The Behaviour of Property Prices when Affected by Infrequent Floods ⋆

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Abstract

The reduction in property values following a major flood event is significant to individuals, communities and governments alike. Property owners who purchase properties just before a major flood risk significant personal loss on their largest single asset. The costs of a major event are shared across communities through government funded recovery efforts in the short term, and changes to insurance premiums and house values in the long term. Designing protections, adaptations and insurance mechanisms that can equitably ameliorate future impacts requires a detailed understanding of how flood risk affects property prices. This paper explores patterns of discounting of property prices following infrequent flooding events. It relates property value discounting in response to floods to various theories of market behaviour. There are alternative behavioural theories which explain why agents may react in this manner. We use a behavioural framework proposed in earlier literature to construct econometric measurements that provide the opportunity to make statistical inferences on whether the expected behaviours are

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supported by the data. The patterns found are consistent with a market where buyers are either unaware of the risk of flood or unable to evaluate it probabilistically.

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JEL: R32, Q54, C43

1. Introduction

Around the world, economic losses due to extreme environmental events, such as flooding, have increased dramatically in recent decades (Crompton and McAneney, 2008; Ortega and Taspinar, 2018; de Koning and Filatova, 2020). Although some of this increase may be driven by changing environmental risk profiles (Bouwer et al., 2010; Nicholls et al., 2007), by far the larger part comes from the increased value of infrastructure developed in risky areas (Bouwer et al., 2010; Netusil et al., 2019; Pielke et al., 2008).

Why do we keep building in risky areas? Risky properties are often in high value locations, and the impacts of risks arise only infrequently (Neumayer and Barthel, 2011; Seo et al., 2020). Between flood events these properties provide similar levels of utility to those of their risk-free neighbours. Continuing to develop risky properties is rational for the individual as long as the long term average loss of utility that occurs due to infrequent floods is internalised as a devaluation to the property price. In order for this to be effective, however, agents in the market must be good at estimating long-term average risk. There have been a range of studies showing that people are poor at estimating the economic value of long term risk in general (Camerer and Kunreuther, 1989; Kunreuther 1976, 1996; Kunreuther et al., 1978; McDaniels et al., 1992; Slovic, 1987; Smith, 1986), and in terms of floods and property values specifically (Bin and Kruse, 2006; Bin and Landry, 2013; Gallagher, 2014). Several interpretations of such behaviour have been proposed. These are summarised in Section 2.

Even when individual investment decisions are reasonable over the long term, however, the change of prices through time following a flood (Atreya et al., 2013; Bin and Landry, 2013; Gallagher, 2014), and the fact that some locations will be more affected than others, will create winners and losers across communities (Fletcher et al., 2016). Because houses represent such a large proportion of individual's wealth, this distribution of impacts can create significant inequities (Fletcher et al., 2014, 2016; Ball et al., 2013), and lead governments to intervene with financial support (Queensland Government, 2011; Fletcher et al., 2016). When this happens, the costs of flood impacts are shared across entire communities, including to those secure from flooding. Together, these factors mean that better understanding how the housing market responds to irregular flood events, and what factors contribute to this response, is vitally important to ensuring equitable individual and community-level responses to flood events (Gallagher, 2014; Fletcher et al., 2016). This is likely to be especially important in locations where infrastructure changes, such as the construction of a dam, have led to a changed perception of risk, or changes in demography, such as an influx of new homeowners from outside the region, are likely to have reduced awareness of risk.

To help inform this discussion, this study explores the relationship between flooding events and the patterns of discounting on property prices, and relates them to underlying theories of market behaviour. We begin by establishing the current state of understanding in the literature and describing a historical and recent flood event in the city of Brisbane, Australia which we then use to illustrate our approach. We propose a method to measure and relate the quality-adjusted price of properties located in the flood-free zone to the quality-adjusted price of properties exposed to flooding. We use the estimated empirical distribution of the actual quality-adjusted prices to conduct statistical inference on property price responses following minor and major flooding events. Finally, we consider the implications of these effects in terms of equitable risk management.

2. Theories of market behaviour and the case of infrequent floods

We consider three broadly related but distinct theories of market behaviour capable of generating mismatches between long term risk valuations and short term prices: unawareness, Bayesian learning, and myopia and amnesia.

The concept of unawareness (for a recent survey see Schipper (2014)) extends the concepts of risk and ambiguity in Knightian or Keynesian uncertainty (Keynes, 1921; Knight, 1921). This perspective assumes that, under risk, the decision maker conceives of the space of all relevant contingencies and is able to assign probabilities to them. Under ambiguity, the agent still conceives of the space of all relevant contingencies but has difficulty in evaluating them probabilistically. Under unawareness, the agent cannot even conceive all relevant contingencies. In the context of the current study, an agent new to the area may be unaware that a property they plan to purchase has previously faced flooding, and so they do not factor that into the price they are willing to pay to purchase the property. Alternatively, an agent suffering ambiguity may be aware of flood risk, but unable to accurately assign a probability to it and therefore unable to value it. An agent that both understands flood risk and can assess its likelihood can accurately incorporate the net present value of economic flood damages into the price they are willing to pay for a property at risk of flooding.

Bayesian learning is a way of describing the process by which agents build experience over time to more accurately estimate risk. An agent that knows how flooding affects property values can build an estimate of the economic value of that risk and factor it into the price they are willing to pay. However, agents can only fully update their learning, in a Bayesian sense, if enough information about the process generating the risky outcome is available. Such uncertainty is structural, as distinct to parameter or model uncertainty. In the current study, structural uncertainty refers to the degree to which agents understand the 'structure' of the value and risk profile faced by properties at risk of flooding. Payzan-LeNestour and Bossaerts (2011) studied Bayesian learning in unstable settings and concluded that the ability of participants to distinguish between types of uncertainties relied on sufficient revelation of the payoff-generating model. Specifically, when uncertainty about the structure of the risk faced was included, the participants did not gain awareness of changes in risk, and fell back to model-free reinforcement learning. Thus, in the context of the current study, agents can only build an accurate estimate of the probability of flood risk if they are first aware of how it affects house prices. This is also consistent with Bin and Landry (2013)'s framework.

In the specific context of the response of the housing market to flood danger, Pryce et al. (2011) proposed a framework based on what they termed 'myopic and amnesiac' assessment of risks by housing market actors. Their work is based in the earlier theoretical work of Tobin and Newton (1986) and Tobin and Montz (1994). Amnesia is a form of unawareness in the population. Myopia effectively discounts information from anticipated future events, and the rate of discount rises progressively as the event becomes less probable or imminent. In this study we use Pryce et al. (2011)'s graphical framework, presented in Figure 1, as a basic economic model from which econometric measurements can be defined. There are three interrelated prices of interest that can characterise the behaviour of a market affected by infrequent flooding events. They are: the zero-risk constant quality property price, $P(ZR)$, which describes the price of properties which have zero flood risk, a risk-adjusted constant quality property price, $P(RA)$, which describes the price of properties which accurately price actual flood risk, and the actual quality adjusted price, $P(A)$, of properties exposed to some flood risk. $P(A)$ tends upwards toward $P(ZR)$ as the time since the most recent flood, $t(F1)$, increases. With very occasional flooding (top panel of Figure 1), the prices of flood-prone properties approach $P(ZR)$ until a flood occurs, $t(F2)$. There is an initial over-reaction of $P(A)$ which drops below the risk-adjusted price level, $P(RA)$, but recovers to that level and above subsequently. More regular flooding will see prices more regularly pulled down and staying around $P(RA)$ (bottom panel of Figure 1).

We use this formulation of the interactions and the dynamic behaviour of these three prices to develop measurements that can be applied to data to study how the market values flood risk. Prior to a flood event, agents that are either truly unaware of the risk or unable to conceive of the structural risk of flooding, or who have forgotten previous events and assume future events are distant, will pay close to the zero risk value for a property. Immediately following the event, the risk of flooding is apparent to all. Previously unaware agents suffering ambiguity will attempt to assess the probability of similar future events. Bayesian agents will understand the structural risk of flooding and start to assign a probability to it, and the market will "forget its amnesia" and return its valuation of the properties at risk of flooding to near or below the risk-adjusted price. Over time, as agents refine their assessment of, or better learn the risk, and new, perhaps unaware, agents move into the area and the market begins again to forget, property values will recover.

We propose an econometric framework to compute measures for P(ZR), P(RA) and P(A) from the data and an empirical distribution of P(A) which can be obtained by bootstrapping. We then discuss to what degree the results support the behavioural theories.

2.1. An Opportunity to Learn from a Natural Experiment

The city of Brisbane (in the state of Queensland, Australia) has a long history of significant flood events dating back at least to 1893. It has suffered two major floods in the past fifty years, in January 1974 and January 2011 (Bureau of Meterology, 2017). We focus our analysis on the impacts of the January 2011 flood due to data availability and the unique historical

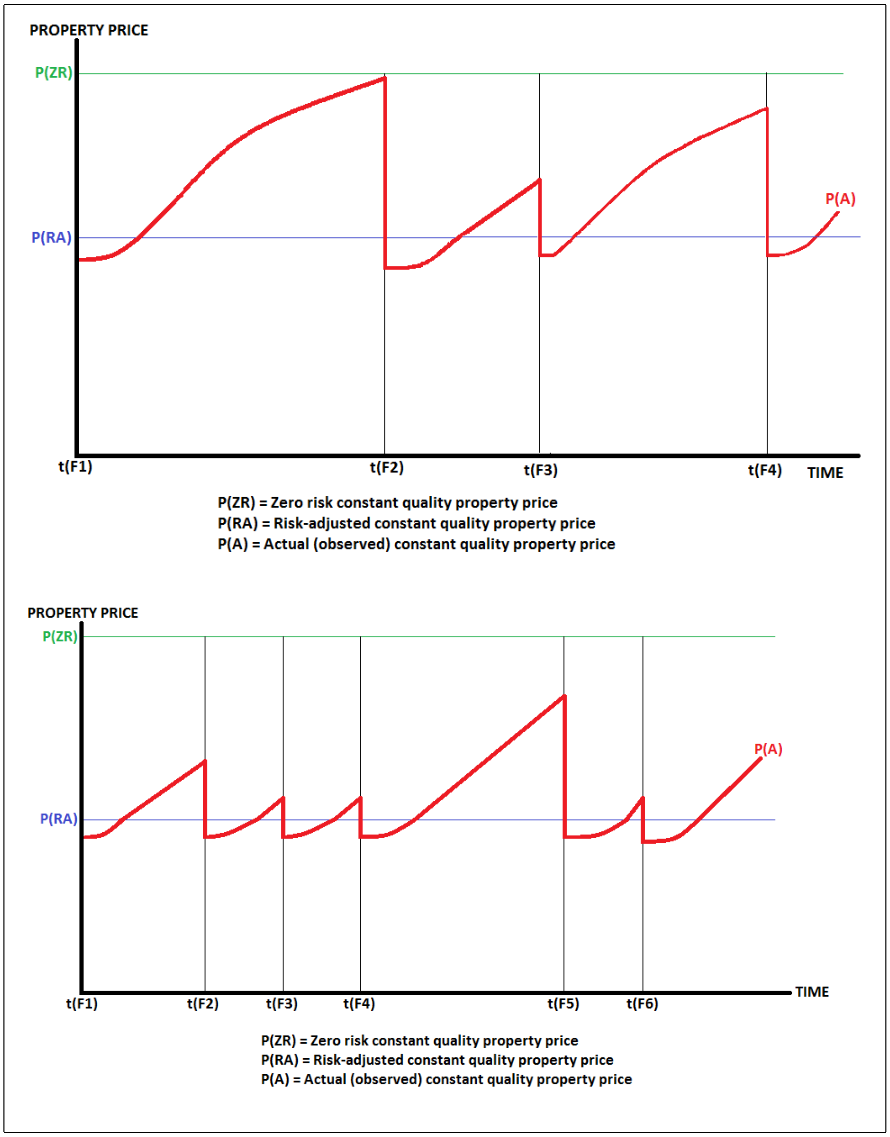

Fig. 1: Responses of Housing Market to Flood Events
Source: *Adapted from (Pryce et al., 2011)*

circumstances that preceded it, which provide a natural test for myopic and amnesic behaviour of real estate markets.

Following the 1974 flood, the Queensland government constructed Wivenhoe Dam for water storage and flood mitigation. After the new dam was completed in 1985, the inhabitants and the real estate market of Brisbane grew increasingly confident, over the following 26 years, that the city was no longer in danger of major flooding. However, in January 2011, after an extreme weather event and torrential rain, water from the Wivenhoe Dam had to be released over a short period of time to preserve its structural integrity, and Brisbane suffered a major flooding event (see Bureau of Meterology (2017)).

Our study covers property transactions over the period 1990 – 2017 for an inner Brisbane area located 5 km from Brisbane Central Business District (CBD), a prime real estate location. Brisbane City Council has released updated data since the 2011 event, and thus we have accurate information on the flood levels suffered by each property in the sample during the 2011 flood (Brisbane City Council, 2019). For a comprehensive paper on the 2011 Brisbane flood see van den Honert and McAneney (2011). We do not identify the exact location of our case-study as agreed with stakeholders. Around 30% of properties sales in our data/location are of properties in the flood zone. These properties are close to waterways within the tidal reaches of the Brisbane River; however, sufficiently far from the Brisbane river front that we avoid the possibility of confounding the effects of 'river views' with high risk of flooding (see Section 4).

The location has some unique characteristics that allow us to investigate both the impact of flooding and perceptions of risk on property values. While minor flooding directly impacts only very few houses, the visibility of swollen waterways can provide reminders of flood risk in between major events, and thus we expect the prices in the study area to show a pattern which combines these two theoretical scenarios. Figure 2 shows historical minor flooding events impacting the Brisbane River, in addition to the major floods in 2011, 1974, and earlier. Across the period of our analysis, the minor flood event in 1996 is most relevant to the area studied.

Peak gauge height does not necessarily capture the how these flood events impacted individuals and their perceptions of the risks they faced, however the Australian Bureau of Meteorology (2016) also records descriptive information of flood events. Relevant excerpts of the impacts experienced during these events include:

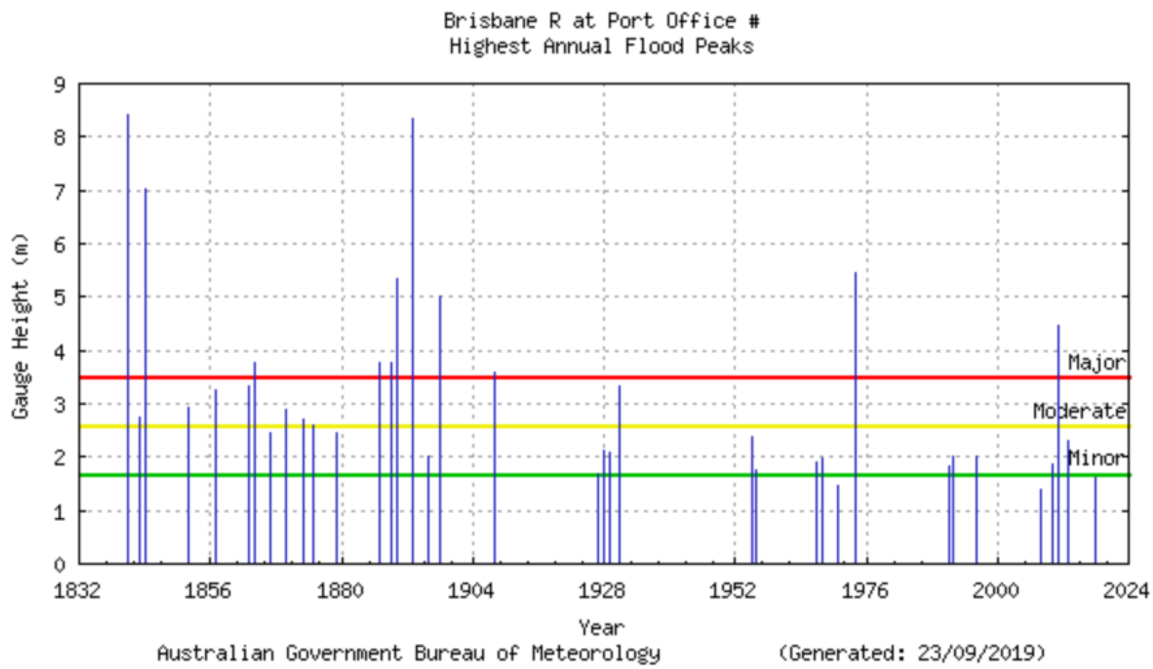

Fig. 2: Brisbane Flood History (Bureau of Meterology, 2019)

1996 Heavy rainfalls and flooding were reported throughout the Brisbane catchment during the first week of May 1996 with widespread 7 day rainfall totals of up to 600mm. A tidal surge caused by the low pressure system and gale force winds caused higher than normal tides in the Brisbane River which also contributed to flooding in low lying areas.

2011 Rainfalls in excess of 1000mm were recorded in the Brisbane River catchment during December 2010 and January 2011 with the vast amount of this rainfall falling in the 96 hours to 9am on the 13th of January 2011. The most significant rainfall intensities were well above the 1% Annual Exceedance Probability (100 year Annual Recurrence Interval). Major flooding in the Bremer and Brisbane Rivers produced the largest flood heights at Brisbane and Ipswich since the infamous '74 flood'.

If behaviours such as myopia and amnesia do affect property values, we would expect to see a divergence of the actual price of flood affected properties, $P(A)$, from the flood-free level, $P(ZR)$, in both 2011 and 1996. In addition, we may expect the actual price of flood-prone properties, $P(A)$, to fluctuate below the risk-free level, $P(ZR)$, more generally due to the high proportion of properties from which regularly flooding waterways are visible. The actual price of flood-prone properties, $P(A)$, observed at the risk-free level, $P(ZR)$, could be, at least partly, driven by unawareness. Data from successive Australian censuses suggest that only 45% of those living in the statistical area (SA2 level) in which this study took place lived there five years prior (Table 1). Ten percent of those living there in 2011, when the last major flood event took place, reported living abroad five years prior, compared to 8% in 2016. It is not unreasonable to think that the residents that moved from abroad or another state might have not been aware of Brisbane history and the 1974 flood, although it seems more difficult to argue that those that have moved to the area between 2011 and 2016 are likely to be unaware.

3. Proposed Empirical Strategy

We aim at constructing empirical estimates of $P(ZR)$, $P(RA)$ and $P(A)$ (Figure 1) over the sample period, and assessing the statistical significance of

Table 1
Characteristics of the SA2 Study Area by Census Year.

Census Data	*2006*	*2011*	*2016*
% persons living in detached or semi-detached dwellings	*65.73*	*69.93*	*63.74*
% persons owning detached or semi-detached dwellings	*37.59*	*35.90*	*39.72*
% persons renting (all types of dwellings)	*44.30*	*45.22*	*44.15*
% persons lived in the same address five years ago	*44.09*	*44.68*	*43.26*
% persons lived in the same SA2 five years ago	*5.15*	*4.00*	*4.76*
% persons lived in different SA2 five years ago	*50.77*	*50.00*	*50.69*
% persons lived overseas five years ago	*6.54*	*10.55*	*8.06*

Source: Australian Bureau of Statistics - `https://www.abs.gov.au/geography`; `https://www.abs.gov.au/census`

the behaviour of prices. A bootstrap approach is used to obtain an empirical distribution of $P(A)$ and construct a 95% confidence band. First note that these theoretical sets of prices are defined as 'quality-adjusted' prices. To obtain a quality-adjusted price using a sample of sold properties, a relevant price indicator needs to be constructed. The median price is an example of a price indicator; however, it is a quality unadjusted measure as it does not control for the type and quality of the properties transacted at any given time. Quality adjusted representative prices are obtained by constructing price indices (see the Handbook of Residential Property Price Indices –European Commission, Eurostat, OECD, and World Bank (2013)-HRPP, or the recent review by Hill and Rambaldi (2021)). As noted in the HRPP, price indices are used for a number of purposes (e.g. macro-economic indicators, and as a financial stability or soundness indicator to measure risk exposure, amongst others). Section 3.1 explains how the constructed price indices are used to compute empirical estimates of $P(ZR)$ and $P(A)$. The risk adjusted constant quality price level $P(RA)$ is obtained by using the 2011 event as the treatment (Section 3.2), which provides for the identification of the percent of discount in property prices due to flood risk. Details of the methodology are discussed below.

3.1. Computing $P(ZR)$ and $P(A)$

In this section we show the proposed approach that allows us to apply the theoretical concepts. We first must define two quality adjusted price references (Appendix A describes the method used to construct these price indices). The first represents the prices of the properties in the no-flood zone and it is denoted by $P_{NF,t}$. The second represents the prices of the properties in the flood zone and it is denoted by $P_{F,t}$. At each time period (here one year), $P_{NF,t}$ becomes the reference and it is normalised to 100, defining $P(ZR)_t$ for that year. $\widehat{P(A)}_t$ is then defined as the deviation (in ratio form) between $P_{F,t}$ and $P_{NF,t}$. This is shown in equations (1) and (2),

$$\widehat{P(ZR)}_t = 100 \tag{1}$$

$$\widehat{P(A)}_t = \frac{P_{F,t}}{P_{NF,t}} \times 100 \tag{2}$$

for each t, $t = 1, \ldots, T$.

These definitions allow us to compare the actual quality-adjusted prices at each period relative to the risk-free and risk-adjusted quality-adjusted price levels.

In this study we compute quality-adjusted price indicators by computing annual price indices from the observed transaction prices of the properties in the sample. We use the time-dummy hedonic price index approach (see Bailey et al. (1963), de Haan (2010), European Commission, Eurostat, OECD, and World Bank (2013), Hill (2013), Hill and Rambaldi (2021)). A price index is computed for properties located in the flood zone, using the definitions in Brisbane City Council (2019), and a separate index is computed from transactions of properties located the flood-free zone (Section 4.1). The underlying model used to obtain a time-dummy hedonic price index controls for characteristics of the land and structure that make up each property in the sample. Further details are provided in Appendix A.

The estimate in (2) is a ratio of two empirically computed indices, and it is not straightforward to compute standard errors for this estimate. Thus, we use a bootstrapping approach to obtain an approximate 95% empirical confidence interval for $\widehat{P(A)}$. The bootstrap design preserves the time ordering of the data. Within each time period, a year in our case, we use an i.i.d. bootstrap by type (see Politis (2003) and the many references therein for a discussion on bootstrapping with dependent data, block sampling and subsampling, and Chapter 3 of Chernick (2011) for a bootstrapping methodology to construct confidence sets). Our approach is summarised by the following steps:

- within each time period and flood type, *sample with replacement* properties that have sold to create a replication sample, r, of the same size as that of the observed data, i.e. N transactions over T periods with the same proportion of sales in the flood/flood-free areas for each time period.
- with sample r construct the corresponding indices $(P_{F,t}/P_{NF,t})$
- repeat the above R times. In the empirical implementation we use $R = 10,000$
- compute the quantiles, 0.025 and 0.975, from the R bootstrapped price indices of each type (i.e. $P_F(0.025)$, $P_{NF}(0.025)$, $P_F(0.975)$, $P_{NF}(0.975)$).
- compute an empirical 95% confidence interval for $P(A)_t$, $P(A)(0.975)$ and $P(A)(0.025)$, using equation (2)

We use the confidence interval to test hypotheses that quality-adjusted actual prices are 'not at the zero-risk level' and 'not at the risk-adjusted level'. If the distribution of the bootstrapped $P(A)$ includes $P(ZR)$, i.e., 100, we reject the null hypothesis of 'not at the zero-risk level' and conclude there is evidence of behaviours consistent with both myopia and unawareness. Similarly, if following a flood event the bootstrapped distribution goes below the $P(RA)$ and then recovers to levels above $P(RA)$, we find this consistent with both amnesia and Bayesian learning behaviours more generally.

3.2. Identifying the risk-adjusted price level, $P(RA)$

In order to obtain $P(RA)$ we must find the size of the discount due to flooding (refer to Figure 1). In this study the 2011 flood event provides the natural experiment required to identify the discount. We provide two alternative empirical estimates: 1) a difference-in-difference approach (used in previous studies such as Bin and Landry (2013) and Seo et al. (2020) to obtain an estimated discount due to flooding, Ortega and Taspinar (2018) in the context of Hurricane Sandy, Kim (2020) in the context of climate change adaptation, and Lee et al. (2021) in the context of an underground explosion); and 2) a hedonic modelling approach, which is used in de Koning et al. (2018). We compare the discount estimated by these two approaches, and use them to indicate the breadth of the range of likely discount values.

This is similar to the approach taken by (Netusil et al., 2019), and provides robustness to the empirical estimations in the study.

We use the 2011 flood event and the date of the sale contract to define the treatment. Post-treatment property sales are those that signed a sale contract after the flooding event. Those properties that did not flood in this event are the control group. The treatment occurred in mid January 2011, and thus we define a transaction as treated if it was in the flood zone ($Flood = 1$) and the sale contract was signed from February 2011 onwards ($After = 1$).

Alternative 1). Difference-in-difference approach. The model is estimated with the full sample of transactions,

$$\begin{aligned}\log(price_{it}) \ &= \beta_0 + \textstyle\sum_{t=2}^{T} \delta_t D_{it} + + \sum_{k=1}^{K} \beta_k x_{k,it} + \gamma_1 Flood_i \\ &\quad + \gamma_2 After_i + \gamma_3 (Flood_i \times After_i) + u_{it} \end{aligned} \tag{3}$$

where,

$Flood_i = 1$ if the ith property was flooded in the event, zero otherwise

$After_i = 1$ if the sale contract for the ith property was after the flood, zero otherwise

To ensure there is not bias due to omitted variables the model includes controls for property characteristics and time effects,

$D_{it} = 1$ if property i was sold in year t, zero otherwise. These are fixed time effects, with the intercept capturing the first year.

$x_{k,it}$ is the value of the k^{th} control variable for property i sold in year t. Control variables include land, location and structure characteristics (see Table 2).

The estimate of $100 \times \gamma_3$ provides a percent average discount suffered by properties that were affected by the flood, which we denote by Dis_{DID}.

Alternative 2). Hedonic model approach. The model is *estimated over a restricted sample*, the sample of properties in the treated group ($After = 1$) with $Flood_i$ included in the model,

$$\log(price_{it}) = \beta_0 + \sum_{t=\tau}^{T} \delta_t D_{it} + \sum_{k=1}^{K} \beta_k x_{k,it} + \phi Flood_i + e_{it} \tag{4}$$

where again,

$Flood_i = 1$ if the ith property was flooded in the event, zero otherwise

To ensure there is not bias due to omitted variables the model includes controls for property characteristics and time effects,

$D_{it} = 1$ if property i was sold in year t, zero otherwise. These are fixed time effects, with the intercept capturing the first year.

$x_{k,it}$ is the value of the k^{th} control variable for property i sold in year t. Control variables include land, location and structure characteristics (see Table 2).

Estimating the model for the sample of properties for which $After = 1$, labelled as $t = \tau, \ldots, T$ in (4) will provide an alternative estimate of the discount which we denote by $Dis_{HED} = \hat{\phi} \times 100$.

Thus, two alternative estimates of $P(RA)$ are then given by $P(RA)^{DID} = 100 - Dis_{DID}$ and $P(RA)^{HED} = 100 - Dis_{HED}$.

Description of the data and estimation results are presented in the next section.

4. Data and results

The data in this study are an extension of Rambaldi et al. (2013), which originally covered property sales up to early 2010. Variable definitions and descriptive statistics for the dataset used in this study, covering the period 1990 to 2017, including the hedonic characteristics for land, structure, location and flood status of each property used in the empirical part of the study are presented in Appendix B.4. Table 2 provides a summary of the available hedonic characteristics.

Since the 2011 flood, the Brisbane City Council (BCC) has been working to provide more accurate flood risk information to residents. On 5 May 2017, it released online tools such as "Flood Wise" Brisbane City Council (2019) Property Reports and a "Flood Awareness Map" based on recently completed flood studies, providing specific and detailed flood risk information for each parcel, which we use in this study to define which properties were flooded in the 2011 event (Brisbane City Council, 2019). More specifically, the Flood Awareness Map includes various flood overlay maps. We define properties in the sample as flooded in 2011 when the parcel is either: a) located on the overland flow layer (this flood event is likely to occur during a single lifetime (70 years), and a flood of this size or larger has a 1% chance of occurring in any year), or b) on the creek and storm tide flood layer with a high (5% annual) or medium (1% annual) likelihood of flooding. The sample contains

Table 2
Hedonic Characteristics Available in the Data

Type	*Variables*
Land	*Lot Size (sqMts), Vacant*
Location	*Distances to: River, Industry, Park Land, other Waterways, CBD, Shops, Rail Station, School, Bus Stop*
Structure	*Footprint (SqMts), Construction Period (Pre-War, Post War, Late 20th, 21st), Bedrooms, Bathrooms, Car Parks*
Flood=1	*A property is in the floodplain (n^*=1335)*
After=1	*Sale contract signed February 2011 onwards (n^*=1244)*

* n number of transactions of property
Full sample n=4626 transactions over the period 1990-2017.

4626 transactions, out of which 1335 were associated with properties flooded in the 2011 event. The properties that flooded during the 2011 event are at a median distance from a waterway of 540 metres and 1,485 metres from the river (Table B.5). The flood-free properties in our data are at a median distance from a waterway of 830 metres and 1,827 metres from the river (Table B.6). These waterways are within the tidal reaches of the Brisbane River; however, our sample location is sufficiently far from the Brisbane river front as to minimise the possibility of confounding the effects of 'river views' with high risk of flooding.

4.1. Estimation of basic price indices

Estimates of P_F (Flood) and P_{NF} (No Flood) are presented in Figure 3. We test whether the underlying time-dummy models for the two types of property, those that flooded in 2011 and those in the flood-free area, are statistically equal over the full sample (1990-2017) and reject the null (p-value=0.0000) in support of two different price trends over the sample period. The figure shows prices increased six-fold over the period 1990-2017 in this area of Brisbane. Although the price index for those properties in the flood plain, P_F, is mostly below that obtained from the flood-free sample, the two are almost identical until 2010. Prices grew at a lower rate around the Global Financial Crisis (2008-2009), and the drop in P_F after the 2011 flood event is visually clear.

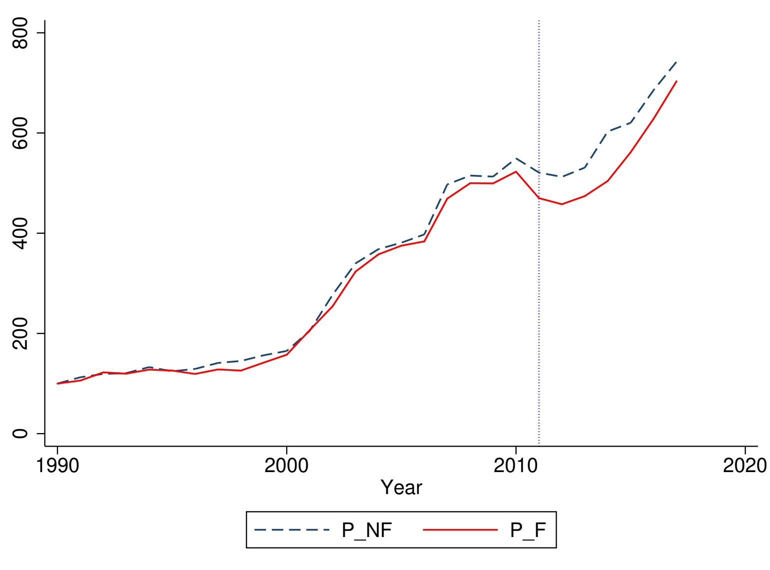

Fig. 3: Price Indices for Properties in the Flood/NoFlood Zone, 1990=100.

4.2. Estimation of a risk-adjustment discount

In Section 3.2 we proposed two alternative modelling approaches to obtain an estimate of the size of the discount due to flooding risk. Here, the aim is to try to establish the fully risk-adjusted discount. By using two alternatives we obtain a range estimate of the size of the discount.

Table 3 shows the estimates of the discount due to flood risk obtained from the difference-in-difference (DID) specification, model (3), and the hedonic alternative, model (4). The average estimated discount from the DID specification is 7.08%. For the hedonic specification, the model including all transactions after the flood estimated a discount of 9.26%. In the next section the estimate of $P(RA)$ is provided as the range between these two values. The estimated size of the discount is comparable to other estimates reported in the literature in the range of 4 - 12% Bin and Landry (2013); Netusil et al. (2019); de Koning et al. (2018); Ortega and Taspinar (2018).

4.3. Empirical Estimates of Figure 1- $P(ZR)$, $P(RA)$, $P(A)$

Figure 4 plots the estimates of $P(ZR)$ (Zero Risk Constant Quality Price Index), the empirical $P(RA)$ (Risk-Adjusted Constant Quality Price Index) range (estimates from Table 3), the estimated actual Quality-adjusted Price

Table 3
Estimated Discount due to Flood Risk.

Model	Diff-in-Diff		Hedonic Reg	
var.dep: $\log Price$	**Coefficient**	**t value**	**Coefficient**	**t value**
$Flood$	*-0.0523******	*-5.73*	***-0.0926******	*-5.06*
$After$	*0.0289*	*0.30*		
$Flood \times After$	***-0.0708******	*-4.10*		
Models Controls and Significance				
R-Sq	0.8896		0.5445	
N	4626		1244	
Sample	1990-2017		2011-2017	
Controls	time effects		time effects	
	hedonics		hedonics	

*** Significance at 1% level (robust standard errors).

Index, $P(A)$, labelled "P(A)(Sample)", and the empirical 95% interval for $P(A)$ obtained from the bootstrap exercise[2]. As discussed in Section 2, there was a heavy rain event in May 1996 which did not cause a generalised flood in Brisbane; however, there was localised flooding in low lying level areas of the city, which would have been visible in the study area due to proximity to waterways. The January 2011 event was a generalised event as the Brisbane river broke its banks affecting all suburbs adjacent to the river in addition to other low lying level areas close to other waterways.

The empirical 95% interval constructed for $P(A)$ is above the $P(RA)$ level prior to 1996. A price signal is clear after the localised event of 1996 when the empirical distribution of the quality-adjusted actual price falls to the risk-adjusted price level for the next three years. The estimated distribution of $P(A)$ varies well above $P(RA)(HED)$, and approaches or encompasses $P(ZR)$ levels during the 00's until 2010 with the exception of 2002. The Australian Bureau of Meteorology's Severe Storms Archive (Bureau of Meteorology (various)) shows rain with severe flash flooding affected Brisbane suburbs on 30 December 2001 which would have affected the study area and produced a price signal captured in the 2002 data, when the actual price

[2]note that "P(A)(Sample)" and the 0.5 quantile estimate of the $P(A)$'s bootstrapped distribution overlap (the latter not shown).

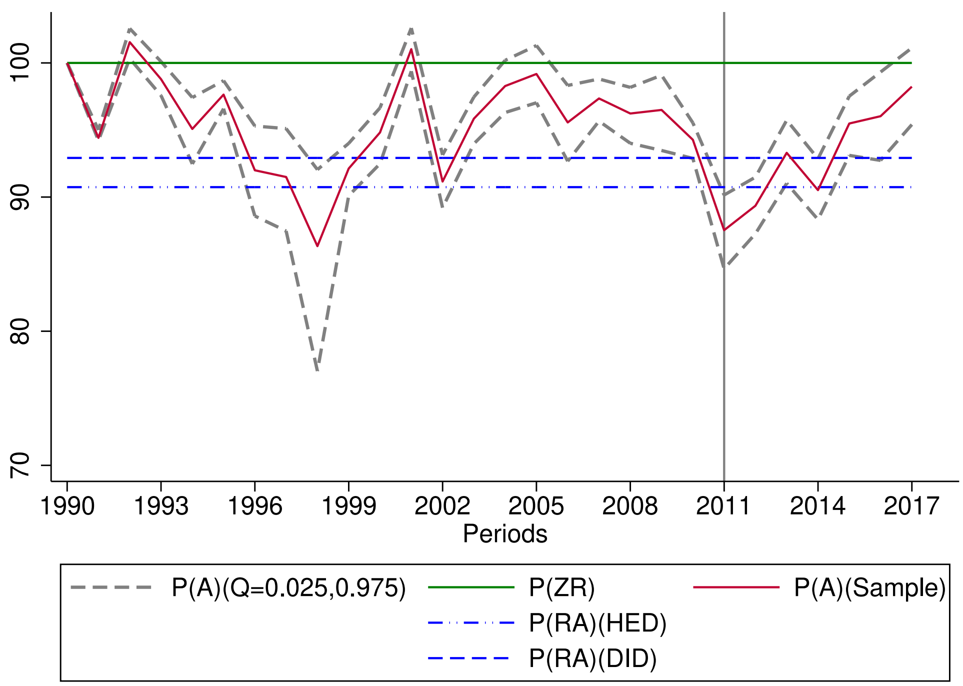

Fig. 4: Estimated Quality Adjusted Price Levels and Distribution of the Price of Property in the Flood Zone.

distribution is at the $P(RA)$ level for that year. The Global Financial Crisis of 2007-2008 and increasing rainfall in coastal areas close to the city of Brisbane between 2008-2010 (Callghan and Power, 2014) appear to have produced some volatility in that P_F and P_NF separate from each other leading to an estimate of $P(A)$ which is below the zero-risk level although still above the risk-adjusted price level until the January 2011 flood. In 2011 we can observe a significant fall in $P(A)$ with the distribution completely below the $P(RA)$ estimated range. Prices adjust to the risk-adjusted level by 2013. However, from 2015 we see signs of recovery and a steady increase in $P(A)$, which sits well above the $P(RA)$ estimates by the end of 2017. These findings support the expected patterns from Pryce et al. (2011)'s behavioural framework for infrequent flood events, and are in line with Bin and Landry (2013)'s observation that the discount due to flooding diminishes over time and essentially disappears about five or six years after an event.

Overall, these findings provide empirical evidence to reject both stated null hypotheses. First, there is evidence that quality-adjusted actual prices of properties in the flood zone do reach the same prices as those that are in the flood free zone. This is shown as the empirical distribution of $P(A)$ includes $P(ZR)$ for periods when the last recorded flood event is several years in the past, and indicates amnesic and unawareness behaviours in the market. Second, the distribution of $P(A)$ falls to or is below $P(RA)$ following flooding events; however, it quickly recovers and returns to levels above $P(RA)$. This provides evidence of myopic behaviour which leads to a short-lived effect and is consistent with Atreya et al. (2013).

5. Discussion and implications

Our results clearly show the prices of properties in the flood zone reach levels at a par with those in the zero-risk zone when major flood events are in the distant past, react immediately to minor and major events, but recover to levels above the risk-adjusted price level within a few years after a major flooding event. This is consistent with the results of a number of studies (Atreya et al., 2013; Bin and Landry, 2013; Gallagher, 2014),(Atreya et al., 2013; Bin and Landry, 2013; Gallagher, 2014), and with expected behaviours. It suggests that, prior to the 2011 floods, agents were either unaware of the risk or, alternatively, were aware of potential risk but estimated that it was low based on data suggesting that no major weather event could result in a repeat of the 1974 devastation to the areas of the city in the floodplain.

Between the two major floods of 1974 and 2011 the city of Brisbane underwent a major transformation. Its population grew by 30%, with most new inhabitants arriving from overseas and interstate. In addition, the dam built in the 1980s to provide flood mitigation led those that knew the city's history to conclude there would be no repeat of the conditions experienced during the 1974 flood.

If agents in the market were able to incorporate flood risk into property values immediately after the flood, why did the price gap between flood-prone and flood-free properties then close so quickly after the 2011 flood? This is consistent with market myopic and amnesiac behaviour, if the time taken for the market to forget or discount risk is only a few years. However, due to the way information was shared following the flood, especially information around the operation of the Wivenhoe Dam, it is potentially also consistent with Bayesian learning. In the time immediately following the 2011 floods, a widely publicised independent review, the Queensland Floods Commission of Inquiry (2012), concluded that Wivenhoe Dam had been operated in breach of the manual that governs its management. It was found that the dam operators had failed to use rainfall forecasts in making decisions about dam operating strategies. This conclusion provided grounds for one of the largest legal class actions in Australian history; 6800 claimants (including insurance companies) who suffered loss and damage as a result of the negligent operation of the dams made a claim against the two state-owned dam operators and the State of Queensland[3]. If agents in the market believed that these circumstances were unlikely to occur again following the Inquiry, this could explain why the market pricing of future risk recovered so quickly after experiencing the actual event.

How will agents behave if flooding becomes more frequent? In February of 2022 many areas of Brisbane were flooded again after an extreme weather event ((Bureau of Meterology, 2022)). Total rainfall was 479% higher than the monthly average and there were three consecutive days, 26 to 28 February, with daily totals over 200 mm. Major flooding occurred without the river breaking its banks. Pryce et al. (2011)'s theoretical pattern for the

[3]Almost nine years after the flood disaster, on 29 November 2019, the Supreme Court of New South Wales (the case was heard in a NSW court because it was initiated before class actions were allowed in Queensland in 2017) decided in favour of the claimants (Maurice Blackburn Lawyers, 2020). The state government's dam operators appealed the court's decision in February 2020, and at the time of publication the case is still before the courts.

case of more frequent events is presented by the bottom panel of Figure 1. The implication is that, with frequent flooding, the discount-adjusted price of properties in the flood-prone areas will not fully recover their value to reach the zero-risk price between events, moving the long-term average $P(A)$ downwards towards $P(RA)$. This could lead to increased long-term reductions in property values, beyond those previously reported for this case study area (Rambaldi et al., 2013).

There are a number of possible implications. The first is that changes to both the short-term and longer-term valuation of risk over time will lead to individual wins and losses as properties change hands before and after a flood event, and that these impacts may become more frequent and severe as climates change (Fletcher et al., 2014). Moreover, these losses can be significant, because in many places the family home is individuals' largest asset. The scale and uneven distribution of asset loss risk across communities can lead to severe and inequitable financial hardship (Fletcher et al., 2016; Ball et al., 2013), and drive calls for government intervention. Designing effective responses to such issues requires an understanding of where impacts accrue, their magnitude, and the likely effect of interventions. The values $P(A)$ and $P(ZR)$ in this study provide an improved method to compute the actual loss of value to properties that flood, relative to those that don't, following major flood events. In future, these detailed estimates could be integrated across communities to inform understanding of how these property-level losses accumulate at the regional scale, to help make government responses to floods more efficient and equitable.

This is important, because in practice the financial impacts of flood events, and the costs of measures to avoid those impacts in future, are shared across communities through government-funded responses and initiatives (Fletcher et al., 2016). The complete cost of the 2010/11 major flood event for Brisbane was estimated at \$20 billion. In the year after the flood, Australian taxpayers who were not affected by the flood contributed to recovery costs through a levy (Queensland Government, 2011). Although these funds primarily supported emergency flood response, rather than compensating property owners for devaluation, the belief that governments will step up to fund recovery after a flood is likely to influence how assets in vulnerable areas are valued. Understanding these values, using the techniques in this paper, is the first step to better understanding how such short-term responses to major events drive longer term market dynamics.

Following a major flood event, the longer-term risk costs can be borne individually or shared through the distribution of insurance premiums (Bin and Kruse, 2006; Kunreuther, 1996), and so the insights from this analysis also have implications for the design of insurance systems that can deal with large-scale events. Following the 2011 floods, it became apparent that while a large number of affected households believed they had been insured for flood, a significant proportion (27%) of their claims were refused, many because their policies did not cover riverine flooding (Queensland Floods Commission of Inquiry, 2012). Following the Inquiry, it became evident that there was no standard definition of flood used by insurers, and confusion amongst consumers regarding the coverage in case of floods (Insurance Council of Australia, 2008). In the context of this study, this is important because Bayesian agents are only able to update their learning to appropriately incorporate risk into property values if they have accurate information about the risk. Better and agreed definitions of what is covered by insurance allow Bayesian agents to more accurately price risk into the market, more efficiently internalising the long-terms costs of flood events into property prices. A year after the Queensland Floods Commission of Inquiry (2012), a standard definition of flood among insurance companies was introduced (Insurance Council of Australia, 2012).

Confusion around insurance coverage creates significant impacts for the individuals affected, and potentially also reduces engagement with and therefore the efficiency of the insurance industry as a whole. These issues are likely to become even more important if the number and intensity of major events increase under changing climates to the point that certain properties become uninsurable or so expensive to insure that they are effectively uninsurable and people leave the insurance market. The distributional effects of public flood and disaster insurance have been considered in the literature. Shilling et al. (1989) studied the wealth transfer effects of the National Flood Insurance Program introduced in 1968 in the United States, and recent work by Bleemer and van der Klaauw (2019) studied the long-run net effects of federal disaster insurance provided following Hurricane Katrina. Gallagher (2014) studied the uptake of insurance prior to and following a major flood, and found significant uptake in flood insurance persisting five years after the event, compared to zero uptake in years prior to the flood.

Following the 2011 floods, insurance premiums for residential property in Australia increased very significantly for those properties at risk of flooding. As a consequence, a number of those properties affected in 2011 were uninsured when they were impacted by the February 2022 event. It is likely that this has increased inequality as those that owned uninsurable land bore the entire cost individually. Although unlikely to be applicable to the area covered in this study, the Australian Government has begun to address such concerns in Northern Australia. In March 2022, the Treasury Laws Amendment (Cyclone and Flood Damage Reinsurance Pool) Bill 2022 was passed, establishing a cyclone and related flood damage reinsurance pool, backed by a $10 billion Government guarantee, to improve insurance affordability in cyclone-prone areas in Northern Australia (Parliament of Australia, 2022). Such initiatives redistribute financial risk across communities in an effort to improve coverage and affordability, encouraging increased uptake of private insurance and the efficiency of the private insurance market. Designing such effective government responses at these scales will require a good understanding of current distribution and valuation of risk within communities to understand the redistributive effects of such policies. The techniques developed in this paper provide an important estimate of how residential property markets internalise such risk values during and following major events.

6. Conclusions

Around the world, economic losses due to extreme environmental events, such as flooding, continue to rise, largely because we keep building in high-value but risky areas. In an economic sense, this behaviour is rational as long as the property market accurately reflects the long term discounted value of that risk. This study, however, finds that, following a major flood event in Brisbane Australia in 2011, the dynamics of urban property prices in flood affected areas were consistent with a market that was either unaware of the risk of flooding, or had forgotten or depreciated the risk after several decades without a major flood. This is consistent with results found in property markets facing flood risk elsewhere in the world (Atreya et al., 2013; Bin and Landry, 2013; Gallagher, 2014; Ortega and Taspinar, 2018).

The impacts of this are potentially significant to individuals and the community alike. Property owners who purchase properties just before a major flood suffer significant personal losses on their largest single asset (Rambaldi et al., 2013). Taxpayers not directly affected by the floods ultimately pay for government efforts to fund recovery and underinsured properties.

Designing more equitable public policy to reduce the risk faced by communities, and to efficiently, effectively and equitably manage that risk when events do occur requires a solid understanding of how the market values risks and the factors that contribute to that valuation. By investigating how market valuations changed in Brisbane between 1990 and 2017, following both major events that actually impacted properties and minor events that informed perceptions of risk, this study provides important insights to these questions.

Improving our understanding of the way flood risk devalues properties, as provided by the current analysis, provides opportunities for individuals, industry and communities and governments to make informed decisions about how best to protect against damage in future. Understanding the economic costs of flood risk can underpin refinements to insurance premiums and allow communities and governments to decide when to invest to protect against future flood risk.

Appendix A. Computing Quality Adjusted Price Indicators

The purpose of a price index is to provide a quality adjusted representative price. In the case of residential real estate, the most comprehensive summary of available methods to construct quality adjusted price indices was first provided by the Handbook of Residential Property Price Indices (European Commission, Eurostat, OECD, and World Bank, 2013)-HRPP, which on page 12 states that price indices are used for a number of purposes (e.g. macroeconomic indicators and financial stability or soundness indicator to measure risk exposure, amongst others). In this study the quality adjusted price indicators are obtained using an approach known as time-dummy hedonic price indices (see Chapter 5 of HRPP)

The model to obtain a time-dummy hedonic price index is of the form in (A.1),

$$\log(price_{it}) = \sum_{t=1}^{T} \delta_t D_{it} + \sum_{k=1}^{K} \beta_k x_{k,it} + \varepsilon_{it} \tag{A.1}$$

where x'_{it} is a row vector containing *land and structure hedonic characteristics*, and *location* variables for each property in the sample (see Table 2 in the data section for specifics). The parameters β_k $(k = 1, \ldots, K)$ are those associated with the shadow prices of these hedonic characteristics. Time dummy variables, $D_{it} = 1$ if i sold in year t, zero otherwise, control for the price trends in the data, and the hedonic adjusted price indices are obtained by exponentiating the time effects parameter estimates $(\hat{\delta}_t)$ and rescaling them to set the base period equal to 100 (Hill (2013).

The price index obtained from the sample in the flood zone provides an index we will denote by $P_{F,t}$, and we denote by $P_{NF,t}$ the quality-adjusted price index for period t obtained from the sample of properties with zero risk of flooding. Properties are sorted into flood/flood-free samples depending on whether they flooded in the 2011 event (further details are provided in the data section). The assumption here is that both the δ_t and the $\beta_k, k = 1, \ldots .K$ vary across the two types (flood/flood-free). This is a testable hypothesis which is sample dependent. We formally test for parameter homogeneity as part of the empirical estimation.

Appendix B. Dataset - Descriptive Statistics

Table B.4
Descriptive Statistics - Whole Sample (n= 4626 transactions)

Variable	min	max	median	mean	Std	Description/Source
Price (thousands)	9.7	3600	420	479	354	Observed sale price (CL,APM)
Age1	0	1	1	0.473	0.495	Pre-war (CL,APM)
Age2	0	1	0	0.088	0.283	War (1942 1947) (CL,APM)
Age3	0	1	0	0.305	0.460	After War (CL,APM)
Age4	0	1	0	0.071	0.257	Late20thC (CL,APM)
Age5	0	1	0	0.063	0.244	contemporary (CL,APM)
NoH	0	1	0	0.021	0.145	Vacant Land
Land Area	84	2555	607	604	204	Sq Mts -CL,APM, BCC
Structure Area	28	678	175	187	65	Sq Mts -DERM (LiDAR) 2010
Bath	0	6	1	2	1	CL,APM, BCC, or RE
Beds	0	8	3	3	1	CL,APM, BCC, or RE
Cars	0	8	2	2	1	CL,APM, BCC, or RE
dist_river	17.436	3671.676	1713.618	1697.686	922.833	Mts -BCC and geospatial tools
dist_waterway	17.436	2147.959	733.058	750.720	462.366	Mts -BCC and geospatial tools
dist_industry	8.237	1844.367	1058.348	987.943	452.520	Mts -BCC and geospatial tools
dist_parks	1.000	638.425	164.036	190.473	135.922	Mts -BCC and geospatial tools
dist_busStop	3.177	488.568	152.083	174.393	100.647	Mts -BCC and geospatial tools
dist_schools	116.797	3342.636	1301.606	1382.787	703.653	Mts -BCC and geospatial tools
dist_city	4100.107	7899.440	5912.959	5881.397	959.639	Mts -BCC and geospatial tools
dist_shops	97.634	2572.540	1247.296	1289.517	599.877	Mts -BCC and geospatial tools
dist_rails	95.311	3661.013	1780.968	1755.592	872.391	Mts -BCC and geospatial tools
dist_hosp	1238.348	4089.892	2568.854	2565.619	609.377	Mts -BCC and geospatial tools

Source/notes: CL,APM, - Data from Corelogic (up to 2015) and Australian Property Monitors for 2015 to 2017.
BCC Planning and Development Online (`http://pdonline.brisbane.qld.gov.au/`) (BCC)
Google View (GV) or `www.realestate.com`(RE)

Table B.5
Descriptive Statistics - Flood Plain (n = 1335 transactions)

Variable	min	max	median	mean	Std	Description/Source
Price (thousands)	9.7	1572	356	398	257	Observed sale price (CL,APM)
Age1	0	1	1	0.476	0.495	Pre-war (CL,APM)
Age2	0	1	0	0.082	0.275	War (1942 1947) (CL,APM)
Age3	0	1	0	0.312	0.464	After War (CL,APM)

Age4	0	1	0	0.068	0.252	Late20thC (CL,APM)
Age5	0	1	0	0.061	0.24	contemporary (CL,APM)
NoH	0	1	0	0.021	0.145	Vacant Land
Land Area	150	1770	556	562	176	Sq Mts -CL,APM, BCC
Structure Area	45	590	160	171	60	Sq Mts -DERM (LiDAR) 2010
Bath	0	4	1	1	1	CL,APM, BCC, or RE
Beds	0	6	3	3	1	CL,APM, BCC, or RE
Cars	0	6	2	2	1	CL,APM, BCC, or RE
dist_river	17.436	3538.351	1485.369	1482.28	838.905	Mts -BCC and geospatial tools
dist_waterway	17.436	2069.799	539.758	612.14	449.591	Mts -BCC and geospatial tools
dist_industry	8.237	1844.367	1055.923	979.971	466.331	Mts -BCC and geospatial tools
dist_parks	1.000	638.425	113.881	180.622	163.25	Mts -BCC and geospatial tools
dist_busStop	4.154	475.519	151.565	177.513	102.049	Mts -BCC and geospatial tools
dist_schools	191.961	3157.05	1176.437	1214.699	618.251	Mts -BCC and geospatial tools
dist_city	4100.107	7719.363	5662.729	5652.424	878.864	Mts -BCC and geospatial tools
dist_shops	166.964	2401.976	1061.353	1145.667	522.006	Mts -BCC and geospatial tools
dist_rails	124.875	3444.285	1569.261	1536.211	788.998	Mts -BCC and geospatial tools
dist_hosp	1379.579	4089.892	2611.332	2588.084	613.301	Mts -BCC and geospatial tools

Source/notes: CL,APM, - Data from Corelogic (up to 2015) and Australian Property Monitors for 2015 to 2017.
BCC Planning and Development Online (`http://pdonline.brisbane.qld.gov.au/`) (BCC)
Google View (GV) or `www.realestate.com`(RE)

Table B.6
Descriptive Statistics - Flood Free (n= 3291 transactions)

Variables	min	max	median	mean	Std	Description/Source
Price (thousands)	27	3600	450	511	381	Observed sale price (CL,APM)
Age1	0	1	1	0.471	0.495	Pre-war (CL,APM)
Age2	0	1	0	0.090	0.286	War (1942 1947) (CL,APM)
Age3	0	1	0	0.302	0.459	After War (CL,APM)
Age4	0	1	0	0.073	0.260	Late20thC (CL,APM)
Age5	0	1	0	0.064	0.245	contemporary (CL,APM)
NoH	84	2555	607	621	212	Vacant Land
Land Area	28	678	184	194	65	Sq Mts -CL,APM, BCC
Structure Area	0	1	0	0.018	0.135	Sq Mts -DERM (LiDAR) 2010
Bath	0	6	1	2	1	CL,APM, BCC, or RE
Beds	0	8	3	3	1	CL,APM, BCC, or RE

Cars	0	8	2	2	1	CL,APM, BCC, or RE
dist_river	91.504	3671.676	1827.397	1785.066	940.939	Mts -BCC and geospatial tools
dist_waterway	33.229	2147.959	830.046	806.935	455.651	Mts -BCC and geospatial tools
dist_industry	23.583	1795.832	1059.774	991.177	446.828	Mts -BCC and geospatial tools
dist_parks	1.000	614.282	172.363	194.469	122.922	Mts -BCC and geospatial tools
dist_busStop	3.177	488.568	152.260	173.127	100.061	Mts -BCC and geospatial tools
dist_schools	116.797	3342.636	1394.198	1450.972	724.525	Mts -BCC and geospatial tools
dist_city	4146.206	7899.440	6062.582	5974.281	975.446	Mts -BCC and geospatial tools
dist_shops	97.634	2572.540	1306.421	1347.869	619.340	Mts -BCC and geospatial tools
dist_rails	95.311	3661.013	1917.912	1844.585	888.833	Mts -BCC and geospatial tools
dist_hosp	1238.348	4080.319	2556.441	2556.507	607.635	Mts -BCC and geospatial tools

Source/notes: CL,APM, - Data from Corelogic (up to 2015) and Australian Property Monitors for 2015 to 2017.

BCC Planning and Development Online (`http://pdonline.brisbane.qld.gov.au/`) (BCC)

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