Testing for Myopia and Amnesia in Property Prices. The Case of Infrequent Floods

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Testing for Myopia and Amnesia in Property Prices. The Case of Infrequent Floods*

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Abstract

In this paper we explore the relationship between flooding events and the patterns of discounting of property prices. We develop an estimation and testing strategy to implement a recently proposed theoretical framework and use a unique natural experiment to demonstrate how this framework provides a test for myopic and amnesic responses to flooding frequency and severity in urban property prices. Infrequent floods is where myopic and amnesic perceptions of risk should dominate. In this regime observed quality adjusted prices are expected to drift away from a risk-adjusted constant quality property price towards the zero-risk constant quality property price as the years pass since the last flood. When a flood occurs, actors become aware of the true flood risk and observed prices quickly adjusts downwards towards the risk adjusted price. We define empirical versions of the zero-risk threshold (P(ZR)) and the actual quality adjusted price (P(A)) as functions of hedonic price indices. The risk-adjusted constant quality price (P(RA)) is obtained via hedonic regressions and a difference-in-difference

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estimation. To test the hypothesis of amnesic and myopic behaviour in property prices, we construct an empirical distribution of P(A) using a bootstrapping approach. We use the confidence interval to test hypotheses of \'no amnesia\' and \'no myopia\' in property prices. If the distribution of the bootstrapped P(A) includes P(ZR) we reject the null hypothesis of \'no myopia\' and conclude there is evidence of myopia. Similarly, we reject the null of no amnesia if following a flood event the bootstrapped distribution goes below the P(RA) and then recovers to levels above P(RA). The city of Brisbane suffered two major devastating floods in 1974 and 2011. The construction of a dam with two compartments, flood and water reservoir, in the mid 1980s lead inhabitants and the market to underestimate the risk of another major event after that of 1974. Our dataset covers property transactions for an inner Brisbane (Australia) area located 5 km from Brisbane Central Business District(CBD) with 30% of each year\'s sales being properties in the flood plain (defined by the 2011 flood) and with proximity to a waterway within the tidal reaches of the Brisbane River. While minor flooding directly impacts only very few properties, the visibility of swollen waterways can provide reminders of flood risk in between major events. This ideal setting allows us to test for myopic and amnesic behaviour for this area over the period 1990- 2015. We find strong support for the behaviour and discuss some of the implications for public policy.

Keywords: risk-adjusted prices, constant quality prices, bootstrapping
JEL: R21, Q51, C43, C15

1 Introduction

Around the world, economic losses due to extreme environmental events, such as flooding, are estimated to have increased substantially. Although some of this increase is driven by changing environmental risk profiles , by far the larger part comes from the increased value of infrastructure developed in risky areas.

Why do we keep building in risky areas? Risky properties are often in high value locations, and the impacts of risks arise only infrequently. Between flood events these properties provide similar levels of utility to those of their risk-free neighbours. Continuing to develop risky properties is rational 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, in general, are very poor at estimating the economic value of long term risk in general, and in terms of floods and property values specifically (Bin and Landry 2013, Gallagher 2013). Several interpretations have been proposed: the idea that agents' behaviour show a large and immediate change in beliefs after a disaster could be consistent with the common Bayesian learning model (Viscusi and Magat, 1992); that agents may suffer both myopia, in that they underestimate future risks, and amnesia, in that they forget the past (, Pryce et al 2011, Agarwal et al (2009)); and that agents might be unaware (Schipper 2014, Bin and Landry 2013).

One outcome consistent with both learning and market myopia and amnesia is that the price of affected properties fall immediately following a flood to a value that internalises the risk devaluation, then recover gradually to the risk-free value. This changing memory and valuation of risk over time will lead to individual wins and losses as properties change hands before and after a flood event. These losses can be significant, because in many places the family home is by far individuals' largest asset.

The scale and uneven distribution of asset loss risk across communities can lead to severe and inequitable financial hardship. In practice, the financial impacts of flood events are often shared, at least partially, across communities though government recovery funds, although these are focussed on immediate needs rather than property value loss.

Over the longer term, risk costs can be borne individually or shared through the distribution of insurance premiums. Whether the individual households affected bear the brunt of asset loss or, alternatively, the costs of inundation or proactive protection are shared across the community, there will be a distribution of costs and benefits, winners and losers, and perceptions of inequitability. The only way to make informed decisions about how to equitably and efficiently manage this risk is to understand it.

To help inform this discussion, this manuscript explores the relationship between flooding events and the patterns of discounting on property prices. We begin below by establishing the current state of understanding in the literature and describing historical and recent flood events in the city of Brisbane, Australia. We then develop new techniques to obtain estimates of quality adjusted zero-risk, risk-adjusted and actual price levels for properties exposed to flooding. We propose to use the estimated 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

Standard Bayesian learning, Knightian or Keynesian uncertainty (Keynes, 1921; Knight, 1921) is a form of structural uncertainty as supposed to parameter or model uncertainty. Full Bayesian updating is reflected in agents learning only if enough structural information of the outcome generating process is provided. Payzan-LeNestour and Bossaerts (2011) study Bayesian learning in unstable settings and conclude that the ability of participants to distinguish between types of uncertainties relies on sufficient revelation of the payoff-generating model. Specifically, when structural uncertainty was induced the participants did not gain awareness of the jumps in the tasks, and fell back to model-free reinforcement learning.

Unawareness (for a recent survey see Schipper (2014)), extends Knight's distinction between risk and ambiguity. Then 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 difficulties to evaluate them probabilistically. Under unawareness, the agent cannot even conceive all relevant contingencies.

In the specific context of studying the response of the housing market to flood danger, Pryce et al (2011) proposed a framework funded upon myopic, amnesiac risk assessment by housing market actors. In this framework agents are aware of the contingency (flood), and myopia and amnesia mean that perceived risk could diverge considerably from actual risk. Myopia is the discounting of information from anticipated future events, with the discount rising progressively as the event becomes less imminent. Amnesia is the discounting of information from past events, with the discount rising progressively as time elapses, although both under Pryce et al (2011)'s amnesia and Agarwal et al (2009)'s agents, who learn and forget, the response would be observationally equivalent. Nevertheless, the Pryce et al (2011) theoretical framework, presented in Figure 1, provides an economic model from which econometric measurements can be defined. There is a zero-risk constant quality property price ($P(ZR)$) i.e. the price of properties which have zero flood risk, adjusted for hedonic characteristics) and the risk-adjusted constant quality property price ($P(RA)$ i.e. the price of properties which accurately price actual flood risk, adjusted for hedonic characteristics). For properties with some flood risk, their actual prices, $P(A)$, tend upwards toward $P(ZR)$, depending on how recently floods have been observed. With very occasional flooding, flood-prone property prices approach $P(ZR)$ and periodically drop (top panel of Figure 1). More regular flood will see prices more regularly pulled down around $P(RA)$ (bottom panel of Figure 1). In this paper we propose an econometric framework that defines measures for $P(ZR)$, $P(RA)$ and $P(A)$ that can be obtained from data and an empirical distribution of $P(A)$ which can be obtained by bootstrapping. These are discussed in Section 3.

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 more recently, in January 1974 and January 2011 (Bureau of Meteorology (2013)). We focus our analysis on the impacts of the January 2011 flood due to data availability and the unique historical circumstances that precede 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 a 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

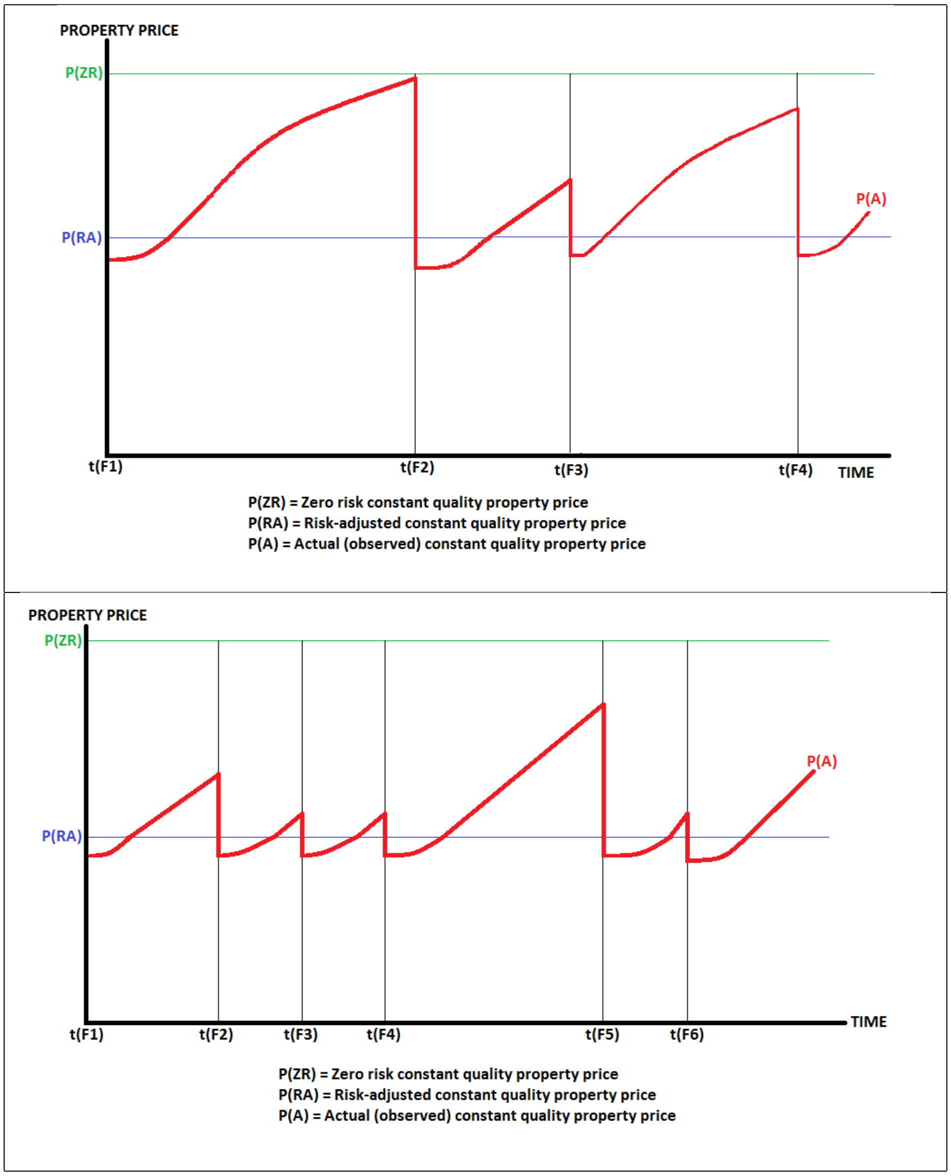

Figure 1: *Adapted from Pryce et al (2011)* - Figures 2 and 3

(see Bureau of Meteorology (2016) and Appendix A).

Our study covers property transactions over the period 1990 – 2015 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. 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 for properties in the flood plain. These properties have a median distance from a waterway of 540 metres (Table 5), compared to 840 metres for flood-free properties in our dataset (Table 4). These waterways are within the tidal reaches of the Brisbane River.

The location has some unique characteristics that add interest beyond the natural experiment that played out around the 2011 Brisbane River floods. 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 other minor flooding events in addition to the major flood in 2011. Most interesting for our sample is a 1996 event.

In addition to these quantitative measurements of flood intensity, the Australian Bureau of Meteorology (2016) records descriptive information of flood events:

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 the behaviours such as myopia, amnesia or learning and forgetting 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. From successive Australian census of population data, Table 1, of the residents of the statistical area (SA2 level) that is used in the empirical part of this manuscript, we observe that only 45% of those living in the study area in 2011 were there five years prior, and we note that 10% of residents in the year of last major flood, 2011, reported living overseas five years prior. The figure is 8% for 2016. It is not unreasonable to think that the residents that moved from overseas 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 Econometric Approach

The aim is to obtain empirical estimates of $P(ZR)$, $P(RA)$ and $P(A)$. We first note these are quality adjusted prices. To obtain a quality adjusted price using a sample of sold properties, a price index needs to be constructed. In this study we construct two time-dummy hedonic price indices (see Bailey et al. (1963), de Haan (2010), Hill (2013)), one for properties in the flood zone and one for those in the flood free area. These indices are then used to compute empirical estimates of $P(ZR)$ and $P(A)$. To assess statistical significance and test the behaviour of prices, we use a bootstrap approach. The level $P(RA)$ is obtained by estimating the per cent of discounting in property prices due to flooding risk using the 2011 event as the treatment. Details of the methodology are discussed in the next subsections.

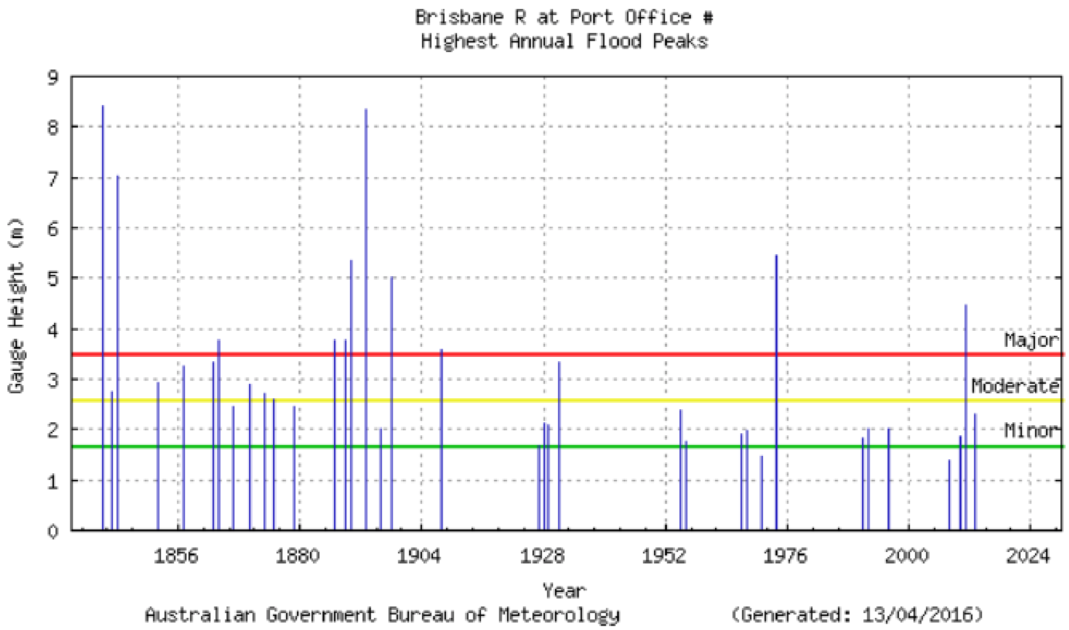

Figure 2: Brisbane Flood History- Source: Bureau of Meterology (2016)

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

	2006	**2011**	**2016**
% persons living in detached or semi-detached dwelling[a)]	53.70	60.70	44.70
% persons renting (all types of dwellings)	42.90	45.30	44.10
% persons lived in the same address five years ago	44.10	44.67	43.26
% persons lived in the same SA2 five years ago	5.20	4.00	5.00
% persons lived in different SA2 five years ago	38.62	34.86	36.65
% persons that lived in different SA2 five years ago but in same state	84	84	88
% persons lived overseas five years ago	6.54	10.00	8.00
[a)] The sample used in the study excludes units and apartments			
Source: Australian Bureau of Statistics - Census by Geography - `http://www.abs.gov.au/websitedbs/D3310114.nsf/home/census`			

3.1 Computing Quality Adjusted Price Indices

The quality adjustment is obtained using a hedonic price index approach. The model to obtain a time-dummy hedonic price index is of the form in (1),

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

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), and $D_{it} = 1$ if i sold in year t, zero otherwise. These variables control for the price trends in the data and the hedonic adjusted indices are obtained by exponentiating $\hat{\delta}_t$ and rescaling to set the base period equal to 100.

The price index obtained from the sample in the flood zone area provides an index denoted 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 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.

From these two indices we compute estimates of $P(ZR)$ and $P(A)$ as follows,

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

$$\widehat{P(ZR)}_t = 100 \tag{2}$$

$$\widehat{P(A)}_t = \frac{P_{F,t}}{P_{NF,t}} \times 100 \tag{3}$$

These definitions allow us to establish where the actual quality adjusted prices are located at each period with respect to the risk-free and risk-adjusted quality adjusted price levels.

3.2 An Estimated Distribution of $P(A)$

To asses the behaviour of property prices statistically, we propose to construct an empirical distribution of $P(A)$ using a bootstrapping approach. By (3) we know it is obtained from the price indices $P_{F,t}$ and $P_{NF,t}$ via estimating model (1), and thus the bootstrap design requires understanding of the structure of the underlying data for this model. We first note that the data have a clear time ordering that needs to be taken into account. However, within each time period, a year in our case, a number of properties are transacted for each flood type (flood/flood-free) and there is no natural ordering in this dimension. The proposal is then to use an i.i.d bootstrap within each time period and type (see Polities (2003) and the many references therein for a discussion on bootstrapping with dependent data, block sampling and subsampling, and Chapter 3 of Chernick, M. R. (2008) for bootstrapping methodology to construct confidence sets). Our approach is summarised in 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.
- estimate the models (1) with sample r and 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. $P_F(0.025)$, $P_{NF}(0.025)$, $P_F(0.0975)$, $P_{NF}(0.0975)$).
- compute an empirical 95% confidence interval for $P(A)_t$, $P(A)(0.0975)$ and $P(A)(0.025)$, using equation (3)

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 unawarness. 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 learning and forgetting.

3.3 The Risk Adjusted Price Level, $P(RA)$

In order to obtain $P(RA)$, we must find the amount of discount due to flooding (refer to Figure 1). We suggest two alternative empirical estimates can be considered, the first using a difference-in-difference approach (this is also used by Bin and Landry (2013) to obtain an estimated discount due to flooding), the second using a hedonic modelling approach.

To obtain the discount via a difference-in-difference approach, we define the flood event as a treatment, in our case the 2011 flood is the treatment. Using a standard setting we have a pre- and post treatment period defined by those properties that signed a sale contract after the flooding event, $After = 1$. 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 plain ($Flood = 1$) and the sale contract was signed from February 2011 onwards ($After = 1$). The difference-in-difference model is estimated as follows,

$$\log(price_{it}) = \beta_0 + \sum_{t=2}^{T} \delta_t D_{it} + \gamma_1 Flood_i + \gamma_2 After_i + \gamma_3 (Flood_i \times After_i) + u_{it} \qquad (4)$$

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

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

The difference-in-difference result can be compared to what is obtained by estimating a standard hedonic model with $Flood_i$ in the model and estimated over the sample of properties in the treated group ($After = 1$). To compute these we estimate (5)

$$\log(price_{it}) = \beta_0 + \sum_{t=\tau}^{T} \delta_t D_{it} + \sum_{k=1}^{K} \beta_k x_{k,it} + \phi Flood_i + e_{it} \qquad (5)$$

Estimating the model for the sample of properties for which $After = 1$, labelled as $t = \tau, \ldots, T$ in (5) 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 is an extension of Rambaldi et al (2013) which originally covered until early 2010. Variables definitions and descriptive statistics for the dataset used in this study, covering the period 1990 to 2015, 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 the Appendix. Table 2 provides a summary of the available hedonic characteristics.

Since the 2011 flood, the Brisbane City Council (BCC) has been working on providing accurate information to residents. On 5 May 2017, it released an online tool "FloodWise Property Reports" (Brisbane City Council (2017)) based on recently completed studies, providing specific and detailed data for each parcel, which we use in this study to define which properties were flooded in the 2011 event. The sample contains 4252 transactions, out of which 1250 were flooded in the 2011 event.

4.1 Pre-testing and estimation of price indices

We first test whether the parameters of the model to construct the price indices, P_F (Flood) and P_{NF} (No Flood), given in (1), are common across the two types. Specifically we test $H_0 : \beta_k, k = 1, \ldots, K$ are common across all properties (i.e. in flood and flood-free areas). The computed f-statistic is 2.1775 (p-value=0.0297). Thus, we reject the null of common slope coefficients across the two types and construct the indices by estimating two separate models.

Estimates of P_F (Flood) and P_{NF} (No Flood) are presented in Figure 3. The figure shows prices increased six-fold over the period 1990-2015 in this area of Brisbane. The price index for those properties in the flood plain, P_F, is mostly below that obtained from the flood-free sample;

however, it would appear they seem to overlap over a number of periods. The indices show prices grew at a lower rate around the Global Financial Crisis period (2008-2009), and the drop in P_F after the 2011 flood event is visually clear.

Before proceeding to the testing of the Pryce et al (2011) framework, we can consider whether the apparent recovering of the prices after the 2011 event in Figure (3) is statistically significant. To test this hypothesis we estimated a simple quadratic model as follows

$$\log(price_{it}) = \beta_0 + x_{it}'\beta + \phi Flood_i + \tau_1(Trend_{it} \times Flood_i) + \tau_2(Trend_{it}^2 \times Flood_i) + u_{it} \qquad (6)$$

where, β_k is a K by 1 vector of parameters, and the model is estimated over the sample which covers sales in the years 2010 to 2015. Correspondently, $Trend$ takes the values of 1 to 6 depending on the year of sale (i.e. 2010=1, 2012=2,...). The estimates are $\hat{\beta}_0 = 11.5167$, $\hat{\phi} = 0.1237$ (p-val = 0.1022), $\hat{\tau_1} = -0.1630$ (p-val = 0.0008), and $\hat{\tau_2} = 0.0242$ (p-val = 0.0004). This is depicted in Figure 4. These results provide some initial evidence that prices have recovered.

4.2 Estimation of risk-adjustment discount

In Section 3.3 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 what is the fully risk adjusted discount. By using alternative approaches we search for the minimum and maximum range where the discount lies.

Table 3 shows the estimates of the discount due to flood risk obtained from the difference-in-difference (DID) specification, model (4), and the hedonic alternative, model (5). The average estimated discount from the DID specification is 7.31%. For the hedonic specification, we estimated the model including all transactions after the flood for three alternative periods, 2011-2013 (478 observations), 2011-2014 (682 observations) and for 2011-2015 (865 observations), with the estimates using the sample from 2011-2013 providing the largest discount, 9.53%. Bin and Landry (2013) find after major events (e.g. Hurricane) a significant risk premium ranging between 6.0%

Table 2: Hedonic Characteristics Available in the Data

Type	Variables
Land	Lot size (sqMts), Vacant Distances to: River, Wateway, Industry, Parks, Bus stop, Schools, City, Shops, Rail station
Structure	Footprint (sqMts), Construction Period (Pre-War, Post War, Late 20th, 21st), Bedrooms, Bathrooms, Car parks
Flood	A property flooded in the January 2011 is in the floodplain
Sample period	1990-2015
After	Sale contract signed from February 2011 onwards
Transactions	3002 flood-free, 1250 flood plain, 865 for After=1

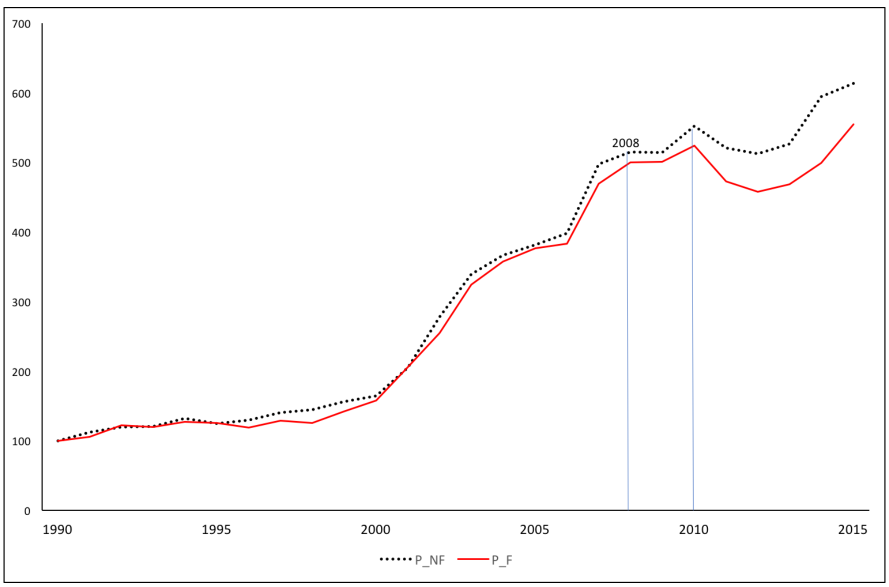

Figure 3: Price Indices for Properties Affected/Not Affected by the 2011 Flood Event

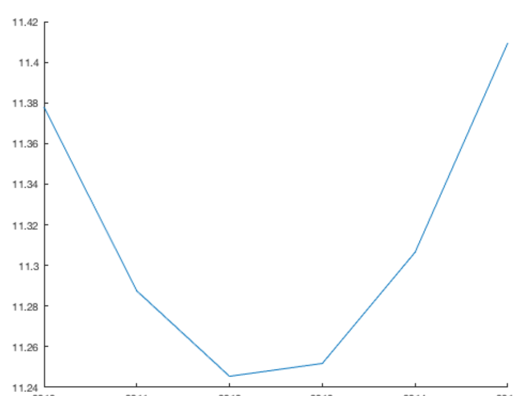

Figure 4: Estimated Quadratic Trend in Prices

and 20.2% for homes sold in the flood zone.

In the next section the estimate of $P(RA)$ is provided as the range between these two values. Gallagher uses DID also, add here their estimates.

4.3 Putting it All Together - $P(ZR)$, $P(RA)$, $P(A)$

Figure 5 presents the estimates of $P(ZR)$ (Zero Risk Constant Quality Price Index), the minimum and maximum empirical $P(RA)$ (Risk-Adjusted Constant Quality Price Index) based on the estimates presented in the previous sections, and the actual Quality Adjusted Price Index, $P(A)$, labelled "P(A)(Sample)", and the empirical 95% interval for $P(A)$ obtained from the bootstrap exercise[1]. 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.

The constructed 95% bootstrapped interval for $P(A)$ is above the $P(RA)$ level and it includes $P(ZR)$ in a number of instances prior to 1996. A price signal is clear after the localised event of 1996, when the actual price is at the risk-adjusted price level. This is clear as the empirical distribution of the actual price contains the $P(RA)$ estimated range. However, prices stay at the risk-adjusted level for only two years and then the estimated distribution of $P(A)$ returns to levels that are close or equal to the $P(ZR)$ during the 00's and until 2010 with the exception of 2002 where the actual price distribution is very close to the $P(RA)$ level again. The Australia 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. The Global Financial Crisis of 2007-2008 and increasing rainfall in coastal areas close to the city of Brisbane (need to cite here) 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

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

Table 3: Estimated Discount due to Flood Risk

Model	Difference-in-Difference	Hedonic		
Sample	1990-2015	2011-2015	2011-2014	2011-2013
$Flood$	-0.0107	-0.0895	**-0.0953**	-0.0780
	(-0.0843)	(-3.9221)	(-3.6711)	(-2.2718)
$After$	-0.1359			
	(-11.033)			
$Flood \times After$	**-0.0731**			
	(-2.5600)			
R-Sq	0.796	0.494	0.504	0.505
N	4252	865	682	478
Controls	time dummies	time dummies and hedonic characteristics		

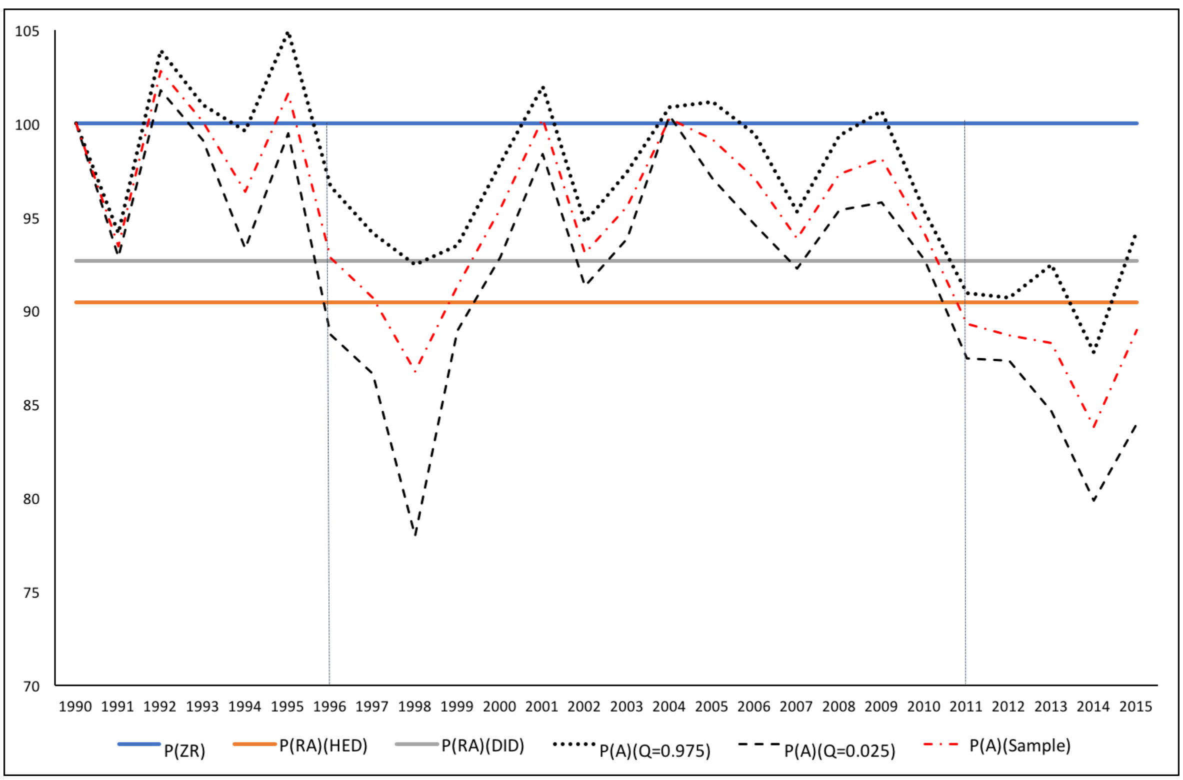

Figure 5: Estimated Zero-Risk and Adjusted Price Levels and Distribution of (Quality Adjusted) Actual Prices.

level. In 2011 the distribution of $P(A)$ goes completely below $P(RA)$ estimates until 2014, but shows signs of recovering by 2015 when the distribution of the actual price is at the risk-adjusted price level again (i.e. it includes the $P(RA)$ estimates). This is the expected behaviour from Pryce et al (2011)'s theoretical framework to the case of an infrequent flood. Bin and Landry (2013) using hedonic valuation models find flood impacts on prices ranging between 6% and 20%; however, this effect diminishing over time, essentially disappearing about 5 or 6 years.

Overall, these estimates provide evidence to reject the stated null hypotheses that quality adjusted prices behaving efficiently in the case of infrequent floods in Brisbane. Following the 2011 flood prices dropped to a level significantly below the risk-adjusted level; however, after five years the level although above the $P(RA)$, is not close to the zero-risk level. Given a number of litigations have been filed arguing negligent management of the dam, which are are still ongoing in 2017, it is unclear weather agents have learned about the flood risk or they do not have enough information to update their perceptions of the likely effect of another major weather event. Pryce et al(2001) propose that when the observations moved to the case of more *frequent* floods, then $P(RA)$ will no longer be constant, but have a downward trend (shown in Figure 6).

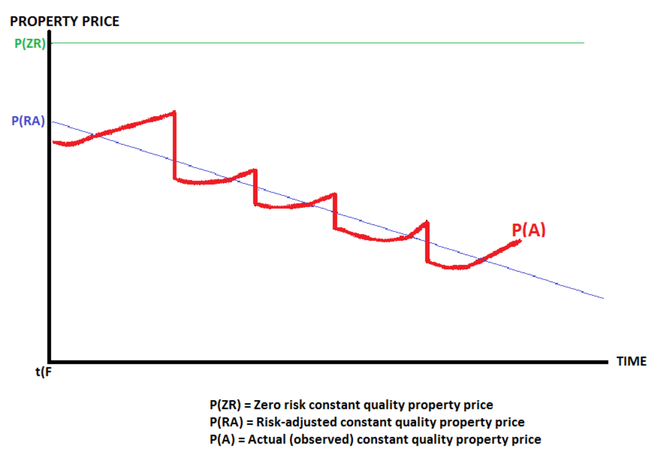

Figure 6: *Adapted from Pryce et al (2011)* - Figure 4

5 Discussion and Implications

Our results clearly indicate that properties are significantly devalued immediately following a major flood event. We found prices were at the zero-risk level for periods preceding flood events, and recover to that level following a minor storm event (in 1996) prior to the major flood of 2011. Following the January 2011 event, prices fell up to 26% below the risk-free price level over the next three years and recovered to the risk-adjusted level (estimated between 7.3 % and 9.5% below the risk-free level) by the forth year after the event. This is consistent with the results found by Bin and Landry (2013) of the effect lasting at least five years. Gallagher (2013) studies the take up of insurance prior and after a major flood and finds a significant take up in flood insurance persisting into five years after the event. However, the take-up in years before the flood is statistically zero. Add Atreya et al (2013) here al well.

Our results are consistent with two possible behaviours by agents. The first is that agents were aware and used all available data to come to the conclusion that no major weather event could result in a repeat of the 1974 devastation to the areas of the city in the floodplain. Both learning and forgetting, as well as myopia and amnesia would be consistent with this result. The second is that they were unaware. The reality is that the market is likely composed of both types. Between the two major floods of 1974 and 2011 the city of Brisbane underwent a major transformation. Its population grew by 30% (and the greater Brisbane by 50%) 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 history to conclude there will be no repeat.

Estimating the scale of this result is important because the way the market values the risk of flooding has important implications for designing effective and equitable ways of managing this risk for both individual and communities. An ideal market would appropriately value the long-term average risk of flooding and build an appropriate risk discount into property values. Owners of risky properties would pay less at the time of purchase to cover the costs they incur when flooding does occur.

However, the evidence from this and other studies would indicate that there is evidence of unawareness, forgetting, and myopic and amnesic type of behaviours. Property owners who purchase properties just before a major flood are at risk of losing significant value on what is likely their largest single asset. Moreover, due to the localised nature of flooding, adjacent or nearby properties can face distinctly different levels of flood risk and large devaluation losses may fall on only a small proportion of the community. Individual property owners may not be able to afford to protect or recover from damage to their largest asset. On the other hand, to what degree should an entire community pay to protect the small proportion of properties at risk of flood?

In practice, following a major catastrophic event everyone pays. Recovery usually requires coordinated and costly responses from government, insurers and individuals affected both directly and indirectly. The total cost of the major Brisbane flood event in 2010/11 has been estimated at $XXB. In the year following the flood, those Australian taxpayers not directly impacted contributed to the costs of recovery via a levy of 0.5% on income above $50,000 and 1% of income above $100,000. This money was used to pay for immediate recovery needs and infrastructure repair. For instance, the Premier's Disaster Relief Appeal distributed payments of $2000 in the days following the floods, plus up to $250,000 for owners of homes destroyed by the flood and $80,000 for owners of homes with structural damage (cite Premier's Disaster Relief Appeal Distribution Committee Report).

These payments were focussed on relieving the immediate impacts of flood events, rather than compensating property owners for devaluation. On the other hand, the expectation that governments will step in to finance recovery following a flood is likely to affect how properties are devalued in risky areas. This suggests that the devaluation calculated in the current analysis may underestimate the true devaluation associated with flood risk.

In theory, an efficient private insurance market provides both individualised financial protection against the risk of flooding and a quantitative estimate of average risk costs across communities and over time. There is evidence that markets internalise the discounted long-term average costs of insurance in property values; that is, properties in risky areas with higher insurance costs sell for proportionally less than equivalent nearby properties with lower premiums. This, however, requires that risk or premium information is accurate and readily available.

In the case of the 2010/11 flood events in Brisbane, government recovery payments funded by the community were necessary partly due to the fact that a large number of households that believed they were insured had their claims denied because they were not covered for "riverine" floods. There is evidence that insurance companies and federal regulators were aware of issues around the definition of "flood" in insurance policies prior to the 2010/11 Brisbane floods (Insurance Council of Australia (2008), Australian Competition and Consumer Commission (2008)). In response to these issues, a federal government committee produced a report into the operations of the insurance industry during disaster events in February 2012 (cite Standing Committee on Social Policy and Legal Affairs of the Parliament of Australia). On the 18th of June 2012 the Federal Government enacted regulations to give effect to a definition of flood with a two year transition period.

As a result of these flood events and policy changes, the insurance industry has begun to incorporate a more nuanced understanding of the spatial distribution of flood risk into its premium profiles (cite). This may gradually improve the market valuation of risk as the long-term discounted value of increased premiums are internalised into property values (cite). In turn, this projected change in market valuation of flood risk would be expected to modify the estimate produced by the current analysis for future flood events.

However, changes to insurance premiums have led both to complaints that premiums have unnecessarily risen for properties that face little risk, and that premiums for risky properties have risen so much they're unaffordable. This highlights the issue around perceptions of equity when managing risk. Whatever action is taken to understand and appropriately value flood risk, including taking no action until a major event occurs, creates winners and losers. The only way to understand these issues and manage them equitably is to understand how the market current values risk, in terms of analyses like the one completed here, and how it could manage that risk better in future.

Accurately understanding the scale and cause of the loss of property value provides an opportunity to harness the effect to protect against future events. In addition to the short-term devaluation effects of flood events, previous analyses and our results here show that at-risk properties are marginally less valuable that risk-free properties over the long term. Although this effect is small in a relative sense, the significant absolute value of property suggests that reducing risk could increase the total value of property stock in a community, especially in dense urban areas. In some places, it may make economic sense for local governments and communities to fund proactive actions to manage flood risk today, in order to increase the value of protected properties and the associated property taxes in future.

In the long run reducing the risk of flood damage requires management by government across a number of areas such as land-use, building codes, and investment in physical mitigation measures. Clear adaptation strategies must be implemented.

6 Conclusions

Economic losses due to extreme environmental events, such as flooding, continue to rise, largely because we keep building in high-value but risky areas. This behaviour is rational as long as the property market accurately reflects the long term discounted value of that risk. Here, the dynamics of urban property prices in the flood plain to be consistent with buyers that underestimating future risks and forget the past if they are aware of the non-zero probability of a major flood.

The impacts of this are potentially significant to individuals and the community alike. Property owners who purchased properties just before one of these major floods suffered significant personal losses on their largest single asset (cite). Taxpayers not directly affected by the floods were required to contribute to a levy that helped fund recovery and underinsured properties. Reviews of the insurance industry have led to refined definitions of flood damage and revised premiums across areas perceived to be at risk of flood.

Understanding the way flood risk devalues property may provide opportunities for individuals, industry and communities and governments to make informed decisions about how best to protect against damage in future. Reducing the risk of flood damage through adaptation and mitigation efforts will require coordinated effort across industry and all scales of government. Choosing and funding adaptation equitably will require a detailed understanding of how risk affects prices, as we provide here.

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Appendix

Table A1: Descriptive Statistics - Whole Sample

	min	max	median	mean	Std	Description/Source
Price (thousands)	9.7	3600	375.5	434.93	318.49	observed sale price (RP)
Age1	0	1	0	0.484	0.500	Pre-war (RP)
Age2	0	1	0	0.093	0.290	War (1942_1947) (RP)
Age3	0	1	0	0.304	0.460	After War (RP)
Age4	0	1	0	0.060	0.237	Late20thC (RP)
Age5	0	1	0	0.060	0.237	contemporary (RP)
NoH	0	1	0	0.023	0.151	Vacant Land
Land area	127.000	2555.000	607.000	605.396	202.350	Sq Mts -RP, BCC
Structure area	0	535.630	172.140	180.551	66.474	Sq Mts -DERM (LiDAR) 2010
Bath	0	4	1.000	1.448	0.721	RP, BCC, or RE
Beds	0	8	3.000	3.112	0.952	RP, BCC, or RE
Cars	0	8	2.000	1.638	0.792	RP, BCC, or RE
dist_river	17.436	3671.676	1703.389	1689.597	922.152	Mts -BCC and geospatial tools
dist_waterway	17.436	2147.959	732.750	750.478	463.513	Mts -BCC and geospatial tools
dist_industry	8.237	1844.367	1057.765	987.405	454.121	Mts -BCC and geospatial tools
dist_parks	0.000	638.425	162.961	189.904	136.166	Mts -BCC and geospatial tools
dist_busStop	3.177	488.568	151.565	174.147	100.820	Mts -BCC and geospatial tools
dist_schools	108.911	3342.636	1299.811	1381.371	702.989	Mts -BCC and geospatial tools
dist_city	4088.482	7899.440	5908.961	5873.433	959.630	Mts -BCC and geospatial tools
dist_Shosp	97.634	2572.540	1243.027	1287.023	596.785	Mts -BCC and geospatial tools
dist_rails	95.311	3661.013	1776.348	1749.646	872.990	Mts -BCC and geospatial tools
dis_hos	1238.348	4089.892	2552.549	2562.484	611.644	Mts -BCC and geospatial tools

Source/notes

RPdata.com (http://www.rpdata.net.au/) (RP) - Currently Corelogic

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

Google View (GV) or www.realestate.com (RE)

Table A2. Descriptive Statistics - Flood Plain						
	min	max	median	mean	Std	Description/Source
Price (thousands)	9.7	1520	334.750	368.639	228.104	observed sale price (RP)
Age1	0	1	0	0	0	Pre-war (RP)
Age2	0	1	0	0.086	0.280	War (1942_1947) (RP)
Age3	0	1	0	0.308	0.462	After War (RP)
Age4	0	1	0	0.063	0.243	Late20thC (RP)
Age5	0	1	0	0.057	0.232	contemporary (RP)
NoH	0	1	0	0.030	0.172	Vacant Land
Land area	171	2218	556	563.083	181.831	Sq Mts -RP, BCC
Structure area	0	500.89	156.79	162.964	62.632	Sq Mts -DERM (LiDAR) 2010
Bath	0	4	1	1.319	0.637	RP, BCC, or RE
Beds	0	6	3	2.934	0.907	RP, BCC, or RE
Cars	0	6	1	1.550	0.765	RP, BCC, or RE
dist_river	17.436	3538.351	1466.157	1466.063	838.445	Mts -BCC and geospatial tools
dist_waterway	17.436	2069.799	539.733	610.774	450.070	Mts -BCC and geospatial tools
dist_industry	8.237	1844.367	1055.923	977.793	450.070	Mts -BCC and geospatial tools
dist_parks	0.000	638.425	110.504	179.917	164.126	Mts -BCC and geospatial tools
dist_busStop	21.641	475.519	151.142	176.862	102.241	Mts -BCC and geospatial tools
dist_schools	191.961	3157.050	1163.445	1210.189	616.484	Mts -BCC and geospatial tools
dist_city	4088.482	7719.363	5651.909	5636.395	878.824	Mts -BCC and geospatial tools
dist_Shosp	166.964	2401.976	1060.084	1139.883	520.182	Mts -BCC and geospatial tools
dist_rails	124.875	3444.285	1552.928	1524.128	789.524	Mts -BCC and geospatial tools
dis_hos	1379.579	4089.892	2616.100	2585.189	619.701	Mts -BCC and geospatial tools

Sample Size = 1250

Source/notes

RPdata.com (http://www.rpdata.net.au/) (RP) - Currently Corelogic

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

Google View (GV) or www.realestate.com (RE)

Table A.3. Descriptive Statistics - Flood Free						
	min	max	median	mean	Std	Description/Source
Price (thousands)	26.571	3600	400	462.527	345.604	observed sale price (RP)
Age1	0	1	0	0	0	Pre-war (RP)
Age2	0	1	0	0.096	0.295	War (1942_1947) (RP)
Age3	0	1	0	0.302	0.459	After War (RP)
Age4	0	1	0	0.058	0.234	Late20thC (RP)
Age5	0	1	0	0.061	0.239	contemporary (RP)
NoH	0	1	0	0.020	0.141	Vacant Land
Land area	127	2555	607	623.015	207.807	Sq Mts -RP, BCC
Structure area	0	535.630	180.250	187.874	66.665	Sq Mts -DERM (LiDAR) 2010
Bath	0	4	1	1.502	0.748	RP, BCC, or RE
Beds	0	8	3	3.186	0.960	RP, BCC, or RE
Cars	0	8	2	1.675	0.801	RP, BCC, or RE
dist_river	91.504	3671.676	1831.801	1782.674	939.417	Mts -BCC and geospatial tools
dist_waterway	41.756	2147.959	839.117	808.650	456.631	Mts -BCC and geospatial tools
dist_industry	23.583	1795.832	1059.455	991.408	448.165	Mts -BCC and geospatial tools
dist_parks	5.666	614.282	171.465	194.062	122.450	Mts -BCC and geospatial tools
dist_busStop	3.177	488.568	152.260	173.017	100.218	Mts -BCC and geospatial tools
dist_schools	108.911	3342.636	1392.004	1452.650	724.276	Mts -BCC and geospatial tools
dist_city	4186.145	7899.440	6065.026	5972.133	974.616	Mts -BCC and geospatial tools
dist_Shosp	97.634	2572.540	1308.757	1348.291	615.718	Mts -BCC and geospatial tools
dist_rails	95.311	3661.013	1932.469	1843.549	888.884	Mts -BCC and geospatial tools
dis_hos	1238.348	3980.884	2542.947	2553.029	608.111	Mts -BCC and geospatial tools

Sample Size = 3002

Source/notes

RPdata.com (http://www.rpdata.net.au/) (RP) - Currently Corelogic

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

Google View (GV) or www.realestate.com (RE)