective rivers, covering 84km of land from the estuaries to inland (Figure 2).[24] Geographically, these cities share similar patterns of coastal settlement along major rivers: the Parramatta, Yarra, Swan, and Torrens Rivers, respectively. They are also comparable in terms of demographic composition and industrial development levels. The layouts of their metropolitan areas resemble that of Brisbane, which starts with the Central Business District at the estuary, extends into the suburban areas, and finally reaches the hinterland. Notably, the probability of flooding in the SA4s along all the rivers in the control and treatment groups is not expected to be different.

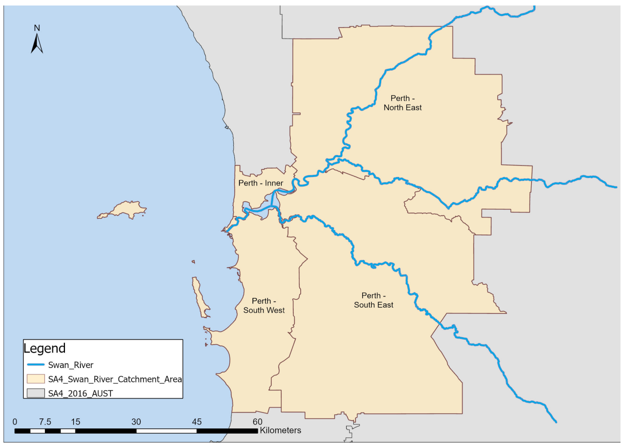
Individuals are selected into the treatment and control groups based on their residency in 2011, i.e., the year of the disaster. This setting enables us to track the 'treated' individuals even if they relocate after the disaster. However, we retain individuals in the control group only if they remained within the same control SA4s for the entire study period. This restriction allows the control group individuals to move only within their designated SA4s, thus isolating changing economic and environmental circumstances which could impede comparability.

[24]The SA4s from Sydney are 'City and Inner South', 'Eastern Suburbs', 'Inner West', 'North Sydney and Hornsby', 'Northern Beaches', 'Parramatta' and 'Ryde'. The Melbourne SA4s comprise 'Inner', 'Inner East', 'North East', 'North West', 'Outer East' and 'West'. From Perth we include the 'Inner', 'North East', 'South East' and 'South West' SA4s, whereas from Adelaide we include the 'Central and Hills', 'North' and 'West' SA4s.



(a) Sydney - Parramata

(b) Melbourne - Yarra



(c) Perth - Swan

(d) Adelaide - Torrens

Figure 2: Map of SA4s comprising the control group

Our sample comprises working individuals, meaning that it is restricted to individuals aged between 18 and 60 years for any given year within our estimation period.[25] Our primary sample includes only individuals who were employed in all three years preceding the disaster (2008-2010).[26] This ensures a consistent history of superannuation contributions prior to the disaster. In a robustness check, we test this assumption by relaxing the employment criteria in the pre-disaster period, first by including all individuals in the sample, and second by including only those who were employed in all seven years in the sample.

Our sample is strongly balanced in all exercises.[27] Applying this selection and other restrictions that we have previously mentioned, the treatment and control groups in our primary sample consist of 44,923 and 182,792 individuals, respectively, with 314,461 and 1,279,544 observations over the 7-year period considered.

3.3 Descriptive Statistics and Comparability of the Treatment and Control Groups

Table 1 provides an overview of the demographic and economic characteristics of the treatment and control groups for the pre- and post-disaster periods. The pre-disaster period comprises the years 2008-2010, while the post-disaster period comprises the years 2011-2014.

[25]This implies that individuals in the treatment and control group are aged between 21 and 57 at the time of the disaster, i.e., in 2011, when they are assigned to age groups. As a result, we restrict our sample to those born between 1954 and 1990.

[26]We define employment as having a positive salary or wage income, being self-employed, or reporting business income.

[27]Results for total contributions for the unbalanced sample are in line with the results for the balanced sample, and are presented in Appendix A3.

The average age in both groups is approximately 36 years, showing a high degree of similarity. This comparability extends to gender, marital status, and number of dependent children. Due to our balanced sample approach, we see a decrease in the average number of dependent children in the post-disaster period relative to the pre-disaster period, reflecting children reaching independence over time.

In the pre-disaster period, the rate of self-employment is notably higher in the control group. Furthermore, the means of monetary variables are slightly elevated in the control group compared to the treatment group, due predominantly to individuals with higher incomes. The same disparity is evident in the average total incomes of the two groups. High-income individuals, particularly those in more developed cities like Melbourne and Sydney, contribute to the higher average monetary values in the control group.

Notably, average total contributions increase by AU$524 for the treatment group compared to AU$354 for the control group, representing 9% and 6% increases respectively. This hints at a change in contribution pattern for the treatment group in the post-disaster period.

Table 1: Demographic and economic comparability of the treatment and control groups

	Pre-disaster (2008-10)		Post-disaster (2011-14)	
	Treatment group	Control group	Treatment group	Control group
Age	35.81	36.82	39.31	40.32
	(10.37)	(10.16)	(10.40)	(10.19)
Gender (% male)	53.15	53.78	53.15	53.78
Partnered/Married (%)	44.45	43.96	55.16	53.61
Number of dependent children	1.02	1.12	0.91	0.95
	(1.15)	(1.13)	(1.12)	(1.11)
Self-employed (%)	11.30	12.95	11.66	13.34
Wage & salary (AU$)	49,017	51,143	53,455	54,861
	(38,301)	(42,860)	(42,239)	(45,996)
Gross income (AU$)	55,607	59,690	61,965	65,741
	(44,453)	(50,809)	(48,800)	(54,347)
Total contributions (AU$)	6,087	5,936	6,611	6,290
	(7,166)	(7,502)	(6,825)	(7,076)

Note: Numbers in parentheses represent standard deviations from the mean.

To examine parallel trends, Figure 3 presents the mean of total contributions across the estimation period 2008-2014, with the disaster taking place between the two red vertical lines in the graph, given for reference. The figure is constructed using the log-transformed versions of this variable, as this is also used in the regressions. Although there is a difference in the levels of the log-transformed values for the two groups, their trends over the pre-disaster period are the same.

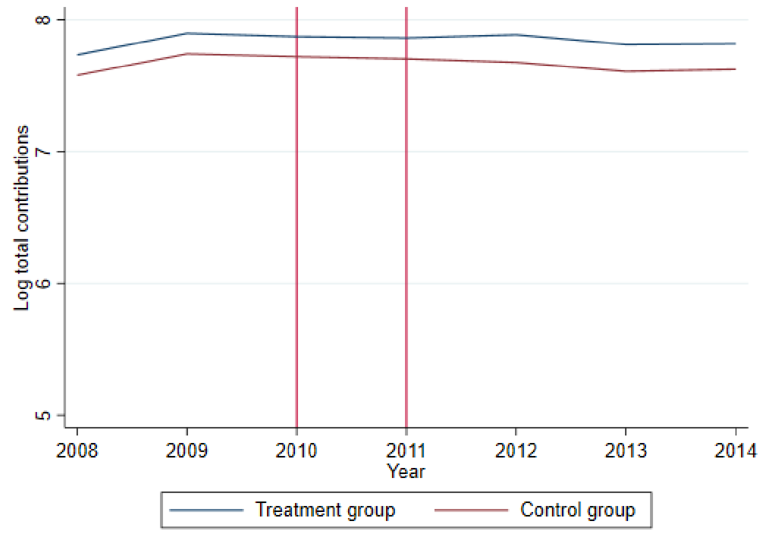


Figure 3: Unconditional mean of log total contributions in 2008-2014

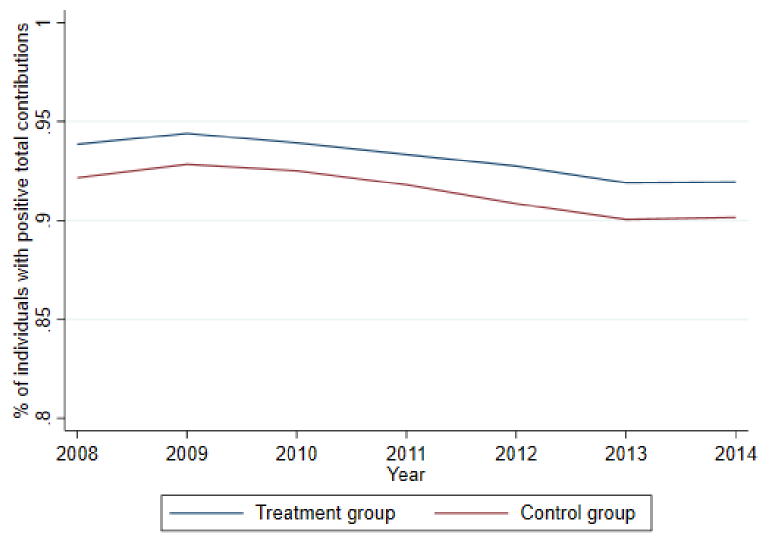


Figure 4: Percentages of individuals with positive total contributions in 2008-2014

Figure 4 presents an overview of the percentages of individuals with positive total contributions from 2008 to 2014. Although the contribution patterns of the treatment and control groups differ, the difference remains stable over the period considered. The share of individuals with contributions remains slightly higher for the treatment group throughout, probably due to the higher share of self-employment in the control group, since the self-employed are not obliged to save for retirement through the superannuation system. Policy changes in the superannuation system in 2013, including decreased caps for concessional contributions and an additional tax on richer individuals' contributions, may explain the slight change in trends observable for both the treatment and control groups around 2013.[28]

[28] Making contributions from post-tax income rather than pre-tax income enabled individuals to continue to add to their superannuation accumulation fund without being taxed for breaching the changed contributions cap.

In summary, the analysis of the treatment and control groups reveals high level of similarity between them, considering both demographic and economic aspects. This similarity is evident not only in average values but also in the trends of economic variables and participation in the superannuation system in the pre-disaster period. Thus, it is reasonable to consider the control group as a representation of the counterfactual scenario for the treatment group, showing the dynamics that would have prevailed had the treatment group not been impacted by the financial consequences of the 2010-2011 Queensland floods.

3.4 Empirical Specification

We implement a difference-in-differences (DID) model to estimate the effects of the 2010-2011 Queensland floods on retirement savings. Initially, we consider a specification that controls for time fixed effects, individual fixed effects and SA4 fixed effects. This specification is given in Equation (1), where Y_{it} is the output variable for individual i at time t, T_i is a dummy variable indicating the treatment for individual i, P_t is a dummy variable for differentiating the pre- and post-disaster periods, $SA4level_{it}$ indicates the SA4 region code in which individual i is residing at time t, $year_t$ controls for year fixed effects and γ_i controls for individual fixed effects.

$$log(Y_{it}) = \beta_0 + \beta_1 T_i + \beta_2 P_t + \beta_3 T_i \times P_t + \beta_4 SA4level_{it} + \beta_5 \sum_{t=2008}^{2014} T_i \times year_t + \gamma_i + \epsilon_{it} \quad (1)$$

Here, β_3 captures the estimated effects of the floods. Next, we include time-varying covariates to investigate how the estimated treatment effect, β_3, varies as we control for other potential confounding effects.

We examine the dynamics in flood effects by expanding Equation (1), interacting the treatment indicator with year fixed effects. Under the parallel trends assumption, we do not expect any significant treatment effects in pre-disaster years. Our benchmark specification is the one that accounts for time-varying characteristics as given in Equation (2).

$$log(Y_{it}) = \beta_0 + \beta_1 \sum_{t=2008}^{2014} T_i \times year_t + \beta_2 \sum_{t=2008, t \neq 2010}^{2014} T_i \times year_t + \beta_3 SA4level_{it} + \beta_4 X_{it} + \gamma_i + \epsilon_{it} \quad (2)$$

The time-varying covariates, X_{it}, comprise age, age squared, marital status, self-employment status, log income and income squared. In all specifications thus far, ϵ_{it} denotes the error term and standard errors are clustered at SA4 level, since the treatment status is based on SA4-level residency information.

4 Results

4.1 Benchmark Results

Table 2 presents the estimation results for Equation (1) in columns (1) to (3), and Equation (2) in columns (4) to (6). On average, individuals in the flooded areas contribute 3.6% more than their untreated counterparts (column (1)). Adding age, age squared, marital status and self-employment status to the regression in column (2) reduces the treatment effect to 1.7%. This suggests that contributions are partly driven by individual characteristics, though the disaster still has an independent and significant effect on contributions. Column (3) additionally includes the log income and income squared in the model, as income itself may change following the disaster. This results in a treatment effect of 2.4%, which again suggests that the disaster has an independent and significant effect.

Columns (4) to (6) present the results for Equation (2). We start without including time-varying characteristics in column (4) and gradually add them leading up to column (6). Importantly, insignificant treatment effects before the disaster year imply that the parallel trends assumption is satisfied. Column (4) reveals that the post-disaster estimated effects are all positive and significant, with the impacts being the strongest and most precisely estimated in 2012, the financial year following the disaster, then tapering off in subsequent years. Including the control variables in column (5) reduces the post-disaster treatment effects to 2012 only. This stands at 4.6% and is significant at the 1% level. Accounting for changes in income in column (6), we estimate a treatment effect of 2.8% in 2012. Overall, this shows that part of the increase in contributions is driven by income changes; however, the disaster still caused an increase in contributions towards retirement savings even after accounting for the effects of income and individual characteristics.

Table 2: Regression results for log total contributions

	Total contributions (Log)					
Mean value	AU$6,087					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	0.036***	0.017*	0.024*			
	(0.013)	(0.012)	(0.013)			
Treatment × 2008				0.003	0.015	-0.010
				(0.018)	(0.016)	(0.009)
Treatment × 2009				0.004	0.009	0.001
				(0.011)	(0.011)	(0.009)
Treatment × 2011				0.005	-0.001	0.014
				(0.011)	(0.011)	(0.010)
Treatment × 2012				0.056***	0.046***	0.028**
				(0.016)	(0.016)	(0.012)
Treatment × 2013				0.050**	0.035	0.031
				(0.023)	(0.024)	(0.019)
Treatment × 2014				0.042*	0.020	0.010
				(0.022)	(0.023)	(0.019)
SA4 FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Age and age squared		YES	YES		YES	YES
Partnered/Married		YES	YES		YES	YES
Self-employed		YES	YES		YES	YES
Log income and income squared			YES			YES
Observations	1,594,005	1,594,005	1,594,005	1,594,005	1,594,005	1,594,005

Columns (1)-(3): OLS with a single treatment effect estimate. Columns (4)-(6): OLS with yearly treatment effects. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. FE = fixed effects. Mean values constitute the pre-disaster (2008-2010) averages for the treatment group.

4.2 Analysis by Age Groups

Considering that generational characteristics affect retirement saving choices, as mentioned in the introduction, we conduct an analysis by age groups to delve into the results. Age is particularly relevant in this context because it serves as a proxy for, among other things, the value of assets exposed to the natural disaster. In addition, the difference in planning horizons due to the retirement time frame being much longer for younger individuals might lead to heterogeneous treatment effects. Thus, we group individuals into four distinct categories based on their age at the time of the disaster in 2011: 21-29, 30-39, 40-49, and 50-57 years.[29] Note that our sample includes individuals aged 18 to 60; thus, they are 18-54 in 2008 and 24-60 in 2014.

Appendix A4 provides descriptive statistics for the treatment and control groups by age group for the pre-disaster period. Overall, as expected, average salaries and gross income increase with age, while wage income peaks at age 40-49. Also anticipated are the strong positive gradients in contributions by income and time to retirement.[30]

We estimate Equation (2) across the four age groups and present the results in Table

[29] Our initial checks on the age distributions of the treatment and control groups showed similar distributions in both groups, thus permitting such a heterogeneity analysis while still preserving the parallel trends. According to this classification, 27%, 29%, 27% and 17% of individuals in the treatment group belong to the 21-29, 30-39, 40-49 and 50-57 age groups, respectively, whereas these proportions are 23%, 29%, 29% and 19% for individuals in the control group.

[30] Appendix A5 provides a visual depiction of the time trends in log total contributions by age groups.

3. Crucially, the parallel trends assumption is satisfied across all age groups. Our results uncover stark differences by age cohort. Younger cohorts, specifically those aged 21-29 and 30-39 years, noticeably increase their total contributions following the disaster. Conversely, individuals in the 40-49 age group do not exhibit any significant changes in their contribution patterns, whereas the oldest group, aged 50-57 years, experienced a decrease in total contributions.

Delving deeper, we observe that individuals aged 21-29 years began increasing their superannuation contributions from the year of the disaster, starting at a rate of 3.8%. This escalated to 6% in the following year, before moderating to 5.3% and 5.4% in the following years. Thus, for this age group, the heightened contribution levels persisted throughout the entire post-disaster period considered in this study. However, for the 30-39-year-olds, the elevated contribution pattern was only maintained until 2013, with no significant effect in the third year following the disaster. The 40-49 age group showed no notable changes post-disaster. In contrast, the 50-57 age group saw their contributions decrease by 4.3% and 6.8% in 2012 and 2014, respectively.

Table 3: Results for log total contributions by age group

	Total contributions (Log)			
Age group	21-29	30-39	40-49	50-57
Mean values	AU$3,238	AU$5,706	AU$7,108	AU$9,664
Treatment × 2008	0.009	-0.011	-0.009	-0.014
	(0.022)	(0.019)	(0.015)	(0.020)
Treatment × 2009	0.022	-0.009	0.001	-0.015
	(0.019)	(0.019)	(0.012)	(0.019)
Treatment × 2011	0.038***	0.012	0.007	-0.000
	(0.014)	(0.013)	(0.022)	(0.018)
Treatment × 2012	0.060***	0.055**	0.020	-0.043**
	(0.022)	(0.023)	(0.029)	(0.021)
Treatment × 2013	0.053***	0.061**	0.014	-0.027
	(0.016)	(0.027)	(0.045)	(0.031)
Treatment × 2014	0.054***	0.023	0.001	-0.068**
	(0.016)	(0.028)	(0.037)	(0.027)
Observations	376,670	470,106	451,171	296,058

Results are for the benchmark specification: OLS with individual, year, SA4-level fixed effects and controls (age, age squared, partnered/married, self-employed, log income and income squared). Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Mean values constitute the pre-disaster averages for the treatment group. Individuals are assigned to their respective age groups based on their age at the time of the disaster, i.e., 2011. Note that our sample includes individuals aged 18 to 60; thus, they are 18-54 in 2008 and 24-60 in 2014.

4.3 Understanding the Dynamics Affecting Retirement Savings Post-Disaster

Our results thus far indicate that, on average, retirement savings increased after the disaster. This outcome is consistent with the hypothesis that increases in retirement savings might stem from altered risk perceptions, prompting individuals to save more. Increased retirement savings could also result from portfolio reallocation, as those affected become more risk-averse, preferring safer retirement accounts over riskier investments like real estate, which are commonly used to support retirement consumption. Adding to this, it might also be the high early withdrawal penalties of retirement savings that provide the security of accumulated savings in retirement years and thereby appeals to disaster-stricken individuals (Beshears et al., 2020). As expected, the analysis by age groups reveals significant variation in the impact of natural disasters on retirement savings. This suggests that hypotheses which stipulate a positive change in retirement savings require a nuanced consideration based on age groups. We test our hypotheses and inspect them considering heterogeneities across age groups by conducting several analyses utilising variables from the ALife dataset.

We focus on changes in private health insurance decisions, which correlate with risk aversion. This is because risk-tolerant individuals are less likely to opt for private health insurance (see de Meza and Webb, 2001; Fang, Keane, and Silverman, 2008).[31] Although our dataset includes various monetary variables related to health insurance from 2008 to 2014 (such as private health insurance tax offsets or premiums eligible for Australian Government rebates), none provides continuous data for the entire period. Nonetheless, we can ascertain whether individuals have full-year private health insurance coverage. Table 4 presents these findings.[32,33]

We identify an increase in uptake of private health insurance among all age groups at varying levels of significance. The results clearly support our hypothesis of changing risk perceptions following the disaster. The most prominent change is increased private health insurance uptake by individuals aged 30-39 years. That is, these individuals update their background risk, resulting in increased contributions following the disaster. Individuals aged 21-29 years present a lower increase in private health insurance uptake, which is statistically significant at the 10% level. Whilst individuals in this age group might still have updated their background risk, it is likely that this change simply did not directly translate into private health insurance uptake because health is not among their major concerns, given their young age. Significant increases are also noted in the older age groups, who seem to be updating their background risk too; however, this does not alter their retirement contribu-

[31]Time preferences, risk perceptions and insurance decisions are intertwined. Finke and Huston (2013) find time preferences to be a significant predictor of the importance a respondent places on saving for retirement. Meanwhile, Bradford and Burgess (2010) show that time preferences also appear to be important predictors of health insurance and insurance coverage decisions. Furthermore, several studies (e.g., Andersen et al., 2008) show a positive correlation between risk aversion and time preferences.

[32]Appendix A6 provides figures displaying the evolution of the share of individuals covered by private health insurance.

[33]Breaking down the treatment effect into years and comparing only with respect to the pre-disaster year of 2010 leads to some minor parallel trend issues. Therefore, we choose to proceed with only the post-disaster treatment years and compare the yearly treatment effects relative to the pre-disaster averages (i.e., 2008-2010 averages).

tions. Overall, our finding of increased risk aversion following the disaster is consistent with the findings of Johar et al. (2022), who, using the Household, Income and Labour Dynamics in Australia (HILDA) Survey, found that natural disasters influence risk perceptions by increasing risk aversion, particularly among younger generations.

Table 4: Updating risk perceptions following the disaster

	Dummy: private health insurance			
Age group	21-29	30-39	40-49	50-57
% with private health insurance	37%	55%	57%	63%
Treatment × 2011	-0.008	0.009*	0.006	0.006
	(0.006)	(0.005)	(0.005)	(0.006)
Treatment × 2012	0.002	0.011**	0.009*	0.007
	(0.005)	(0.005)	(0.005)	(0.006)
Treatment × 2013	0.010*	0.020***	0.013***	0.016**
	(0.005)	(0.005)	(0.005)	(0.006)
Treatment × 2014	0.006	0.019***	0.0144***	0.015**
	(0.005)	(0.005)	(0.005)	(0.006)
Observations	376,562	469,999	451,094	296,025

Results are for an OLS specification with year, SA4-level fixed effects and controls (age, age squared, partnered/married, self-employed, log income and income squared). Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shares constitute the pre-disaster percentages for the treatment group. Individuals are assigned to their respective age groups based on their age at the time of the disaster, i.e., 2011. Note that our sample includes individuals aged 18 to 60; thus, they are 18-54 in 2008 and 24-60 in 2014.

We delve deeper into the portfolio choices of flood-affected individuals by analysing changes in the receipt of rental income and interest income. The reallocation of savings towards superannuation accounts could be driven by the vulnerability of existing real estate to natural disasters. Home ownership is a key component of asset-based welfare for retirement in Australia.[34] Additionally, several studies indicate a decline in home ownership post-disaster (see, for example, Sheldon and Zhan, 2019). The trauma of home destruction may prompt younger individuals to shift investments from real estate to retirement savings. Our dataset does not include home ownership data; however, we observe a binary indicator of whether individuals receive rental income, which, in an Australian setting, can reasonably be used as a measure of investment property ownership.

Table 5 displays rental income receipts across age groups. Individuals in the 21-29 age group reduce their uptake of investment properties compared to their unaffected peers. However, increasing numbers of individuals in the 30-39 and 40-49 age groups start receiving rental income post-disaster. For individuals aged 30-39 years, this shows that increasing risk perceptions resulted in both higher contributions to their retirement savings and additional investments in the real estate market. The oldest age group does not change their investments

[34]The Australian residential market often experiences downturns after natural disasters, followed by gradual recoveries. This pattern has made residents hesitant to purchase homes in areas prone to flooding (The Property Tribune, 2022).

in real estate, which is understandable given their shorter time horizon to retirement.[35]

Table 5: Uptake of investment properties following the disaster

	Dummy: having rental income			
Age group	21-29	30-39	40-49	50-57
% with rental income	6%	16%	20%	24%
Treatment × 2011	-0.001	0.015***	0.012***	0.007
	(0.003)	(0.004)	(0.005)	(0.006)
Treatment × 2012	-0.007**	0.009**	0.012***	0.008
	(0.003)	(0.004)	(0.005)	(0.006)
Treatment × 2013	-0.012***	0.012***	0.014***	0.008
	(0.003)	(0.004)	(0.005)	(0.006)
Treatment × 2014	-0.016***	0.009**	0.011**	0.006
	(0.003)	(0.004)	(0.005)	(0.006)
Observations	376,670	470,106	451,171	296,058

Results are for an OLS specification with year, SA4-level fixed effects and controls (age, age squared, partnered/married, self-employed, log income and income squared). Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shares constitute the pre-disaster percentages for the treatment group. Individuals are assigned to their respective age groups based on their age at the time of the disaster, i.e., 2011. Note that our sample includes individuals aged 18-60; thus, they are 18-54 in 2008 and 24-60 in 2014.

In addition to retirement savings and investment property ownership, another portfolio choice is to pursue interest income. We aim to uncover further dynamics by age group following the 2010-2011 Queensland floods by utilising information from the Alife dataset on interest income. This financial instrument also allows as to disentangle whether reductions in retirement contributions stem from increased liquidity needs post disaster or a reshuffling towards precautionary savings in line with Briere, Poterba and Szafarz (2022). The results in Table 6 show that all groups report very similar levels of interest income, with the exception of individuals aged 21-29 years, who report reduced interest income in 2012 and 2013.[36]

[35] Appendix A7 provides an overview of the development in the share of individuals with rental income in the treatment and control groups by age. These pictures clearly show individuals aged 21-29 years in the treatment group beginning to divest from the real estate market following the disaster relative to their untreated counterparts. No clear divergence is visible to the naked eye for the other age groups.

[36] We undertook an additional analysis of dividend receipts by age groups, but found no meaningful results due to the small sample size.

Table 6: Interest-generating portfolio choices following the disaster

	Interest income (Log)			
Age group	21-29	30-39	40-49	50-57
% with interest income	46%	48%	48%	54%
Treatment × 2011	-0.064	0.005	-0.039*	0.003
	(0.041)	(0.028)	(0.028)	(0.020)
Treatment × 2012	-0.088**	0.038	-0.008	0.005
	(0.039)	(0.026)	(0.034)	(0.030)
Treatment × 2013	-0.071*	0.030	-0-033	-0.023
	(0.040)	(0.038)	(0.032)	(0.043)
Treatment × 2014	-0.044	0.039	-0.056	-0.047
	(0.048)	(0.040)	(0.041)	(0.034)
Observations	376,670	470,106	451,171	296,058

Results are for an OLS specification with individual, year, SA4-level fixed effects and controls (age, age squared, partnered/married, self-employed, log income and income squared). Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shares constitute the pre-disaster percentages for the treatment group. Note that our sample includes individuals aged 18-60; thus, they are 18-54 in 2008 and 24-60 in 2014.

Overall, our results by age group can be interpreted as follows. Due to increased risk aversion following the disaster, individuals aged 21-29 years start to divest from both the real estate market and other interest-generating financial instruments, and reallocate these funds to their retirement savings. The strongest effects of the disaster are found for the 30-39 age group, who, following the floods, start to contribute more to their retirement savings and increase their take-up of investment properties. Individuals in the 40-49 age group also show increased risk aversion, but this age group does not start to save more towards retirement. Instead, their increased risk aversion manifests itself through increased investment in investment properties. The oldest age group, comprising individuals aged 50-57 years at the time of the disaster, also updates their background risk. However, interestingly, this age group reduces its superannuation contributions and changes neither their investment property ownership nor their interest-generating savings. Thus, our findings support the hypothesis that this age group chooses to divest from superannuation savings and prefers to hold easily-accessible precautionary savings. This result resonates with the findings of Page, Savage and Torgler (2014) that older individuals are more prone to taking risky gambles and show less risk aversion in the wake of large losses. They also found that home-owners who were victims of the floods and experienced large losses in property values are more likely to accept risky gambles. On the other hand, younger individuals, having a longer planning horizon until retirement, might reassess their background risk following such a disaster and decide to save more through the superannuation system instead of the real estate market.

5 Robustness Checks

5.1 Modifying the employment criteria for inclusion in the sample

For our primary robustness check, we modify the sample selection criteria related to employment. This is done to explore possible variations in how the disaster influenced the saving decisions of individuals in the treatment group based on their employment status. Our first modification involved removing the prerequisite that individuals have been employed in all sample years preceding the disaster. Next, we aim to isolate the impact of employment dynamics on savings decisions. To achieve this, we conduct a robustness check using a subset of individuals who remained employed throughout the study period. Table 7 presents the results obtained by applying Equation (2) to samples using these two distinct employment-based criteria.

Table 7: Results using different employment criteria for sample selection

	Total contributions (Log)	
	No employment criteria enforced	Employed through the entire period
	(1)	(2)
Treatment × 2008	-0.014	-0.012
	(0.010)	(0.010)
Treatment × 2009	0.000	0.001
	(0.009)	(0.008)
Treatment × 2011	0.009	0.017***
	(0.008)	(0.006)
Treatment × 2012	0.019**	0.027***
	(0.010)	(0.009)
Treatment × 2013	0.021*	0.031**
	(0.012)	(0.013)
Treatment × 2014	-0.007	0.018
	(0.014)	(0.011)
Observations	1,779,520	1,482,278

Results are for the benchmark specification: OLS with individual year, SA4-level fixed effects and controls (age, age squared, gender, partnered/married, self-employed, log income and income squared). Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Overall, our baseline results are robust to the two alternative samples. Column (1) presents the results when no employment criteria are enforced for the sample selection, allowing individuals included in the sample to experience all possible employment dynamics. The results are qualitatively similar, being strongest in the year following the disaster but still showing a positive effect that is significant at the 10% level in the next year. Column (2) presents the results when the sample includes only individuals who have been employed through the entire period. In this case, we observe an increase in the significance, magnitude and persistence of the treatment effect. These stronger effects are to be expected, as any increase in retirement savings should come from those who remain employed post-disaster.[37]

[37] Appendix A8 provides the results regarding private health insurance uptake for the two samples given in

5.2 Effects of the Disaster on Early Draw-downs

Our analysis thus far suggests that changes in risk preferences outweigh potential negative wealth effects. This section explores the extent to which affected individuals experienced financial stress, leading them to draw down their retirement savings prematurely (e.g., early draw-downs). Superannuation savings, typically illiquid, allow early withdrawal in extreme circumstances such as financial hardship. Disaster victims experiencing such hardship could be eligible for early withdrawals of superannuation savings, which are usually taxed. These transactions are recorded under the taxed components of income from superannuation and annuities, whether as lump sum payments or in streams.[38,39]

Table 8 presents an overview of the average total draw-downs for the treatment and control groups before and after the disaster. The average total draw-downs for both the treatment and control groups are around AU$ 20-25, as 99.8% of the sample did not have positive draw-downs. The mean value of positive draw-downs is around AU$ 15,100 for both groups in the pre-disaster period.

Table 9 presents the disaster's impact on the incidence of draw-downs and the amount of draw-downs conditional on having a draw-down. Contrary to expectations that the disaster would significantly increase total draw-downs among the treatment group, the results show no significant effects. These results differ from the dynamics observed in the U.S. regarding disaster-induced withdrawals from 401(k) plans following natural disasters in 2020. This leads us to conclude that the disaster did not inflict severe financial hardship that compelled treated individuals to withdraw from their superannuation savings. Thus, the negative wealth effect from the floods does not seem to be as strong, further supporting the positive effects on retirement savings that we have discussed.

Table 8: Descriptive statistics for total draw-down

	Pre-disaster period (2008-2010)		Post-disaster period (2011-2014)	
	Treatment group	Control group	Treatment group	Control group
% with draw-down	0.22%	0.21%	1.01%	1.01%
Total draw-down (AU$)	21	25	115	125
Total positive draw-down (AU$)	15,075	15,164	18,247	17,132
(i.e. actual amount)	(39,385)	(30,690)	(31,614)	(29,875)

Numbers in parentheses represent standard deviations from the mean.

this robustness check. It confirms that changing risk perceptions are observed regardless of the employment dynamics.

[38]We constructed the total draw-down by adding the taxed components of income from superannuation lump sum payments, income from annuity, superannuation lump sums in arrears, and income from annuity and superannuation streams.

[39]Since this early withdrawal is only permitted in certain extreme circumstances, only 0.66% of individuals have positive draw-downs in the entire period. Thus, any removal of outliers would remove these observations, which is why the treatment of this variable did not include winsorisation and the statistics presented for it comprise only the deflated positive observations.

Table 9: Results on accessing retirement savings prematurely following the disaster

	Dummy for having positive draw-down	Log total positive draw-down
Treatment × 2011	0.000488	0.052
	(0.000489)	(0.073)
Treatment × 2012	0.000476	-0.023
	(0.000486)	(0.069)
Treatment × 2013	0.000282	-0.014
	(0.000485)	(0.094)
Treatment × 2014	-0.000128	0.034
	(0.000485)	(0.089)
Observations	1,594,005	10,529

Results for log-transformed monetary values are for an OLS specification with individual, year, SA4-level fixed effects and controls (age, age squared, partnered/married, self-employed, log income and income squared), while results for the binary variable on having draw-down do not control for individual fixed effects. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Concluding Discussions

The past decades have witnessed a considerable accumulation of retirement funds and shifting generational preferences towards retirement worldwide. Global economic shocks, including climate change-driven natural disasters, add significant complexity to decisions regarding saving for retirement. Given that disasters are extremely costly, both economically and psychologically, and that retirement funds constitute a key saving mechanism for millions of individuals, the question of whether and how disasters impact the trajectories of retirement funds is a critical knowledge gap in the literature.

This study uses a large longitudinal administrative dataset from Australia to investigate the effects of the 2010-2011 Queensland floods on retirement savings, revealing several key findings. First, we estimate a noticeable increase in retirement savings following the floods, particularly among younger demographics, 21-29 and 30-39 years of age. This effect is less pronounced or absent in older age groups. In a subsequent analysis, we establish that private health insurance uptake increased in the aftermath of the floods, suggesting that individuals updated their background risk due to the disaster. This raises the natural question of whether and how the disaster affected individuals' portfolio choices, and in turn how retirement savings might have changed. We answer this question by delving deeper into portfolio choices, including investment property ownership and earning income from interest-generating financial instruments.

Crucially, while every age group updates their background risk, this change is manifested in varying portfolio choices. We identify that individuals aged 21-29 years in the pre-disaster year move away from investment property ownership and interest-generating financial instruments, and increase their retirement savings. Individuals aged 30-39 increase both their retirement savings and investment property ownership. For individuals in the

40-49 age group, we identify only a higher investment in property ownership. In contrast, individuals belonging to the 50-57 age group change neither their real estate investments nor their interest-generating instrument ownership, but decrease their retirement savings. One potential explanation is that this demographic cohort prefers to hold easily accessible precautionary savings following the disaster. Our differential findings by age group confirm the importance of planning horizons in portfolio choices due to changed risk perceptions following natural catastrophes.

Our findings have important economic implications. While the increase in retirement savings for the younger cohorts suggests that the retirement system is likely to be robust to climate change, the redirection of funds away from immediate economic reinvestment could negatively impact the region's post-disaster recovery. Furthermore, the shift away from real estate investment for the younger age groups raises concerns about long-term retirement welfare, as it may become important if retirement standards assume home ownership.

The study also draws attention to broader issues related to home ownership and retirement welfare in the wake of climate change-driven disasters. Earlier studies have identified the adverse implications of reduced home ownership on retirement welfare. The increased frequency of natural disasters and the growing number of regions where homes are no longer insurable due to extreme weather events could have adverse effects on retirement welfare and inter-generational asset transfer. This is a growing concern that necessitates further research on how governments can mediate insurance markets.

Finally, the paper suggests various potential avenues for further research. These include examining the long-term savings and expenditure patterns of individuals affected by the floods once they retire, and a comparative analysis of countries with lower rates of home ownership and different retirement systems. Such research could provide deeper insights into the long-term effects of natural disasters on financial planning and security.

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A Appendix

A.1 Superannuation Policy Changes Between 2008 and 2014

This appendix describes the reforms implemented from 2008 to 2014. The range of reformed areas is broad, but Appendix Table 1 presents only those that could have affected the variables considered in this study. The main reform is that concessional contributions caps were reduced. Before 2010, the caps for individuals aged less than and more than 50 years were AU$50,000 and AU$100,000, respectively. In 2010, these caps were halved, before a uniform cap of AU$25,000 was set for all age groups in 2013. In a partial reversal, the cap was then raised to AU$35,000 for individuals aged at least 59 years, but remained the same for those aged less than 59 years. In terms of non-concessional contributions, no changes were made over the study period. The superannuation guarantee rate, which was at 9% throughout, was increased to 9.25% in 2014 as a first step in its gradual increase to the target rate of 12% (ATO, 2021c).

Table A.1: Major relevant superannuation reforms

Financial year	Concessional contributions	Non-concessional contributions	Superannuation guarantee
2008	If age < 50 years, capped at AU$50,000 If age > 50 years, capped at AU$100,000	AU$150,000	9.00%
2009	If age < 50 years, capped at AU$50,000 If age > 50 years, capped at AU$100,000	AU$150,000	9.00%
2010	If age < 50 years, capped at AU$25,000 If age > 50 years, capped at AU$50,000	AU$150,000	9.00%
2011	If age < 50 years, capped at AU$25,000 If age > 50 years, capped at AU$50,000	AU$150,000	9.00%
2012	If age < 50 years, capped at AU$25,000 If age > 50 years, capped at AU$50,000	AU$150,000	9.00%
2013	All ages capped at AU$25,000	AU$150,000	9.00%
2014	If age < 59 years, capped at AU$25,000 If age > 59 years, capped at AU$35,000	AU$150,000	9.25%

Caps on contributions play a key role in shaping the amounts contributed but are not the only factors affecting contribution amounts. Looking at the post-disaster period, two other major reforms occurred in 2013, namely the introduction of the Division 293 tax and Low-Income Superannuation Contributions (LISC). The Division 293 tax is an additional tax on superannuation contributions, which reduces the tax concession for individuals whose combined income and contributions exceed AU$300,000 (ATO, 2021d).[40] Conversely, the LISC is a reform that aims to help low-income earners contribute to their retirement savings. The LISC is similar to a tax rebate for low-income earners to compensate them for the tax deductions their superannuation contributions have incurred (ATO, 2021e).[41]

These reforms to the superannuation system over the study period help to identify and explain changes in trends in contribution amounts. However, the use of the DID method in

[40] In 2017, the AU$300,000 threshold was decreased to AU$250,000.
[41] In 2017, the LISC was replaced by the Low-Income Super Tax Offset (LISTO).

the analysis ensures that these changes cancel each other out, since we ensure the parallel trend is satisfied when constructing the treatment and control groups.

A.2 Results for Participation in the Superannuation System

Table A.2: Treatment effects on participation in the superannuation system, for the entire sample and by age groups

	Dummy: having positive total contributions				
Age group	Entire sample	21-29	30-39	40-49	50-57
% with positive total contributions					
Treatment × 2011	0.001	0.003*	-0.000	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
Treatment × 2012	0.003*	0.005	0.005*	0.001	-0.002
	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
Treatment × 2013	0.003*	0.004**	0.005*	0.001	0.000
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)
Treatment × 2013	0.002	0.004	0.002	0.001	-0.005*
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Observations	1,594,005	376,670	470,106	451,171	296,058

Results are for an OLS specification with year, SA4-level fixed effects and controls (age, age squared, partnered/married, self-employed, log income and income squared). Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Shares constitute the pre-disaster percentages for the treatment group. Individuals are assigned to their respective age groups based on their age at the time of the disaster, i.e., 2011. Note that our sample includes individuals aged 18-60; thus, they are 18-54 in 2008 and 24-60 in 2014.

A.3 Results for the Unbalanced Sample

Table A.3: Results for log total contributions for the unbalanced sample

	Total contributions (Log)					
Mean value	AU$7,903					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	0.017	0.012	0.023***			
	(0.010)	(0.010)	(0.008)			
Treatment × 2008				0.013	0.018	-0.006
				(0.019)	(0.018)	(0.010)
Treatment × 2009				0.001	0.003	0.002
				(0.010)	(0.010)	(0.008)
Treatment × 2011				0.002	0,000	0.020***
				(0.007)	(0.008)	(0.009)
Treatment × 2012				0.038***	0.038***	0.027***
				(0.012)	(0.012)	(0.009)
Treatment × 2013				0.027	0.023	0.025
				(0.023)	(0.023)	(0.017)
Treatment × 2014				0.022	0.015	0.011
				(0.020)	(0.021)	(0.016)
SA4 FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Age and age squared		YES	YES		YES	YES
Partnered/Married		YES	YES		YES	YES
Self-employed		YES	YES		YES	YES
Log income and income squared			YES			YES
Observations	2,132,242	2,132,242	2,132,242	2,132,242	2,132,242	2,132,242

Columns (1)-(3): OLS with a single treatment effect estimate. Columns (4)-(6): OLS with yearly treatment effects. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. FE = fixed effects. Mean values constitute the pre-disaster (2008-2010) averages for the treatment group.

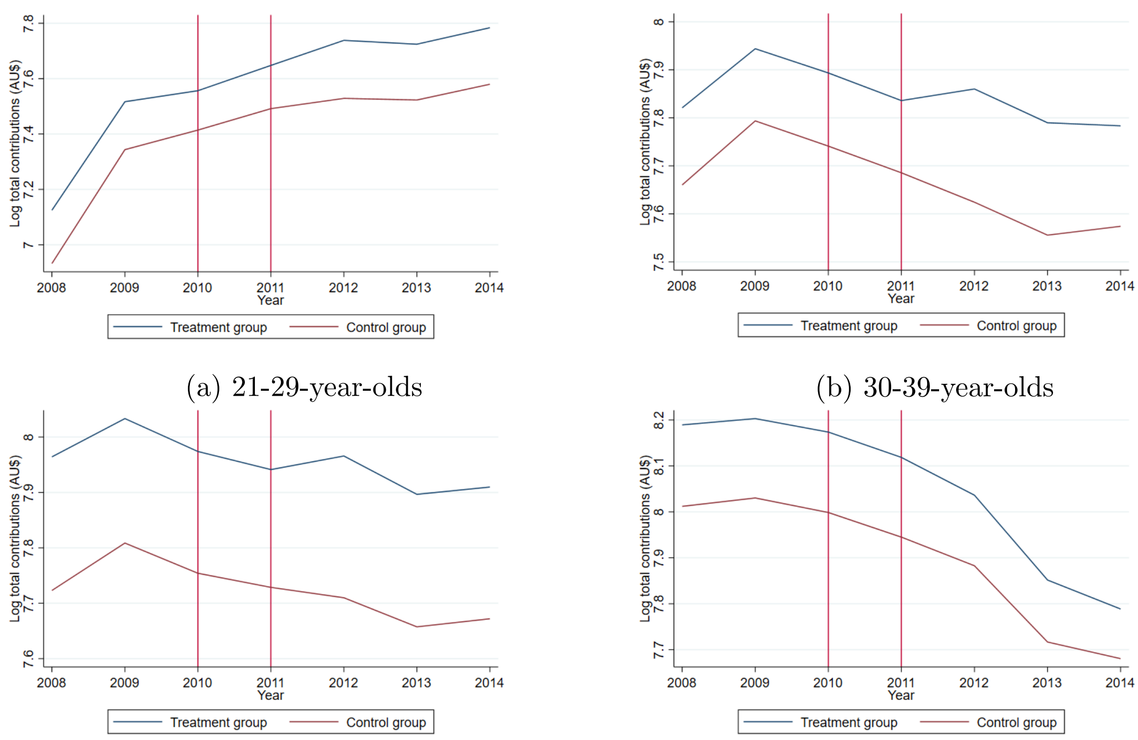
A.4 Descriptive Statistics by Age Groups

Table A.4: Descriptive statistics for the pre-disaster period (2008-2010) by age group

	21-29		30-39		40-49		50-57	
	Treatment group	Control group	Treatment group	Control group	Treatment group	Control group	Treatment group	Control group
Age	23.12	23.32	32.47	32.56	42.47	42.43	51.23	51.24
	(2.69)	(2.66)	(3.02)	(3.01)	(3.03)	(3.01)	(2.41)	(2.42)
Wage & salary	33,389	32,799	53,434	55,394	56,918	58,945	54,265	55,059
(AU$)	(21,317)	(22,749)	(36,434)	(40,624)	(45,442)	(50,605)	(43,851)	(47,036)
Gross income	36,419	36,328	58,482	61,584	65,632	70,383	65,560	68,606
(AU$)	(22,262)	(24,200)	(39,237)	(44,336)	(52,976)	(60,089)	(53,959)	(58,916)
Total contributions	3,238	2,889	5,706	5,279	7,108	6,852	9,664	9,240
(AU$)	(2,744)	(2,407)	(4,918)	(4,723)	(7,537)	(7,951)	(11,441)	(11,645)
No. of individuals	12,220	41,590	12,983	54,175	12,041	52,412	7,679	34,615

Numbers in parentheses represent standard deviations from the mean. Note that our sample includes individuals aged 18-60; thus, they are 18-54 in 2008 and 24-60 in 2014.

A.5 Development of Total Contributions (Log) by Age



(a) 21-29-year-olds

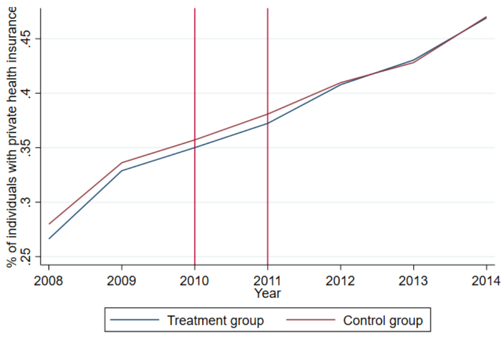
(b) 30-39-year-olds

(c) 40-49-year-olds

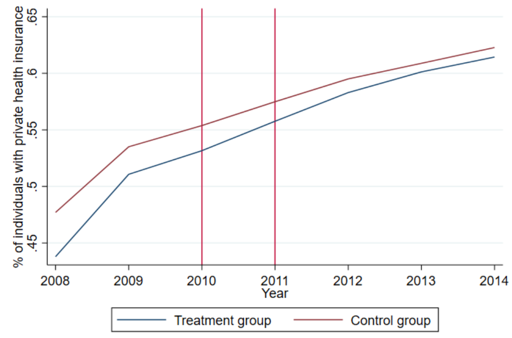
(d) 50-57-year-olds

Figure A.1: Development of log total contributions by age

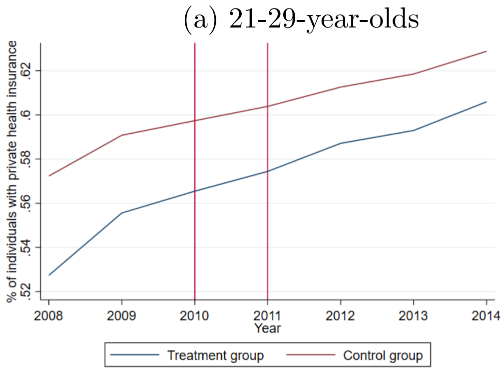
A.6 Evolution of the Share of Individuals with Private Health Insurance by Age



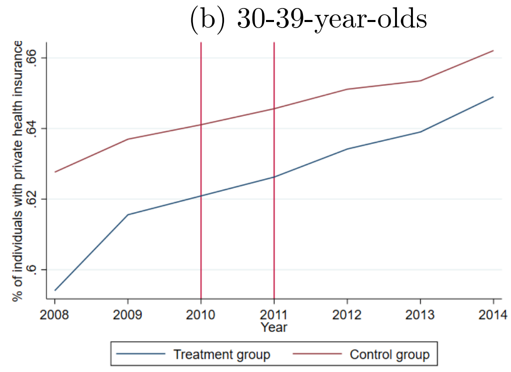
(a) 21-29-year-olds



(b) 30-39-year-olds



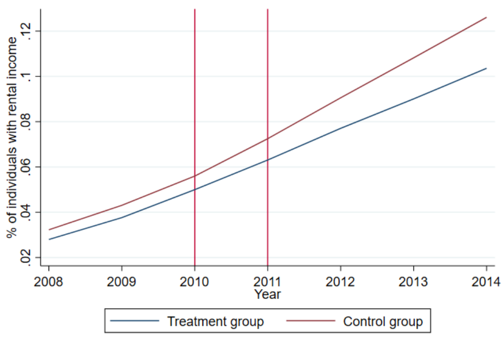
(c) 40-49-year-olds



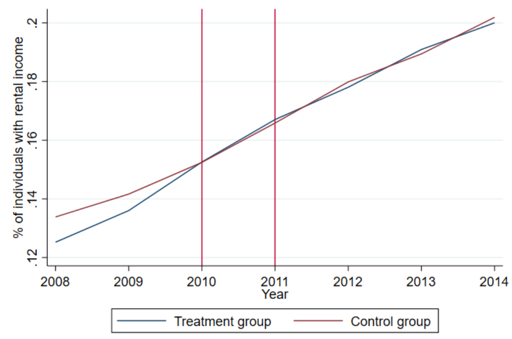
(d) 50-57-year-olds

Figure A.2: Share of individuals with private health insurance by age

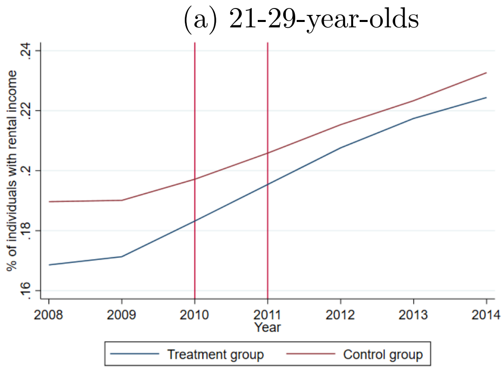
A.7 Evolution of the Percentage of Individuals with Rental Income by Age



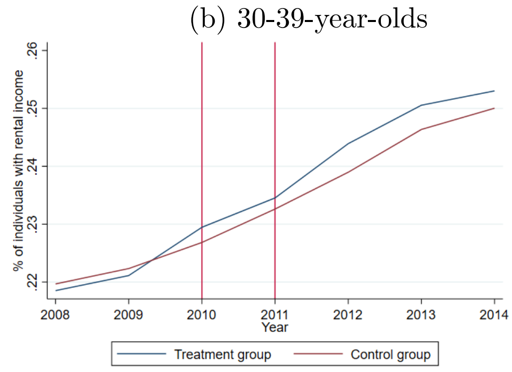
(a) 21-29-year-olds



(b) 30-39-year-olds



(c) 40-49-year-olds



(d) 50-57-year-olds

Figure A.3: Percentage of individuals with rental income by age

A.8 Results for Private Health Insurance Cover by Different Sample Selection Criteria

The effects of the disaster on the decision to take up private health insurance have also been analysed for the sample with continued employment throughout the period. The results show an increased uptake of private health insurance in both samples. Furthermore, the treatment effects are almost identical in terms of magnitude and significance. These findings show that the disaster causes a change to risk perceptions through increased risk aversion, even with either continued employment or changes in employment status.

Table A.5: Uptake of private health care following the disaster under different sample selection criteria

	Dummy: private health insurance	
	No employment criteria enforced	Employed throughout the entire period
% with private health insurance	48%	47%
Treatment × 2011	0.001	0.002
	(0.003)	(0.003)
Treatment × 2012	0.006**	0.006**
	(0.003)	(0.003)
Treatment × 2013	0.015***	0.014***
	(0.003)	(0.003)
Treatment × 2014	0.014***	0.013***
	(0.003)	(0.003)
Observations	1,798,533	1,482,278

Results are for an OLS specification with year, SA4-level fixed effects and controls (age, age squared, partnered/married, self-employed, log income and log income squared). Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$. Shares constitute pre-disaster percentages for the treatment group.