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Climate-related disaster risk in Australia: Are risks higher for disadvantaged households? *

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Abstract

As climate change generates more damaging weather-related events more often, the question of who bears intensifying disaster risk becomes increasingly pertinent. Drawing on disaster sociology and quantitative studies of disaster impacts in real estate markets, this paper contributes to research efforts to explore distributional questions of climate risk. We examine an actual flood event in an area of Australia that is increasingly recognized as vulnerable to rising flood risk. Our analysis combines geospatial analysis of flooding in residential areas, household level socio-economic data and data on house prices to identify socio-economic patterns in the impacts of a flooding disaster that indicate broader patterns in flood risk exposure and resilience, with implications for longer term dynamics of climate-related inequality. Our results show not only that risk exposure was greatest amongst the most disadvantaged communities but also that the most disadvantaged incurred substantially greater losses in comparison to equally flooded locations in wealthier areas, indicating exacerbated balance sheet losses on the part of disadvantaged households who are pushed into acute financial distress as a result of the floods. Variation in both risk exposure and impacts reflect that the costs borne as a result of climate-related disasters play out distinctly amongst different socio-economic groups. Our analysis of key data sources at a high level of granularity contributes to much needed empirical research on the socio-economic distribution of unfolding climate-related risks outside of heavily studied US locations.

JEL classification: I32, Q54, R11, R23, R31

Keywords: climate risk, natural disasters, socio-economic distribution, housing prices

1. Introduction

As climate change generates more damaging weather-related events more often, the question of who is bearing the cost of that risk becomes increasingly important. On the one hand, establishing better knowledge about the socio-economic profile of at-risk populations is important for the kinds of rapid disaster response policy that is becoming increasingly mainstream as weather-related disasters become more common. On the other hand, such knowledge helps build a better picture of long-term dynamics of inequality as they emerge amidst the unfolding of new climate risks.

Building on earlier work in sociology and human geography (Blaikie et al, 1994; Cutter, 1996), a growing literature on inequality and weather-related disasters explores these issues by asking if a parallel to the disproportionate pollution exposure amongst lower socio-economic groups that is identified by the environmental justice literature (Bullard, 1983; Walker, 2012; Mitchell & Dorling, 2003) is found in relation to disaster exposure. Much of this literature looks at hurricane-related flooding using flood zones linked to mandatory and subsidized flood insurance for American mortgagees. Some studies find risk concentrated amongst lower socio-economic groups (Collins et al., 2019; Smiley et al., 2022; Rolfe et al, 2020), especially in the case of inland flooding. Other studies find that wealthier areas are more exposed, particularly in coastal areas where waterfront amenity attracts wealthier groups despite relatively high flood risk (Qiang, 2019; Chakraborty et al., 2014; Galster et al., 2024). However, in the UK, these patterns between coastal and inland flooding are reversed (Walker & Burningham, 2011; Sayers et al., 2018).

The mixed nature of these findings provides unstable footings for new research on climate gentrification (Keenan et al., 2018; Thompson et al., 2023), which tracks emerging trends of polarization in real estate markets as wealthier groups move into areas that are safer from rising flood risk, leaving lower socio-economic groups 'trapped in place' (Logan, 2016). Without a clear picture of existing distributional patterns of flood risk, the starting point from which processes of climate gentrification might take off remains unclear.

Moreover, the disaster literature opens up questions as to the role of disasters in the asset market dynamics that climate gentrification identifies. Sociologists explore dynamics within and between communities as well as in community relationships with funding bodies and charities that slow disaster recovery in lower socio-economic areas (Medwinter, 2020; Elliott et al., 2010; Smiley et al., 2022). These dynamics may well play into gentrification, driving the slower real estate recovery in disadvantaged areas for which there is some existing evidence (Ellen & Meltzer, 2024; Rajapaksa et al., 2017). Yet there is little research on house price recovery that differentiates between different socioeconomic areas. This is especially true in relation to more recent disasters, which might be more broadly understood as symptomatic of the elevation of climate risk in particular locations associated with climate change (e.g., Herring et al., 2022). For the link between disaster events and climate gentrification to be better established, there is a need for much more empirical research on the distribution of disaster impacts in housing markets.

This paper contributes to research efforts to explore distributional questions of climate risk by identifying socio-economic patterns in the impacts of a flooding disaster that indicate broader patterns in flood risk exposure and resilience, with implications for longer term dynamics of inequality. Specifically, our analysis explores an actual flooding disaster to identify if lower socio-economic groups were more likely to live in impacted areas and if they were more likely to sustain significant damage. Like the climate gentrification literature, we focus on the value of the home, which is a prescient indicator of household economic security, but we combine the analysis of real estate dynamics with an array of socio-economic indicators.

We examine an area of Australia that is increasingly recognized as vulnerable to rising flood risk as a result of climate change using flood footprint data from February 2022 flooding. Key to this contribution is the use of geospatial analysis to identify flooded and non-flooded locations at a high level of granularity, which we combine with census data and point-level house price data. This allows our analysis to combine the kind of demographic data that is familiar to the environmental justice literature with the house price data that are examined in the climate gentrification and broader real estate economics literature. Moreover, we are able to include a suite of controls for house characteristics that allows us to analyse changes in house prices without distortions driven, for example, by variation in the size of homes.

As a result, we can compare streets that were flooded with those that weren't flooded: before and after the flood, and across and within wealthier, coastal communities and poorer inland towns. This allows us to observe different patterns in areas that experienced similar levels of flooding but have different socio-economic profiles. The analysis thereby provides an important perspective into the dynamics by which the costs of climate risk are experienced differently in different socio-economic areas, as well as the role of a climate disaster in accelerating enduring patterns of socio-economic polarisation.

Breaking our sample into two regions – a wealthier coastal region, where house prices sit at a range above the average for the state, and poorer inland towns, where house prices sit at a range below the average for the state – we find clear patterns in line with the expectations of the environmental justice literature. That is, both before and after the floods, the most heavily flooded areas in both the wealthier coastal region and the poorer inland towns had lower house prices and stronger indicators of disadvantage than areas within the same region that remained unflooded.

Our analysis of house prices shows, however, that when the 2022 floods hit, substantially greater losses were incurred in heavily flooded locations in the poorer inland towns in comparison to heavily flooded locations in the wealthier coastal areas. This represents substantial balance sheet losses for the most disadvantaged households that did not occur in equally flooded but higher socio-economic areas. This indicates exacerbated losses on the part of disadvantaged households who are pushed into acute financial distress as a result of the flood and are consequently unable to repair their property and hold out on selling until real-estate markets have recovered.

The variation in outcomes between heavily flooded locations in wealthier areas and heavily flooded locations in poorer areas reflect the ways that the costs borne by climate-related disasters such as the 2022 floods play out distinctly amongst different socio-economic groups. Our results show not only that risk exposure was greatest amongst the most disadvantaged communities but that the most disadvantaged groups also incurred the greatest losses, while equally flooded locations in wealthier areas do not see comparable declines in the value of homes.

These results contribute much needed empirical evidence to research efforts to understand the relationship between disasters and inequality, showing that the kinds of questions that the environmental justice literature asks are relevant to the climate-related disaster context outside of the US. By charting the different trajectories of different socio-economic groups in both the wealthier coastal region and poorer inland towns, we show how wealthier areas were able to maintain the value of housing assets regardless of flood impacts while poorer areas that experienced comparable damage realized substantial losses. These results cast light upon the impact of a climate-related disaster in exacerbating existing inequalities, which is consistent with climate gentrification but focuses not on asset inflation in the safest areas but asset deflation in the least safe areas. Our results point to the dwindling asset values and greatest risk exposure of the most disadvantaged households.

The climate gentrification literature provides an innovative empirical approach to exploring the dynamics of inequality that emerge as new climate risk unfolds (Keenan et al., 2018; McAlpine & Porter, 2018; Bernstein et al., 2019; Thompson et al., 2023). Seeking to track increasing demand for safety from climate risk in the housing market, seminal research by Keenan et al. (2018), for example, analyses growth rates in house prices in Miami-Dade County with respect to flood risk. This approach is well suited to a homeownership economy – such as the US, but also Australia – where the asset value of the home provides a prescient indicator of socio-economic status. The premium on safer homes that Keenan et al. (2018) identify is consistent with the emergence of new climate inequalities as wealthier households use their greater resources to secure housing assets in safer locations, pushing up prices in safer areas.

2. Literature

The climate gentrification approach thus ties into the growing body of work in disaster research that explores the role of disasters in both expressing and driving greater inequality (Smiley et al., 2022; Tierney, 2007; Howell & Elliot, 2019). Hurricane Katrina did much to advance this research agenda. Echoing earlier work by those such as Cutter et al. (2012) and Blaikie et al. (1994) on the social embedding of disaster impacts in social vulnerability, the literature on Hurricane Katrina identified that lower socio-economic groups were exposed to the greatest impacts of the Hurricane as well as the slowest recovery (Elliot & Pais, 2006; Fussell et al., 2010). In addition to incurring greater damage, for example, lower socio-economic groups were found to suffer higher rates of mental illness (Adeola, 2009; Rhodes et al., 2010; Sastry & VanLandingham, 2009; Escobar Carias et al., 2022) and of housing and employment insecurity in the wake of the hurricane (Elliott et al.

2009; Sastry, 2009; Groen & Polivka, 2008); as well as greater limitations on access to government, philanthropic and social resources (Elliot et al., 2010), which slowed recovery and revitalization in lower-socio-economic areas (Finch et al., 2010).

These findings present a rich context for the kinds of trends in real estate markets that are picked up on in the climate gentrification literature. By demonstrating an array of distributional impacts of climate risk that generate variation across different socio-economic areas, the disaster literature foregrounds the long-term changes that climate gentrification studies seek to identify. Yet although this area of study is growing rapidly, there is much scope for development, especially in empirical research.

Establishing the degree to which climate risk exposure correlates with socio-economic status in line with the patterns identified in the environmental justice literature is an important first step. Indeed, the environmental justice literature has long recognized that lower socio-economic groups tend to bear greater exposure to environmental risks than wealthier groups (Bullard, 1983; Walker, 2012; Mitchell & Dorling, 2003). Yet while it is often assumed that climate risk will reflect socio-economic status much as pollution risks have been found to do so, this has not been unequivocally established in the literature. A number of studies that examine individual towns or cities find a correlation between low socio-economic areas and flood risk, especially in the case of inland flooding (Collins et al., 2019; Smiley et al., 2022; Rolfe et al., 2020); but some, particularly in coastal areas, find exposure concentrated amongst the wealthy (Qiang, 2019; Chakraborty et al., 2014; Galster et al., 2024) and some find mixed results (Maantay & Maroko, 2009; Mazumder et al., 2022; Billings et al., 2022). Perhaps more pressing, moreover, is the need to extend this literature beyond the US, given the focus on Florida, Texas, Louisiana and, to a lesser degree, New York, in existing research on the socio-economic distribution of flood risk.

More empirical research on how disaster recovery feeds into socio-economic polarisation is also important. Research primarily in economics has found relatively muted economic and financial impacts of disasters on credit access and use as well as debt servicing (Deryugina et al., 2018; Gallagher & Hartley, 2017). However, some studies have found that disadvantaged groups display the greatest increases in indicators of financial distress after a disaster (Ratcliffe et al, 2020; Billings et al., 2022), which, in the US, is particularly prevalent amongst those who are unable to access Federal Emergency Management Agency (FEMA) support (Roth Tran & Sheldon, 2017). In Australia Johar et al. (2022) find that among households that have their home damaged by a disaster those that have a low socio-economic background and are affected by an event that attracts little governmental aid are more likely to experience financial hardships. There is also some evidence that the asset value of homes in lower-income areas recover at a slower pace in comparison to higher-income areas following a disaster (Ellen & Meltzer, 2024; Zhang & Peacock, 2009; Peacock et al., 2014; Rajapaksa et al, 2017),[1] with foreclosures and home abandonments posing a distinct problem for local recovery in the US context (Zhang, 2012).

These household-level outcomes, combined with the variable access to recovery and revitalization resources at the community level that is explored in the sociology literature (Medwinter, 2020; Gotham & Greenberg, 2014; Pais & Elliot, 2008), implies a slower recovery with potentially long-term impacts on the socio-economic character of lower socio-economic areas relative to wealthier areas, which is consistent with the climate gentrification thesis. However, especially outside of extensively studied US locations, there is much research that must be undertaken to better understand these trends and their pervasiveness within the dynamics by which climate-related disasters might feed into process of socio-economic polarization as new climate-related risks unfold.

Our use of census and real estate data as well as flood footprint maps contributes to empirical research on disaster impacts with implications for long-term dynamics of socio-economic polarization with respect to climate risk. By focusing on the asset values of the home – the most important asset on the household balance sheet for a homeowner society such as Australia – we are able to explore climate risk exposure and impacts in a recent flooding disaster at an exceptionally granular level. This uncovers variation in impacts across different socio-economic areas that point towards a rapid acceleration in the kind of asset market polarization that the climate gentrification literature identifies at a longer-term scale.

3. Methodology

3.1 Data

Our geographical focus is on an area known as the Northern Rivers, which lies on the East Coast of Australia's most populous state, New South Wales (see Fig.1a). This location was selected for the analysis because it was heavily affected by the 2022 floods and is increasingly recognized as exposed to climate risk, notably in relation to flooding. The area is bound by the sea to the East and mountains South and West. The border to the neighbouring state of Queensland marks the Northern boundary. The area includes four main inland towns with populations of 10–20,000 people each, which serve as regional hubs for their districts, three similarly sized coastal towns, and several smaller communities spread across inland and coastal areas.

[1] Note that these findings are distinct to the bulk of the literature on disaster impacts on house prices in economics, however, which focuses primarily on price differentials linked to the specific dynamics of US flood zones (Atreya et al., 2013; Bin & Landry, 2013; Kousky, 2010; Hennighausen and Suter, 2020; Ortega & Taspinar, 2018; see also Beltran et al., 2018) rather than heterogeneity related to socio-economic indicators. Similarly, key papers on household-level financial and economic outcomes, such as Deryugina (2018) and Groen & Polivka (2008), do not address variation across different socio-economic groups.

Figure 1a Map of New South Wales

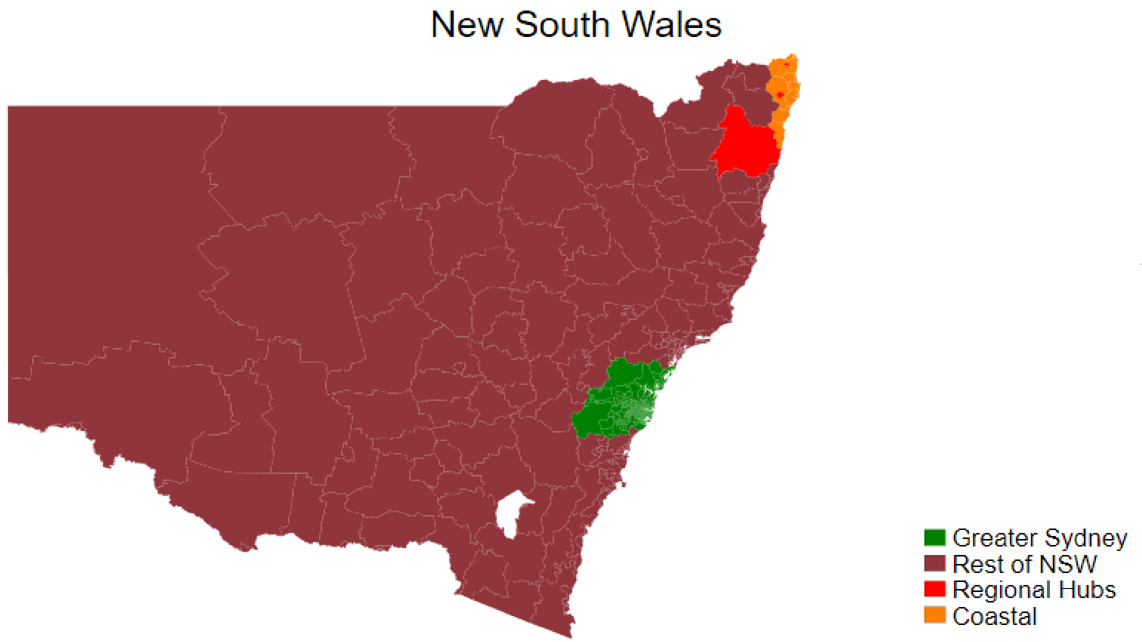
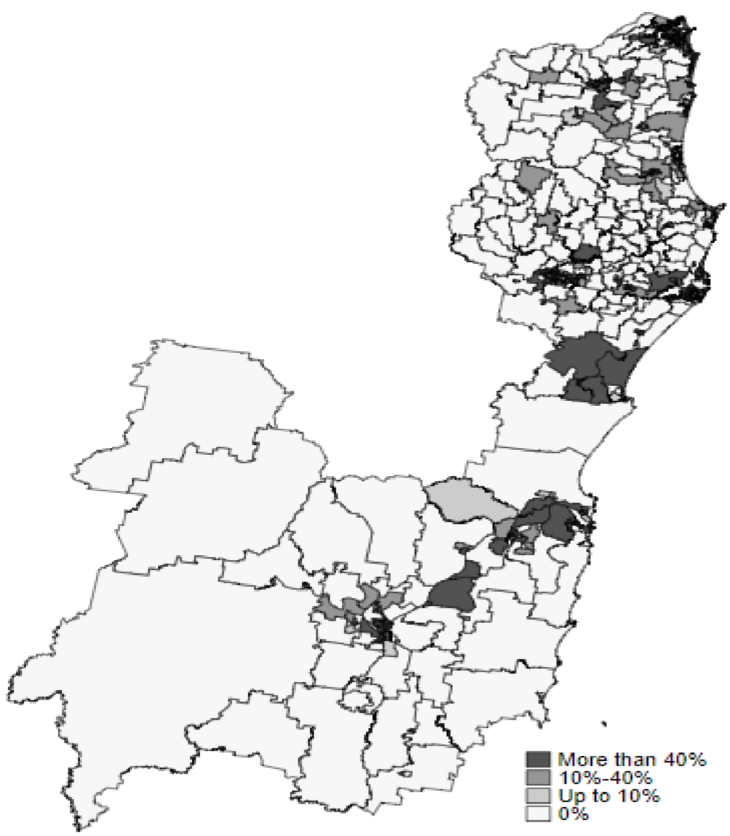


Figure 1b Map of the Northern Rivers floods in 2022



Source for flood footprint data: JBA Risk Management
Note: The legend shows the percentage of the residential area of each SA1 census tract that was flooded.

The total population of the area is approximately 275,000. Although many locations within the area did not flood in 2022, the floods affected the entire region through road closures and other disruptions in addition to substantial flooding in many locations. In order to compare areas with different levels of flooding, we first establish the percentage of each census tract that was flooded using flood footprints provided by JBA Risk Management.[2] To do this, we overlaid the flood footprint on the Australian Bureau of Statistic's residential mesh-blocks, which cover only a handful of houses and exclude public land such as parks and slipways. With an indicator for the percentage of land flooded calculated for each mesh-block, we then combined the mesh-blocks into the Bureau's census tracts, known as Statistical Area 1 (SA1), which are compatible with the smallest unit of analysis for census data. The granularity granted by the relatively small size of SA1-census tracts, which are defined by population to cover an average of 400 people,[3] is thereby strengthened further by the exclusion of public land in the measure of relative flooding intensity.

We establish three groups of flood impact, ranging from 'heavily flooded' SA1 census tracts, which experienced flooding in more than 40% of residential areas; 'moderately flooded' SA1 census tracts, which experienced floods in 10–40% of residential areas; and low and non-flooded SA1 census tracts (henceforth referred to as 'unflooded' areas for brevity), which experienced less than 10% of flooding in residential areas. This measure of impact is used as a representation of flood risk prior to the 2022 floods, discussed in terms of high, moderate and low risk locations to correspond to eventual flooding in each location as heavily flooded, moderately flooded and unflooded.

This then allows us to overlay census data as well as property market data, made available by Australian Property Monitor both for homes put on the market and homes sold, for a five-and-a-half-year period from 2018 to 2023. We can thus compare real-estate market details along with census indicators with respect to the percentage of residential land flooded in each of the 726 SA1-census tracts that fall within the Northern Rivers region. With details such as the size of properties and number of bedrooms, moreover, we can control for property characteristics in our estimates.

To establish our statistical approach to the data, we first examined potential variation within the Northern Rivers region by mapping median prices of houses sold prior to the floods at the SA1 level across the areas under examination. This revealed distinct geographical trends. As shown in Table 1, house prices in the four major inland towns were found to be somewhat lower than those both in the towns near the coastline and in the rural areas outside towns. Specifically, the median price in 2018 for 3-bedroom homes in the four major inland towns was AU$356,100 compared to AU$563,300 in the coastal area. Moreover, these patterns were distinct to the median for the state of New South Wales as a whole: excluding the metropolitan area of Sydney, where house prices

[2] Footprint data provide JBA Risk Management's best estimate of flood extent and depth but may differ from "truth" for the event.
[3] By contrast, census tracts in the US cover an average of 4,000 people.

are much higher than in the rest of the state, the median price for a 3-bedroom home in 2018 was AU$426,300. This reflects that pricing patterns in the inland towns sit at a range below the median for the state (excluding Sydney) that are distinct to patterns in the coastal area, in which prices sit at a range above the median for the state. As shown in Table 1, growth rates in house prices are similarly distinct between the inland towns and the coastal area.

Table 1 Summary Statistics

	House Prices			Socio-economic indicators			
		Bedrooms					
	Year	**3**	**4**	**Year**	**Population**	**No of SA1 census tracts**	**Weekly Household Income**
Coastal Region	Jan 2018	563.3	693.5	2011	196,170		945
	Jan 2022	875.5	1188.2	2016	191,903		1,123
	Growth	55.4 %	71.3 %	2021	201,200	525	1,453
Inland Towns	Jan 2018	356.1	415.0	2011	71,205		845
	Jan 2022	532.4	679.6	2016	71,372		990
	Growth	49.5 %	63.8 %	2021	74,212	201	1,214
Other Regions in NSW	Jan 2018	426.3	561.7	2011	2,352,179		1,069
	Jan 2022	599.0	773.7	2016	2,380,422		1,233
	Growth	40.5 %	37.8 %	2021	2,435,949	6,498	1,522

House prices are median prices (1,000$) deflated at January 2018 levels with the CPI Index. Household income is deflated at 2021 levels.
Source: Australian Property Monitor and Australian Bureau of Statistics Census.(2016, 2021)

As a result, we divide the Northern Rivers region into two distinct regions. The first is the combined coastal and rural hinterland areas (henceforth referred to as coastal areas); the second is inland towns, covering the four regional hubs, each of which have a population of 10-20,000 residents. We corroborate this division of the Northern Rivers with statistics on median income which reflects the same pattern: in 2016 median weekly household income in New South Wales (excluding Sydney) is AU$1,233, which is substantially higher than median household income in inland towns, at AU$990; and slightly higher than median income in coastal areas, at $1,123.[4] We also compare the percentage of residential land in each SA1 census tract that was flooded in 2022 between the coastal areas and the inland towns. This revealed that on average approximately 25% of the SA1 census tracts was flooded in both regions.

[4] These figures are from 2016 census data, which is the closest year available to 2018.

3.2 Methods

In this paper, we first study the correlation between flood-risk exposure, socio-economic disadvantage and house prices in the years preceding the floods, and then we examine the impacts of the floods on house prices, listings and property sales across areas with different flood exposure and across the two Northern Rivers regions.

To estimate price differentials across locations with different flood-risk exposure in the years preceding the floods, we run the following regression

$$\ln p_{ict} = \alpha + \lambda_t + \sum_{y=-4}^{-1} \theta_{Hy} H_c I_{y(t)} + \sum_{y=-4}^{-1} \theta_{My} M_c I_{y(t)} + \sum_{y=-4}^{-1} \theta_{Ry} R_c I_{y(t)} + X_i' \beta + \varepsilon_{ict} \quad (1)$$

$y = -4, \dots, -1$

where p_{ict} is the price of property i, located in census tract c sold at time t; λ_t is a time fixed effect (a month-year fixed effect); $I_{y(t)}$ is an indicator for property being sold y years prior to the flood with $y = -1$ denoting the twelve months before the floods; H_c is a dummy for properties in heavily flooded tracts; M_c is a dummy for properties in moderately flooded tracts; R_c is a dummy for houses in the other regions of NSW; and X_i is a set of property characteristics, such as number of bedrooms, type of property, number of bathrooms, parkings, land size. In regression (1), θ_{Hy}, θ_{My} and θ_{Ry} are the parameters of interest that estimate the average price differentials between low-risk areas and, respectively, high-risk locations, moderate-risk locations, and other regions of NSW y years prior to the flood.

The impact of the floods on house prices is estimated using a difference in differences (DiD) design, which is applied separately for the inland towns and the coastal region. Essentially our DiD model compares changes in house prices in affected census tracts prior and after the floods with changes in prices in census tracts within the same region that did not experience any floods. The equation of the model is

$$\ln p_{ict} = \alpha + \gamma_c + \lambda_t + \delta_H H_c I_{t \geq Feb2022} + \delta_M M_c I_{t \geq Feb2022} + \delta_R R_c I_{t \geq Feb2022} + X_i' \beta + \varepsilon_{ict} \quad (2)$$

where, $I_{t \geq Feb2022}$ is a dummy for the period after the floods (February 2022 − June 2023); γ_c is a census tract fixed-effect; and δ_H and δ_M are the parameters of interest, which estimate the decline in prices due to the floods respectively in heavily and moderately flooded areas compared to the unaffected census tracts. Note that DiD model (2) estimates differences in price changes while parameters in equation (1) estimate differences in price levels across the areas.

The DiD model relies on the parallel-trend assumption; that is, in the absence of the floods, prices in the affected and unaffected tracts would follow the same trend. Although the parallel trend assumption is not testable for the post-flood period, we can verify whether there were differences in price growth between flooded and unflooded tracts in the preceding years. To do this we estimate a DiD model that allows for flexible price growth across the tracts in the years preceding and after the floods. The equation is

$$\ln p_{ict} = \alpha + \gamma_c + \lambda_t + \sum_{y=-3}^{1} \theta_{Hy} H_c I_{y(t)} + \sum_{y=-3}^{1} \theta_{My} M_c I_{y(t)} + \sum_{y=-3}^{1} \theta_{Ry} R_c I_{y(t)} + X_i' \beta + \varepsilon_{ict} \quad (3)$$

$y = -3, \ldots, 1$

where $y = 0$ refers to the twelve months after the floods and $y = 1$ indicates the 12 months starting one year after the floods. Finding that δ_{Hy} or δ_{My} equal 0 for $y<0$ would provide evidence in support of the parallel-trend assumption as prices in areas that came to be moderately and heavily flooded grew at the same pace of unflooded areas in the years preceding the floods. If the parallel-trend assumption holds, any difference in price growth in the years after the floods would be attributable to the flood events.

As we will see in the next section, the unflooded census tracts are a good comparison group for moderately and heavily flooded tracts in the inland towns. In the coastal region, prices of moderately and unflooded tracts in the years preceding the floods increased faster than in heavily flooded tracts. For this reason, we also present estimates that use the regions in the rest of NSW as the control group.

In the analysis of the impacts of the floods on listings and property sales we use DiD models similar to equation (2) and (3) except for the fact that the data are aggregated at census-tract level.

4. Results

4.1 Risk exposure and socio-economic patterns in the pre-flood period

Following the lead of the environmental justice literature, we begin by addressing the question of risk distribution and socio-economic status: are lower-socio economic groups disproportionately exposed to disaster risk? To isolate flood risk exposure from the dynamics of recovery, we consider the degree to which areas that came to be flooded in the 2022 floods were home to lower socio-economic groups in the period prior to the flood. The degree of eventual flooding in 2022 is explored here as an indicator of flood risk for the years prior to 2022 and examined in relation to socio-economic indicators within each of the two regions under analysis.

The analysis demonstrates a clear relationship between socio-economic indicators and flood risk exposure, both within the wealthier coastal areas and the poorer inland towns. Table 2 shows that high-risk locations that came to be heavily flooded in 2022 were characterized by lower incomes and higher unemployment rates than low-risk locations in both regions respectively. Using 2016 data, which is clear of temporary covid-related economic stimulus, Table 2 shows that the unemployment rate in locations that remained unflooded in the wealthier coastal region was slightly lower than the state average (excluding Sydney) of 6.5%. In locations that came to be heavily flooded in the coastal region, the unemployment rate was higher, but still somewhat lower than low-risk locations in inland towns and substantially lower than high-risk parts of inland towns, where the unemployment rate was a full 10.5%.

Table 2: Socio demographic indicators by flood-risk exposure

		Socio-economic indicators					Household type				
	Census year	Household Income ($/week)	Unemp. Rate	Age	% aged 65 or older	% with long term health condition	Couples no children	Couples with children	Single Parents	Singles	Other households
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Inland Towns											
Unflooded	2016	1,139	8.8	43.7	20.0		28.5	24.1	14.8	28.1	4.6
	2021	1,264	5.8	43.9	21.6	35.0	28.7	23.4	15.1	28.3	4.6
Moderately	2016	1,110	7.6	44.8	23.9		27.1	23.8	13.6	30.6	4.9
flooded	2021	1,218	5.9	45.6	25.1	35.7	26.9	23.0	14.0	31.9	4.2
Heavily flooded	2016	984	10.5	43.6	20.8		22.0	20.6	15.3	35.6	6.6
	2021	1,114	7.0	44.1	22.8	37.7	22.9	19.3	15.0	36.7	6.1
Coastal Region											
Unflooded	2016	1,383	6.3	45.5	19.4		30.9	29.1	11.5	23.8	4.7
	2021	1,598	4.4	46.0	21.8	27.9	31.6	28.4	11.1	23.8	5.1
Moderately	2016	1,259	6.7	45.9	21.4		28.6	25.5	12.6	27.4	5.9
flooded	2021	1,489	5.0	45.5	22.8	29.2	29.1	25.7	11.9	27.2	6.2
Heavily flooded	2016	1,011	7.4	53.7	35.0		31.6	16.4	11.2	36.3	4.5
	2021	1,107	4.6	53.9	36.4	39.0	31.2	16.6	11.5	35.9	4.9
Other Regions of NSW											
	2016	1,381	6.5	42.6	20.2		29.1	27.8	11.9	27.4	3.9
	2021	1,526	4.5	43.5	22.2	33.6	29.6	26.4	11.7	28.3	3.9

The left panel reports the average socio-economic indicators for the Census tracts with the same flood-risk exposure within the same region. Household income deflated at 2021 levels with the CPI index. The right panel reports the average share of each household type.
Source: Australian Bureau of Statistics Census 2016, 2021.

Similar patterns pertain to income, with the highest incomes recorded in low-risk locations in the coastal region and lowest incomes recorded in high-risk locations in the inland towns. Other socio-demographic indicators reinforce the general picture of relative disadvantage in higher risk locations within both the wealthier coastal region and the poorer inland towns. The indicators in columns 3–5 of Table 2 suggest that relative disadvantage in high-risk coastal locations is largely driven by a sizable elderly population. This is reflected in the older average age, the high proportion of households with a long-term health condition, and the high share of uncoupled households without children (column 9 of Table 2). These characteristics distinguish the high-risk locations in the wealthier, coastal region from low and moderate risk locations in the same region. By contrast, the standout demographics in Table 2 for high-risk locations in inland towns are the high proportion of single parents, uncoupled households without children, and the high number of households living with a long-term health condition despite the much younger age profile in comparison to high-risk coastal locations.

Table 3: Housing tenure by flood-risk exposure

	Census year	Own outright	Own with mortgage	Rent	Other type of tenure
		(1)	(2)	(3)	(4)
Inland Towns					
Unflooded	2016	39.9	31.7	27.9	0.6
	2021	40.2	32.2	26.2	1.3
Moderately flooded	2016	38.3	31.7	29.4	0.5
	2021	38.8	31.8	27.2	2.2
Heavily flooded	2016	33.3	28.4	37.7	0.5
	2021	34.6	27.4	36.4	1.7
Coastal Region					
Unflooded	2016	40.9	32.6	25.7	0.8
	2021	42.3	32.5	23.0	2.2
Moderately flooded	2016	40.1	30.0	29.2	0.7
	2021	40.8	31.0	26.8	1.4
Heavily flooded	2016	47.6	20.2	30.6	1.6
	2021	47.0	21.0	28.6	3.4
Other Regions in NSW					
	2016	38.4	31.9	28.9	0.8
	2021	38.9	31.5	27.4	2.2

The table reports the average share of each type of tenure for the Census tracts with the same flood-risk exposure within the same region.
Source: Australian Bureau of Statistics Census 2016, 2021.

In Table 3 we present statistics on housing tenure by flood-risk exposure. Renters, who tend to have lower incomes and be the least economically secure, are predominant in high-risk locations in inland towns, where the lowest proportions of outright owners are also found. These figures track consistently across moderate and low-risk locations in the inland towns, reflecting the progressive reduction in housing security from the low-, to mid- to high-risk locations. This relationship is not consistent within the wealthier coastal region, however. Here, both higher shares of renters and outright owners are found in the high-risk locations, likely reflecting both the economic insecurity of younger generations and a sizable older population that managed to purchase their property over the working life.

Taken together, the most disadvantaged locations in the sample as a whole are the high-risk locations in inland towns, where incomes are substantially lower than the state average, unemployment rates substantially higher and single parents and other single income households are predominant. Although economic indicators are somewhat stronger in locations that proved equally risky in the wealthier coastal areas, they are weaker in these locations than moderate and low-risk locations in the same region, demonstrating relative disadvantage within the wealthier coastal region amongst households in locations that came to be heavily flooded in 2022.

Figure 2 House prices by flood-risk exposure

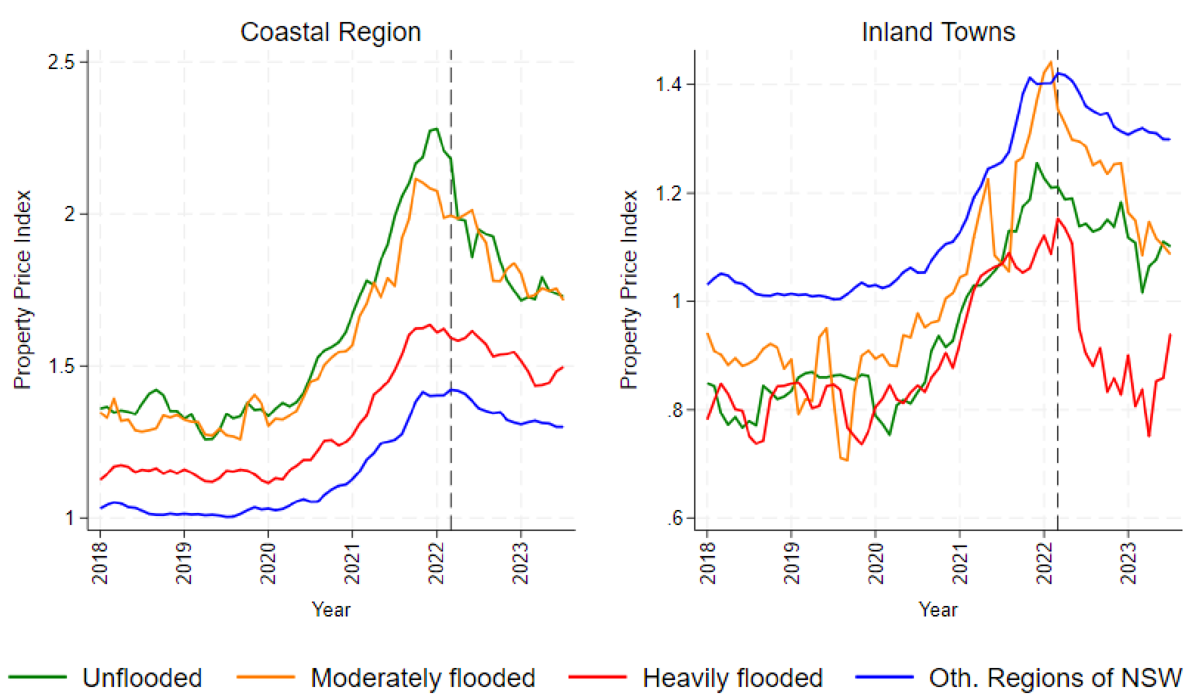


Figure 2 shows property prices between the 1st quarter of 2018 and the 3rd quarter of 2023 across areas with different flood-risk exposure in the Northern Rivers coastal region and the inland towns. The vertical line indicates the time of the flood event.

Moving to house price data, we find the similar picture of disadvantage that we have shown with the socio-economic indicators. Figure 2 shows the development of house prices, aggregated into high-, moderate- and low-risk groups in coastal areas and inland towns. In each panel, the blue line shows prices for the other regions in New South Wales (excluding Sydney). Note that the lines use controls for the size of land, the number of bedrooms and other property characteristics, thus revealing differences in prices over and above any differences that might arise, for example, because houses might be larger in coastal areas than in inland towns.

In the left panel of Figure 2, we observe a distinct trajectory for the coastal region with prices increasing until 2022 and sitting at a range substantially above the average for the rest of the state. Although experiencing price growth, properties in inland towns were sold at a range somewhat below the state average.

In coastal areas, houses in the riskiest locations – that is, those that were in the most heavily flooded areas in the 2022 floods – sold at consistently lower prices than those in the moderate- and low-risk groups. The line for the moderate-risk locations can be observed lying slightly below the low-risk unflooded group, indicating that homes in the moderate-risk group sold at slightly lower prices than those in the low-risk group. This indicates that flood risk was generally priced into coastal markets in the lead-up to the floods.

In inland towns, patterns are much less clear. The low-risk group represented by the green line is rarely observed below the high-risk group represented by the red line in the years preceding the floods. Differences across flood-risk groups are not substantial and trends appear similar until February 2022.

Table 4: House price differentials between moderate-, high-risk areas and low-risk areas.

	Coastal region		**Inland Towns**	
	Moderately flooded	**Heavily flooded**	**Moderately flooded**	**Heavily flooded**
	(1)	(2)	(3)	(4)
4 years prior	-0.037	-0.157***	0.099*	-0.021
	[-0.122; 0.049]	[-0.229; -0.084]	[-0.018; 0.215]	[-0.150; 0.108]
3 years prior	-0.012	-0.163***	-0.064	-0.080*
	[-0.101; 0.078]	[-0.234; -0.093]	[-0.266; 0.137]	[-0.169; 0.008]
2 years prior	-0.027	-0.200***	0.096**	-0.020
	[-0.118; 0.065]	[-0.283; -0.117]	[0.002; 0.191]	[-0.111; 0.071]
1 year prior	-0.028	-0.254***	0.098*	-0.039
	[-0.129; 0.072]	[-0.348; -0.160]	[-0.003; 0.199]	[-0.127; 0.048]

*p-value<0.1 ** p-value<0.05 *** p-value<0.01

The table reports the results of regressions of log-property price on interactions between indicators for years to the floods and dummies for flood-risk groups, time fixed effect and property characteristics. Omitted category is low-risk group. Confidence intervals at 95% level. Standard errors clustered at SA1 level.

The patterns in Figure 2 are reflected in the regression estimates presented in Table 4, which compare low-risk locations with moderate- and high-risk locations in coastal areas and inland towns respectively. In inland towns, prices in high-risk locations were consistently below those in low-risk locations, but at relatively small magnitudes and with estimates not statistically significant.

In coastal areas, the clear tracking of the red, orange and green line in Figure 2 is reflected in discounts of 17-25% on homes in high-risk locations in comparison to those in low-risk locations with estimates statistically significant at one percent level.

Taken together, the census and house price data from the pre-flood period show that, outside of a particular flood event, the distribution of flood risk is indeed concentrated amongst lower socio-economic groups.

4.2 Flood impacts and socioeconomic patterns in the post-flood period

We now turn to the flood event that occurred in early 2022 to explore any differentiation in flood impacts across the wealthier coastal region and poorer inland towns. To do this, we analyse the development of house prices in the period following the floods in these two regions, which reveals costs born in declining home asset prices.

Figure 2 shows a clear drop off in prices in the period after February 2022 that is unique to heavily flooded locations in inland towns. More specifically, the market as a whole experienced a downturn as interest rates started to rise after the covid boom. In coastal areas, the drop in prices in heavily flooded areas after the floods was similarly in line with the rest of the state. In inland towns, the downturn in prices in unflooded areas was similarly in line with the downturn in the state as a whole. However, heavily flooded areas in inland towns were unique in the sharp drop in prices observed following the floods.

The graphical evidence is confirmed by the findings presented in Table 5, which are estimated using the DiD models described in Section 3.2. Columns 1–4 and 9–10 show the estimates from the simplified DiD model of equation (2) and columns 5–8 and 11–12 present the estimates of the model that allows for flexible price growth of equation (3). In the DiD model, identification of the flood impacts relies on the parallel-trend assumption. Column 6 shows that in the coastal region price growth in heavily flooded locations is slower than in unflooded locations in the years preceding the floods. This violates the parallel-trend assumption, so for the coastal region we also estimate a DiD model with the other regions of the NSW as the control group. Column 8 shows that prices of high-risk locations and the rest of the state follow a similar trend in the lead-up to the floods reassuring that the rest of NSW is a suitable control group for heavily flooded locations. Unlike the coastal region, coefficients for heavily flooded areas in the inland towns in the years prior to the floods are small and not statistically significant indicating that the unflooded areas are an appropriate control group for heavily flooded locations (column 12).

Table 5 Flood impact on property prices.

	Coastal Region								Inland Towns			
	Moderate	**Heavy**	**Moderate**	**Heavy**	**Moderate**	**Heavy**	**Moderate**	**Heavy**	**Moderate**	**Heavy**	**Moderate**	**Heavy**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post Floods	.027 [-.051; .104]	-.007 [-.049; .035]	.019 [-.049; .088]	-.014 [-.035; .007]					-.020 [-.088; .048]	-.259*** [-.374; -.144]		
3 years prior					.060* [-.006; .127]	-.032 [-.122; .058]	.083 [-.023; .189]	-.010 [-.045; .025]			-.149 [-.356; .059]	.006 [-.097; .109]
2 years prior					.041 [-.015; .097]	-0.081 [-0.180; - 0.018]	.127** [.011; .243]	.004 [-.031; .039]			.001 [-.090; .092]	.006 [-.095; .108]
1 year prior					.031 [-.037; .098]	-.143*** [-.195;-.050]	.201*** [.088; .314]	.027 [-.010; .065]			-.024 [-.117; .069]	-.009 [-.104; .086]
Flood year					0.056 [-.055; .167]	-.062* [-.130; .007]	.118* [-.002; .238]	.000 [-.034; .034]			-.065 [-.172; .041]	-.232*** [-.382; -.081]
1 year after					.054 [-.030; .138]	-.086* [-.172; .000]	.112 [-.023; .247]	-.028 [-.072; .017]			-.082 [-.189; .024]	-.258*** [-.407; -.108]
Control group:												
Unflooded locations	x	x			x	x			x	x	x	x
Other regions in NSW			x	x			x	x				

*p-value<0.1 ** p-value<0.05 *** p-value<0.01

Columns (1)–(4) and (9)–(10) report the results of regressions of log-property price on interactions between an indicator for post-flood period and dummies for flood-risk groups, time and census tract fixed effects and property characteristics. Columns (5)–(8) and (11)–(12) report the results of regressions of log-property price on interactions between indicators for years to (since) the floods and dummies for flood-risk groups, time and census tract fixed effects and property characteristics. Confidence intervals at 95% level. Standard errors clustered at SA1 level.

Our findings on the impacts of the floods point to a large decline in prices in high-risk locations in the inland towns. On average the floods reduced house prices by around 25% compared to the unflooded locations within the same region. Estimates of the decline are statistically significant at 1% level. By contrast, heavily flooded locations showed much smaller declines in wealthier coastal regions with regression coefficients not statistically significant.

Data on the numbers of new listings and sales occurring in the post-flood period are consistent with the sharp declines in home values that we observe in heavily flooded locations in inland towns, as distinct to those equally flooded in coastal areas. Figure 3 shows an index of homes put up for sale in coastal areas and inland towns respectively, in each of the three flood-risk groups. The reference period is the first quarter of 2018 and takes value of 1. For coastal areas, the heavily flooded, moderately flooded and unflooded lines consistently move together with the line representing new listings for the rest of New South Wales (excluding Sydney) for the first three years of the data. Although these lines are more disparate from 2021, they continue to move in the same direction. This is confirmed in the regression statistics presented in Table 6, which show that differences in new listings between heavily flooded locations and unflooded locations in the coastal areas were small and not statistically significant.

Figure 3 Property listings by flood-risk exposure

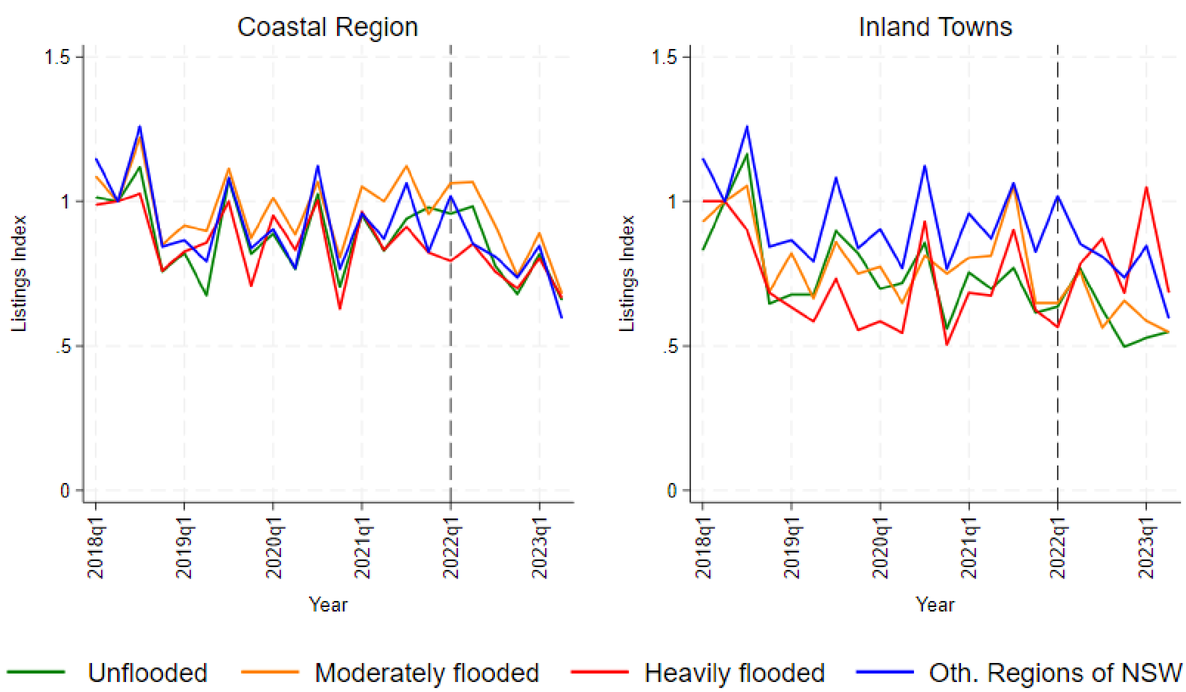


Figure 3 shows property listings between the 1st quarter of 2018 and the 3rd quarter of 2023 across areas with different flood-risk exposure in the Northern Rivers coastal region and the inland towns. The first quarter of 2018 is the reference period and takes value of 1. The vertical line indicates the time of the flood event.

Table 6 Flood impact on property listings

	Coastal region				Inland towns			
	Moderate	Heavy	Moderate	Heavy	Moderate	Heavy	Moderate	Heavy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Floods	.016	-.010			.022	.141***		
	[-.036;.069]	[-.060;.040]			[-.043;.086]	[.066;.215]		
3 years prior			.026	.019			.003	-.017
			[-.043;.095]	[-.048;.085]			[-.089;.095]	[-.109;.075]
2 years prior			.015	-.011			.076	. .053
			[-.058;.088]	[-.079;.058]			[-.019;.171]	[-.042;.148]
1 year prior			.026	.003			.079*	.031
			[-.046;.097]	[-.061;.067]			[-.011;.170]	[-.067;.127]
Flood year			.022	-.031			.043	.115**
			[-.055;.099]	[-.105;.044]			[-.050;.136]	[.013;.217]
1 year after			.058	.044			.099	.240***
			[-.037;.154]	[-.045;.134]			[-.033;.231]	[.085;.395]

*p-value<0.1 ** p-value<0.05 *** p-value<0.01

Columns (1)-(2) and (5)-(6) report regression results for property listings on interactions between an indicator for the post-flood period and dummies for flood-risk groups. Columns (3)-(4) and (7)-(8) report results of regressions of property listings on interactions between indicators for years to (since) the floods and dummies for flood-risk groups. Regressions include time and tract fixed effects, and average property characteristics. The control group is unflooded locations within the same region. Confidence intervals at 95% level. Standard errors clustered at SA1 level.

Table 7 Flood impact on property sales

	Coastal region				Inland towns			
	Moderate	Heavy	Moderate	Heavy	Moderate	Heavy	Moderate	Heavy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Floods	.018	.062			-.036	.198***		
	[-.059;.094]	[-.013;.138]			[-.170;.097]	[.059;.337]		
3 years prior			.017	-.025			-.018	.091
			[-.103;.138]	[-.140;.090]			[-.183;.147]	[-.082;.263]
2 years prior			.012	-.061			.079	.070
			[-.111;.135]	[-.175;.053]			[-.088;.246]	[-.113;.253]
1 year prior			.023	-.025			.057	.089
			[-.097;.142]	[-.138;.089]			[-.115;.228]	[-.089;.268]
Flood year			.023	.006			-.054	. .150
			[-.086;.132]	[-.111;.122]			[-.238;.129]	[-.038;.339]
1 year after			.046	.092			.090	.480***
			[-.099;.191]	[-.040;.223]			[-.153;.334]	[.200;.759]

*p-value<0.1 ** p-value<0.05 *** p-value<0.01

Columns (1)-(2) and (5)-(6) report regression results for property sales on interactions between an indicator for the post-flood period and dummies for flood-risk groups. Column (3)-(4) and (7)-(8) report regression results for property sales on interactions between indicators for years to (since) the floods and dummies for flood-risk groups. Regressions include time and tract fixed effects, and average property characteristics. Control group is unflooded locations within the same region. Confidence intervals at 95% level. Standard errors clustered at SA1 level

In the inland towns, by contrast, the red line moves away from the orange and green line after the floods, representing a spike in listings for homes in heavily flooded locations. The increase in listings in the post flood period is estimated at 14% (column 6 of Table 6)

Figure 4 Property sales by flood-risk exposure on property sales

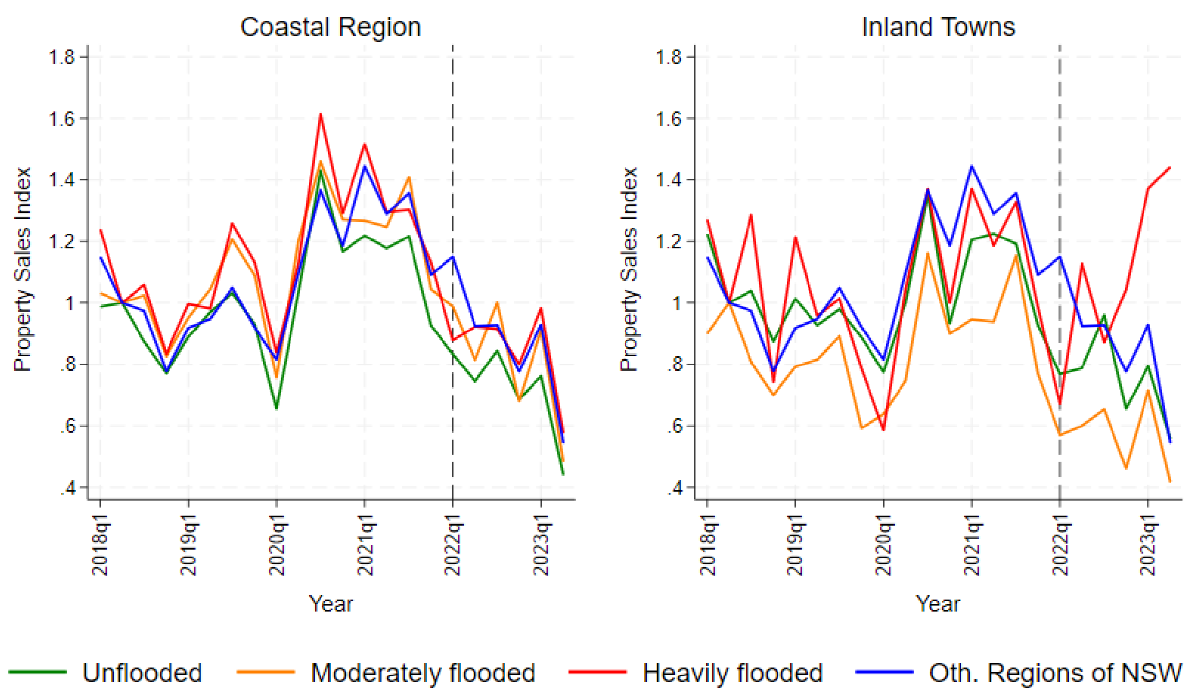


Figure 4 shows property sales between the 1st quarter of 2018 and the 3rd quarter of 2023 across areas with different flood-risk exposure in the Northern Rivers coastal region and the inland towns. The first quarter of 2018 is the reference period and takes value of 1. The vertical line indicates the time of the flood event.

Similarly, Figure 4 and Table 7 show that the number of sales remain relatively consistent in the pre- and post-flood period in coastal areas across each flood-risk group. This reflects that in coastal areas, sales patterns were much the same in unflooded as heavily flooded locations, which in turn were consistent with patterns in New South Wales (excluding Sydney) as a whole.

In inland towns, overall patterns show less consistency. The sharp divergence in the red line in the post flood period is estimated in a 20% increase in sales in heavily flooded locations in comparison to unflooded locations (column 6 of Table 7).

Taken together, these results point towards distress sales in the most disadvantaged locations in the inland towns, which did not occur in equally flooded locations in the coastal areas.

5. Discussion and conclusion

Our results reflect that the relationship between socio-economic status and environmental risk that is explored in the environmental justice literature (Bullard, 1983; Walker & Burningham, 2011;

Mitchell & Dorling, 2003) is relevant to flood risk in Australia. Our examination of the Northern Rivers region in the Australian state of New South Wales finds that flood risk is generally concentrated in areas where homes are worth less, incomes are lower and indicators of social disadvantage more prominent. These findings, in conjunction with the important patterns of variation in flood impacts on house prices that we identify, contribute to research efforts that seek to understand the distributional dynamics of new climate risk.

5.1 Pre-flood risk exposure

We undertake our analysis at the level of Australia's relatively small SA1 census tracts, dividing the area into two geographical regions: a coastal region, where incomes and house prices are above the average for the state (excluding the metropolitan area of Sydney), and a region made up of inland towns, where incomes and house prices are below the average for the state. Using an estimate of the flood footprint of the 2022 floods from (commercial modelling company) JBA Risk Management as a measure of flood risk, we find consistent patterns in socio-economic indicators with respect to flood risk in both regions prior to the floods.

In the wealthier coastal region, for example, the average income in the low-risk locations that remained unflooded during 2022 was substantially higher than the average income in locations that came to be heavily flooded within that same coastal region. Similarly, the unemployment rate and percentage of single parents was lower. In fact, our results indicate that the highest-risk locations in the wealthy coastal areas are home to a disproportionately large share of elderly households, along with which are elevated proportions of households with a long-term health condition. In high-risk coastal areas, the average age is 8 years older than that in low-risk locations in the same region, 10 years older than locations with the same flood risk in inland towns and 11 years older than the state average (refer to Table 2).

These demographic results point towards similar patterns to those in the Southern States of the US, where elderly households are concentrated in risky coastal locations (Qiang, 2019; Park & Franklin, 2023). However, our results are unique in the identification of older households in the most risky and relatively poorer locations within the coastal areas. Studies such as those by Qiang (2019) and Park & Franklin (2023) identify an older demographic in coastal counties but do not disaggregate these counties by risk level to observe whether elderly households are in the riskiest and most disadvantaged locations within those counties. Our results show that, amongst relatively affluent coastal areas, elderly households with relatively low incomes are concentrated in the riskiest locations. As Day (2010) makes clear, old age is an important indicator of disadvantage in the environmental justice context, especially when it overlaps with additional indicators of vulnerability such as low-income or ill health.[5]

Although the concentration of older residents in high-risk locations does not carry over to inland towns, broader patterns by which disadvantage is concentrated in high-risk locations in the pre-flood data are even stronger for these towns. In comparison to both the high-risk locations in the coastal areas and the low-risk locations that remained unflooded in the inland towns, incomes were lower and the unemployment rate higher in the pre-flood years in inland high-risk locations. High-risk locations in inland towns were also home to a higher proportion of single parents and people with a long-term health condition in comparison to low-risk locations, even though the average age was similar to the state average.

Taken together, these data present patterns that are consistent with the thesis of the environmental justice literature. Like those, we find that disadvantage is concentrated in high-risk locations both within the wealthier coastal region and within the poorer inland towns respectively, although the overall strongest indicators of disadvantage are found in high-risk locations in the inland towns.

Similar patterns emerge in the analysis of house price data in the period prior to the floods. In the wealthier coastal region, homes in the low-risk locations that remained unflooded in 2022 sold at a premium of 16–25% in the years prior to the floods compared to those that proved to be high risk in 2022. This suggests a systematic 'pricing in' of climate risk that is consistent with climate gentrification. Although we do not undertake a long-term analysis of sectoral price inflation typical of the climate gentrification approach (Keenan et al., 2018; Thompson et al., 2023), our results reflect unique pricing patterns amongst safer homes in coastal areas that is constituted by a clear and consistent premium, which reflects that safer homes are more attractive to markets than homes in riskier locations. This outcome is consistent with the climate gentrification analysis of pricing patterns over time.

This degree of 'priced in' risk is not as clear in the poorer inland towns. Regression results show that in the pre-flood years, homes in the high-risk locations that became heavily flooded in 2022 were generally cheaper than those in low-risk locations, but the discount is small and not statistically significant.

It is unclear what drives these different patterns of climate risk pricing between the coastal region and inland towns in the pre-flood years. However, it is noted that real-estate markets in the inlands towns are seen as 'entry level' markets that are attractive to first home buyers and those with lower mortgage servicing capacities more broadly. This is reflected both in housing tenure patterns, which show much higher outright ownership in the wealthier coastal areas; as well as in the median

[5] See also Tagtachian and Balk (2023) who similarly find elderly households concentrated in flood-prone coastal parts of the US.

price for 3-bedroom homes, which in high-risk inland towns are 23% cheaper than in the rest of the state and 35% cheaper compared to equally risky locations in the coastal region.

Insofar as the literature identifies that climate risk is less likely to be priced in by less sophisticated investors (Bernstein et al., 2019; Bakkensen & Barrage, 2017; Clayton et al., 2021), the absence of systematic discounts between high-risk and low-risk locations in the inland areas may reflect the ‘entry level’ nature of the market. This is however complicated by the high prevalence of rental properties in high-risk areas in the inland towns. On the one hand, a high proportion of rentals point towards a lower socioeconomic demographic that might be less discerning with regards to climate risk. But on the other hand, this points towards a greater share of investors than owner-occupiers, which is the measure of ‘sophisticated investors’ used by Bernstein et al. (2019) and Bakkensen & Barrage (2017).

In any case, findings that flood risk is concentrated amongst lower socioeconomic groups contribute to the established literature on flood risk and socioeconomic status, the vast bulk of which examines the US. Specifically, our findings are consistent with Collins et al., (2019), Smiley et al. (2022) and Rolfe et al. (2020), although our study examines a large region that covers a number of towns encompassing both inland and coastal areas in contrast to the single city (Collins et al., 2019), county (Smiley et al., 2022) and dual town centres (Rolfe et al., 2020) that are the subject of the existing literature.

In fact, that we find flood risk concentrated amongst relatively disadvantaged groups within the coastal as well as inland regions contrasts with findings from some literature, notably Qiang (2019) and Galster et al. (2024) at the national level in the US and Chakraborty et al. (2014) focusing on the Miami area specifically. The robustness of our findings, moreover, contrasts to studies that found mixed results in the socioeconomic distribution of flood risk, such as Billings at al. (2022), Maantay & Maroko (2009) and Mazumder et al. (2022). Similar to analysis undertaken by Hinojos et al. (2023), our results point towards the importance of fine-grained data in establishing robust findings on socioeconomic status and climate-related risk as well as the benefit of combining additional data sources beyond basic census indicators.

5.2 Disaster impacts in post-flood data

The extension of our house price data beyond the disaster event provides an important second step to the analysis. This step demonstrates how greater risk exposure is compounded by greater impacts for the most disadvantaged groups. Our results show that heavily flooded locations in poorer inland towns saw a substantial shock to asset prices in the wake of the floods that was not observed in locations that experienced similar flooding in the wealthier coastal areas.

The differentiation between losses in heavily flooded lower-socioeconomic areas and heavily flooded wealthier areas in our data is likely to be driven by a combination of factors. The degree of flooding in both locations is comparable, reflecting similar location-specific risk (that is, exposure to the exogenous risk of flooding). However, a home in a lower-socioeconomic area may incur greater damage because the home itself does not entail design measures that mitigate flood risk, for example being raised above the waterline or built from flood-resilient materials. Similarly, lower socioeconomic households are both less likely to be covered by insurance (Kousky, 2011; Settle & Ananyev, 2024) and less likely to have sufficient savings to undertake repairs (Gropper & Kuhnen, 2021).

These findings are broadly similar to those of the small body of existing literature on socioeconomic variation in disaster recovery in real-estate markets insofar as disadvantaged areas were generally found to recover more slowly following Superstorm Sandy in New York in 2012 (Ellen & Meltzer, 2024)[6] as well as Hurricane Andrew in Miami-Dade County in 1992 (Zhang & Peacock, 2009) and Hurricane Ike in Texas in 2008 (Peacock et al., 2014).[7] That said, our results differ from these studies in finding both stronger impacts in heavily impacted low-income areas and minimal impacts on prices in wealthier areas. The greater granularity of our analysis as well as US-specific differences relating to FEMA flood lines may explain these differences. Moreover, the 2022 flooding disaster that we examine may well involve somewhat different market impacts relating to perceived risk in comparison to decades past, when recognition that climate risk is increasing in certain locations as the climate changes was less widespread.

Indeed, where these pricing patterns move from here deserves attention as new data becomes available. It might be proposed, for example, that our results demonstrate a one-off price adjustment to climate risk in high-risk locations in inland towns that has already occurred in the coastal regions, as indicated by the consistent pricing-in of climate risk in the wealthier coastal areas. This would suggest that impacts of disasters in these low-income-high-risk locations might be as muted in the future as they have proved to be in the wealthier region following the 2022 floods. This perspective is consistent with the view common to the economics literature of disasters as information events (Bin & Landry, 2013; Ellen & Meltzer, 2024; Yi & Choi, 2020) and of low-income households as demonstrating less awareness of the underlying risks that are brought to light by those disasters (Bernstein et al, 2019). Alternatively, future disasters might continue to impose differentiated impacts through complicated social and economic processes by which disadvantaged households continue to face the greatest risk and the greatest losses. Indeed, the notion that climate risk is completely 'priced in' even in the wealthier coastal regions would seem unlikely given climate predictions for this region. More likely is that results like Gourevitch et al. (2023) might apply to Australia by which climate risk is found to be poorly reflected in real-estate prices in general but particularly so in low-income areas.

In any case, our results show a prevalence of sales in the direct aftermath of the floods in heavily flooded locations in the poorer inland towns, which indicates a lack of capacity to manage costs

[6] Although, as noted by Ellen and Meltzer, the opposite is found in the analysis of Cohen et al. (2021).
[7] Additionally, Rajapaksa et al. (2017) find evidence of a faster recovery in real-estate prices in the wealthier suburbs that they examine in Brisbane, Australia, following the 2011 floods.

imposed by the floods that is not observed in similarly flooded locations in wealthier coastal areas. This suggests a further compounding effect that is unique to the most disadvantaged groups, as households put their homes on the market at a time when evident devastation wrought across the region by the floods could be expected to depress prices over and above any discounts that reflect actual damage.

That disadvantaged households may be forced to realise additional losses by selling during a market shock is consistent with patterns found in US consumer credit data, which show a series of indicators of financial distress following a disaster that are concentrated amongst disadvantaged households (Roth Tran & Sheldon, 2017; Ratcliffe et al, 2020; Billings et al., 2022). By contrast, in wealthier areas, households were more likely to be able to wait out the post-flood period, consistent with a level of financial resilience that allowed those who might wish to sell to hold off until market conditions had improved.

Indeed, the rush of sales and the drop in prices that were observed in the heavily flooded locations in poorer inland towns are two sides of the same coin: households forced into acute financial distress have no option but to realise the low prices of a freshly disaster-hit market, which decline further with the rush of supply. This points to the absorption of substantial losses by households who sold in the direct aftermath of the flood. As our pre-flood results made clear, these households were already amongst the most disadvantaged in the state.

These results not only confirm that disaster risk – as it is reflected in the flood footprint of the 2022 floods – is disproportionately distributed amongst lower socioeconomic groups; but also reflects an asset channel by which inequality is exacerbated by disaster. That is, losses in asset values in excess of state-wide trends are observed amongst the most disadvantaged groups but are absent in higher socioeconomic areas that experienced similar levels of flooding. This suggests that households are pushed into severe financial distress, forcing them to realise that decline in asset values by selling into depressed markets. This indicates a balance sheet loss with likely long-term effects on the economic security of those households. Such forced sales are absent in equally flooded areas in the wealthier, coastal regions, indicating that households in these heavily flooded areas likely have access to financial resources to endure the disaster without those losses.

These findings contribute to research on the distributional impacts of climate risk outside of the US. This is especially important given that much of the findings in the existing literature engage with distinct US dynamics, such as FEMA flood zones and abandoned properties. Our results show that socioeconomic differentiation is highly relevant, both to risk exposure in line with the environmental justice approach; as well as to the assessment of disaster impacts as reflected in asset values. The analysis thereby helps to fill in the gaps between high level findings of disaster exposure driving inequality, on the one hand, and research on household- and community-level impacts of disaster on the other. Our results point towards a dynamic of cascading costs amongst the most disadvantaged households as heavy flooding drives the realisation of the asset price shock in real-estate markets in low-income locations but not in equally flooded relatively wealthier locations. This reveals dynamics of worsening inequality at the bottom end of the market amidst a slower recovery that is fitting both with the environmental justice thesis and with long-term dynamics of climate gentrification.

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